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A decision support framework to improve the business performance of e-commerce retailers and logistics providers through reverse logistics strategies selection

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Abstract

Purpose – This study evaluates, from a business process management (BPM) perspective, four reverse logistics (RL) strategies (Lockers, Click & Collect, Microhubs and 3PL) once product returns are authorized. It addresses the critical first-stage decision – home collection vs designated drop-off – while explicitly analyzing the detrimental impact of failed collection attempts due to customer absence on urban logistics efficiency, aiming to enhance the business performance of e-commerce retailers and logistics providers.

Design/methodology/approach – A decision support framework is developed, applying the technique for order preference by similarity to ideal solution to assess each strategy and a simulation of 1,000 product return scenarios is conducted. The methodology incorporates a robust sensitivity analysis modeling varying rates of failed first-time collections, quantifying their effect on cost, cycle time, CO_2 emissions and expected customer utility.

Findings – Baseline results identify Urban Microhubs as the most balanced strategy. However, sensitivity analysis reveals that as failed collections increase, the efficiency of attended strategies (3PL and Urban Microhubs) degrades significantly due to re-attempt costs. This shifts the strategic preference toward unattended strategies like lockers.

Originality/value – The study offers original value by integrating operational, environmental and customer-focused metrics into a unified framework for evaluating RL scenarios. Its multidimensional comparison of the four strategies provides novel insights that advance theory and guide the design of more efficient and sustainable return strategies, enabling e-commerce and logistics operators to adopt differentiated policy profiles (cost-driven or green-driven). Ultimately, the primary value of this research resides in providing a structured

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methodology to analyze complex operational scenarios. Additionally, the explicit modeling of failed collections provides novel insights that advance BPM theory, empowering context-specific managerial decision-making.

Keywords Decision support system, Reverse logistics strategies, Business performance, Product returns e-commerce, Synthetic database

Paper type Research article

1. Introduction

E-commerce has driven one of the most significant transformations in distribution systems over the last two decades and its accelerated growth has also prompted the immense development of forward logistics. As is widely acknowledged, the costs associated with last-mile delivery constitute the most expensive element of logistics operations (Allen *et al.*, 2017). In addition, firms must also manage reverse flows triggered by customer dissatisfaction, which ultimately result in product returns, generating additional high costs that erode profitability and reduce competitive advantage.

Specialized literature highlights that returns in e-commerce can exceed 30% of sales in certain categories, presenting a significant operational and financial challenge in terms of management (Govindan *et al.*, 2015). Indeed, it is estimated that around 30% of products purchased online are returned, which is a much higher percentage than in physical shops, where the figure is closer to 9% (Saleh, 2024). Return rates in e-commerce vary considerably depending on the product category, the market context and the country. Li *et al.* (2013) noted that product return rates range from 10% to 20% for casual apparel and can reach 35%–40% for high fashion. More recent studies indicate that books have return rates ranging from 10% to 15% of orders, 10%–18% for IT and electronic components, 30%–40% for fashion items and 5%–15% for fast-moving consumer goods (Das *et al.*, 2020; Nanayakkara *et al.*, 2022). Across Europe, return rates in 2020 ranged from 36% to 56% in countries such as the United Kingdom, Germany, Spain and France, with an average around 43.5% (Dobroselskyi *et al.*, 2021).

When customers decide to return items, reverse logistics (RL) plays a significant role. For the e-commerce industry, the consumer returns process inevitably increases a company's operating costs (Wurjaningrum and Meirina, 2016). Against this backdrop, the efficient, sustainable and customer-friendly configuration of the RL process has become a key factor in business competitiveness. However, RL operations and their supporting supply chains (SCs) are notably more complex than those of traditional manufacturing SCs (Dennis and Kambil, 2003). This is largely because RL operations are demanding to manage due to the variety of activities involved (Amini *et al.*, 2005).

The effective management of RL activities can substantially impact a company's financial performance (Morgan *et al.*, 2018), a finding supported by Cahyono *et al.* (2020), who emphasized that efficient RL practices lead to cost savings and other operational benefits. Designing effective return channels is therefore essential, as is identifying and defining the key elements that influence business performance, particularly in terms of profitability, customer experience and environmental sustainability (Govindan *et al.*, 2015). Furthermore, return cycle time, capturing the interval between the customer initiating the return process and its completion, must be considered. This indicator is a key measure of organizational efficiency across multiple functions and directly influences cost structures and customer satisfaction, as a rapid response to customers is often a major quality attribute (Kanagal, 1991).

In terms of customer satisfaction, it is crucial for companies to address consumer complaints effectively, as satisfied clients are highly likely to recommend the business to others. This tendency is reflected in the Expected Customer Utility (ECU), which will be used from now on to denote customer satisfaction. Janakiraman *et al.* (2016) state that flexible RL systems are a critical mechanism for addressing these complaints. Zhang *et al.* (2005) stated that RL systems address the diverse needs of clients by focusing on effectively meeting these requirements.

However, this focus on service excellence creates a challenging trade-off. While immediate and effective RL can enhance ECU – a key driver of competitive advantage (Daugherty *et al.*, 2001)—it inevitably leads to an increase in operating costs (Wurjaningrum and Meirina, 2016). On average, firms will spend 9–15% of their total revenues on returns, though improvements in RL management could increase enterprise revenues by 5% of total sales (Greve and Davis, 2015). It is therefore essential to implement systems that ensure the efficient movement of goods and information from the point of consumption to the point of origin, in order to generate value for the firm (Farahani, 2018). Pawar *et al.* (2024) also noted that properly implementing good RL practices can decrease return processing costs by around 25%, increase productivity by 10%, boost net profits by 5% and enhance ECU and retention.

Despite the positive aspects of e-commerce as a source of income, its negative impact on sustainability must also be considered. Carbon emissions present a significant challenge to environmental sustainability, arising from transportation, manufacturing and energy consumption (Huang *et al.*, 2023). To avoid these adverse effects, companies are optimizing transportation routes, using eco-friendly packaging and implementing other sustainable practices (Ahmad *et al.*, 2022). However, approximately 30% of online orders are returned, which presents another challenge. Various mitigation strategies have been proposed to address this, such as new e-commerce delivery vehicles that can reduce transportation distances by 2.5%–10%, thereby lowering CO_2 emissions (Buldeo Rai *et al.*, 2022). These strategies enhance environmental performance, support compliance with regulatory frameworks and improve brand perception among environmentally conscious consumers (Liu *et al.*, 2022).

Although RL encompasses around ten different activities (Melo *et al.*, 2022), each with potential implications for cost, carbon emissions, cycle time and ECU, there is a gap in the literature when analyzing the first activity in the RL process after a product return has been authorized by the manufacturer/distributor. We have chosen this activity for our research for four compelling reasons: (1) it is one of the earliest stages in the RL process, occurring in close proximity to the customer; (2) it has a direct impact on operational costs, cycle time and CO_2 emissions in urban areas; (3) it has a significant influence on customer utility; and (4) it can provide guidelines for achieving mutual benefits for customers, businesses and logistics service providers. This activity involves either physically retrieving the item from the customer's location or the customer delivering it to a designated drop-off point (e.g. retail stores or lockers). The four most prominent return strategies – lockers, Click & Collect (C&C), third-party logistics (3PL) and Urban Microhubs (from now onwards "Microhubs") — will be analyzed. Despite the undeniable importance of this scenario, however, there are very few publications in logistics and e-commerce journals and empirical studies are particularly scarce (Kawa, 2021). Furthermore, no existing approach has been identified to support e-commerce firms in selecting the most suitable strategy from these four options. Consequently, the primary goal of this study is strictly rooted in Business Process Management (BPM) and the maximization of corporate profitability. To construct a functional decision support framework (DSF) for internal decision-making, RL alternatives are classified based on how the enterprise orchestrates its resources, rather than solely on the final delivery mode. From a BPM perspective, this study extends existing decision-support approaches by explicitly embedding operational exception management – specifically failed first-time collections – into the early-stage design of RL processes. By doing so, return strategy selection is reframed as a problem of resource orchestration under operational uncertainty rather than conventional channel choice. Additionally, to the authors' knowledge, this is the first study to incorporate uncollection rates as an explicit sensitivity dimension in the assessment of RL return strategies. To address this gap, this study proposes a new framework that enables companies to tailor key operational variables to their specific context to choose the best RL strategy. This framework applies a simulation-based approach utilizing a synthetic database constructed from realistic assumptions derived from academic literature, insights from company managers and an experiment undertaken with a 3PL provider in an urban area. A rigorous MCDM framework is proposed, specifically the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank the strategies and find the most feasible one. The robustness of this determination is evaluated through a sensitivity analysis to assess how the rate of failed attempts to return items to consumers' homes or business facilities impacts the performance and sustainability of both e-commerce retailers and logistics firms.

Unlike previous empirical studies that attempt to prescribe a universal 'best' strategy based on static market snapshots, this research acknowledges that optimal RL strategies are context-dependent. Therefore, the primary contribution of this study is not merely the ranking of strategies *per se*, but the development of a robust, vendor-neutral DSF. The proposed DSF, supported by a methodology, is designed to be utilized by e-commerce practitioners, who can replace the simulated parameters with their specific internal data (e.g. actual fleet costs, local urban geography, local failure rates) to derive tailored strategic decisions.

2. Return strategies

In the logistics literature, delivery and return channels – such as door-to-door, parcel lockers, PUDO and C&C – are primarily defined from the customer's point of view, describing how consumers physically access logistics services. While this classification is well established and widely adopted, it fails to fully capture the complex organizational and process-level decisions faced by e-commerce retailers and logistics service providers when designing RL operations.

Accordingly, this study adopts a rigorous business process perspective, shifting the analytical focus from isolated consumer touchpoints to the selection of RL return strategies. A return strategy, or operational configuration, is defined herein as an integrated orchestration of the initial RL stage following return authorization. This encompasses the customer interface, the physical collection mechanism and the degree of operational and organizational consolidation.

From this perspective, the labels "Lockers" and "Click & Collect" are used as shorthand identifiers for self-service, drop-off-oriented return strategies, whereas "3PL" and "Microhubs" denote door-to-door-oriented strategies governed by fundamentally different organizational and consolidation logics. Crucially, Microhubs are not treated merely as customer-facing return channels, but as back-end process configurations that restructure the RL workflow through urban consolidation and coordinated collection activities. By conceptualizing these alternatives as archetypal RL process configurations rather than literal organizational or infrastructural entities, this process-oriented framing enables an analytically equivalent comparison within a unified decision-support framework, fully consistent with BPM research.

Consequently, this study evaluates the execution of these reverse flows, whether managed internally by the e-retailer, executed via consolidation networks, or outsourced to a third party. Lockers and C&C function as dedicated drop-off nodes; however, lockers provide 24/7 unattended access, whereas C&C points are typically attended facilities with restricted operating hours. In contrast, 3PL and Microhubs require the direct physical retrieval of items from the consumer's location. Ultimately, each configuration represents a distinct strategic trade-off, strategically shifting the burden of logistical effort, operational friction and flexibility between the consumer and the enterprise, as detailed in the subsequent sections.

2.1 Lockers

The boom in online orders has led to longer delivery times, road congestion and higher carbon emissions. Parcel lockers are a proposed solution to these challenges, offering secure, self-service parcel collection (Arslan, 2026). This strategy involves consumers actively in the last-mile delivery and return processes by sending a notification message once the product return is approved, informing them that they can return the parcel by entering a code at the system interface. Consequently, consumers are empowered to return their parcels at their convenience, utilizing a 24/7 service at their preferred location. Self-service returns enable consolidated collection and circumvent the issue of failed first-time return attempts at home or business locations. This leads to more efficient operations, reduced freight traffic and lower CO_2 emissions. This can translate into significant environmental improvements, as well as a substantial reduction in operating costs, because it is estimated that 7.6% of deliveries fail on the first attempt and this rate more than doubles on the second attempt (Choo, 2016). This supports the adoption of lockers in the returns process, as opposed to doorstep returns.

2.2 Click & Collect

C&C services, where customers collect and return products themselves, are increasingly popular as they help retailers avoid costly last-mile delivery operations and can encourage consumers to make additional purchases in-store while collecting or returning goods. In this study, we consider designated collection or return points to include the retailer's physical shops, as well as gas stations, post offices and similar facilities. In 2016, online sales using C&C services accounted for 25% of all online clothing and footwear sales in the UK and some research suggests that across all types of purchases, 4% of individuals always make additional purchases when collecting their goods in-store (Allen *et al.*, 2017). Furthermore, a survey of UK online retailers operating C&C in-store found that approximately 90% offered free deliveries to consumers using this service (Oracle, 2016), although home delivery for non-food retail under C&C costs UK retailers about four times more than traditional in-store purchases (Capistrano and Buluran, 2021). Nevertheless, this research highlights that consumers were generally unwilling to cover these home delivery costs, while others were prepared to pay up to £4 per order for same-day delivery. Conversely, some implementations of this strategy achieved reductions of around 90% in distance traveled and CO_2 emissions associated with last-mile deliveries (González-Varona *et al.*, 2020), similar to those reported by Milewski and Milewski (2021) with a reduction between 74% and 87% in fuel consumption per order.

2.3 Microhubs

Microhubs are derived from the concept of Urban Consolidation Centers (UCCs), which is a logistics strategy for reducing emissions, minimizing congestion and improving quality of life in urban areas and city centers (Katsela *et al.*, 2022). UCCs are located in close proximity to the area they serve. Consolidated deliveries are made within the vicinity while simultaneously integrating RL operations by collecting returned products from shoppers' facilities and optimizing delivery routes. To this end, Microhubs often use environmentally friendly vehicles, such as electric and gas-powered goods vehicles and cargo bikes (Allen *et al.*, 2012; Browne *et al.*, 2005; Quak *et al.*, 2014; Brown and Guiffrida, 2014). By improving the load factor of goods, Microhubs can reduce the total distance traveled and CO_2 emissions through reductions in distance and the use of low-emission vehicles (Allen *et al.*, 2012). Previous authors have reported improvements including increases in vehicle load factors (15%–100%), reductions in vehicle trips (60%–80%) and reductions in gas emissions (25%–80%). Microhubs operate based on a two-stage delivery process to perform at these efficiency levels (Janjevic and Ndiaye, 2014; Macharis and Kin, 2017; Ballare and Lin, 2020): the first stage comprises collecting returned items from consumers and transporting them to the Microhubs. The second stage involves transporting consolidated loads from the hub to facilities outside the city. Small city hubs in inner cities, from which delivery rounds are made using small vehicles, have been developed by urban delivery organizations of European parcel providers (Ducret, 2014). This operational model is identical for RL, leveraging the same delivery infrastructure and vehicle characteristics. The process is mirrored, enabling the consolidation of returned items at the hub before they are transported out of the city center.

2.4 Third party logistics (3PL)

3PL providers enable companies to concentrate on their core businesses by sub-contracting activities, such as logistics, where they possess less expertise, thus offering a platform for outsourcing all or parts of the SC functions. However, the process of selecting 3PL providers begins with the development of decision criteria for defining and assessing potential candidates that can satisfy the firm's service needs (Boyson *et al.*, 1999).

Regarding CO_2 emissions and cost criteria, the challenge lies in balancing the demands of freight consolidation (Ponce *et al.*, 2020). Lower unit transportation costs can be achieved through full vehicle shipments or larger shipments (Satır *et al.*, 2018; Hanbazazah *et al.*, 2019), which, conversely, result in lower delivery/collection frequency and higher cycle time rates. Nevertheless, fewer shipments are generally preferred to reduce the amount of polluting emissions (Stenius *et al.*, 2018).

3. Methodology

Wang *et al.* (2024) stated that while consumers' choice of shopping channels has been extensively studied, limited attention has been given to their selection of omni-channel delivery. This lack of research is even more pronounced concerning the customer's decision to return a product, given the notable scarcity of detailed and reliable information regarding the key operational variables involved in RL. Furthermore, no existing methodology has been identified to effectively assess business, distributor, or logistics services during this initial stage of the returning process. To address this objective, a rigorous MCDM framework is developed, applying TOPSIS for strategy ranking. Figure 1 shows the phases of the proposed methodology.

The methodology begins with *Phase 1* and the identification of the most relevant criteria, key variables and information derived from academic sources and private sector databases. The literature review was conducted *with the specific objective of extracting robust parameters to populate the stochastic simulation model*, thereby transparently aligning our methodology with our BPM-focused goals rather than attempting to restructure existing conceptual consumer taxonomies. In *Phase 2*, due to the limited availability of comparable data across different strategies, a local experiment supported by a 3PL company was conducted in a medium-sized city in Spain to evaluate variations in the selected criteria when a specific number of orders must be collected within a defined inner urban area. In *Phase 3*, the insights obtained from the previous experiment were refined using additional information collected in Phase 1. In *Phase 4*, based on the consolidated dataset, a simulation was designed to assess the performance of each strategy by varying the criteria and associated variables within their defined ranges, as well as considering the dimensions of the return items due to their implications for costs and CO_2 emissions. This simulation consists of 1,000 returns, each evaluated across the four strategies, generating a synthetic dataset from which, in *Phase 5*, statistical measures (e.g. averages, mean deviations) are calculated. Subsequently, the TOPSIS method is applied to identify the most suitable alternative. Finally, in *Phase 6*, a sensitivity analysis is performed to evaluate the robustness of the results under scenarios involving unreturned orders due to customer

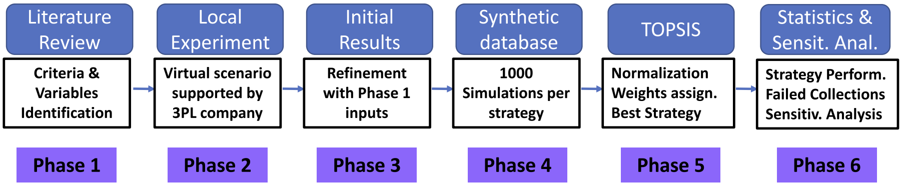

Figure 1. Methodology to determine the best return strategy. Source: Authors' own work

absence at home, specifically for microhub and 3PL strategies. The proposed methodology is adaptable to any e-commerce retailer or third-party operator across diverse sectors and operational contexts. It enables stakeholders to define parameter ranges for fluctuating criteria and key variables, while incorporating realistic failure rates into product collection processes based on their specific operational conditions. Designed as a decision-support tool, this approach assists managers in evaluating alternative product return strategies, ultimately driving improved business performance and sustainability.

3.1 Identification of significant variables and data collection

One of the primary drawbacks identified by the authors of this research is the absence of typical shopper profiles and data on how, how frequently and for what purpose people travel to shops and the quantities of goods purchased. Obtaining such information is problematic due to a lack of behavioral data at the consumer level (Rotem-Mindali and Salomon, 2007). Additionally, micro-level information on consumers' return habits is difficult to obtain, as manufacturers and retailers who conduct their own customer surveys are usually reluctant to make details public. In this context, the research relied primarily on three complementary sources:

(1) Scientific literature: Academic studies, government statistics and technical reports provided baseline values for transportation distances, vehicle types, emission factors and costs associated with each strategy.

(2) Professional insights: Industry benchmarks and operational data from logistics service providers obtained online were incorporated to ensure alignment with real-world practices.

(3) Local experiment: Targeted consultations were conducted with some logistics companies (3PL) operating in the selected city to refine assumptions and validate ranges for key variables such as urban travel distances, handling costs and customer behavior patterns.

A comprehensive literature review was conducted to identify key criteria relevant to the logistics of returned products. Consequently, four criteria were established: CO_2 emissions, ECU, costs and cycle time. Furthermore, the study focused on small non-food items, such as books, clothing, electrical and electronic products and household goods, which collectively account for 62% of online sales (Allen *et al.*, 2018). These items are usually transported as parcels or small packages, representing a significant proportion of e-commerce returns and being handled by a single person. Packaging formats include letterbox-sized parcels and shoeboxes. Based on their own judgment, derived from a literature review and professional insights, the authors assume that consumers use the same channel for the initial purchase and return of these items.

3.2 Development of a local experiment for data collection

To assess the performance of the four criteria across the four RL strategies a hypothetical scenario was simulated involving the following criteria and variables:

(1) Weight (kg) and Volume (dm3) of returned products (including packaging)

(2) Driven distance inside the city (km)

(3) Shipping cost (fuel consumption), facility cost in inner cities (rent of space) and handling cost.

(4) Cycle time (days): Time between the notification of return by the customer, and the product being received by the operator.

(5) Total global CO_2 Emissions (kg of CO_2): according, to the consumption of the vehicle and the driven distance in each strategy and also the CO_2 emissions from customers traveling to the drop-off point for Lockers and C&C.

(6) ECU with each strategy (ECU).

The scenario models a daily return collection operation in a medium-sized Spanish city with a population of approximately 500,000 and an area of 900 km^2. This baseline model requires the collection of an average of 66 return orders of small items over a two-week period, within an eight-hour working day. The pilot was executed over a consecutive four-week period (during an off-peak month to avoid the extreme congestion biases of holiday campaigns). This operational setting was selected as it represents a typical contemporary high-density urban center. Focusing strictly on the urban core provides a rigorous baseline, successfully capturing the complex traffic constraints and routing frictions characteristic of modern city logistics. Data capture was performed in direct collaboration with a regional 3PL provider. Baseline node-to-node distances and service times were captured using the commercial vehicles' GPS telemetry. Furthermore, structural cost parameters and initial workflow assumptions were directly provided and validated by the 3PL's Chief Operating Officer. This expert validation ensures that the subsequent stochastic simulation is firmly anchored in empirical industry constraints rather than purely theoretical estimations. Operations within the urban area are carried out by a single operator using a light commercial van within this time frame.

The analysis then examines how the same collection task would be performed under identical spatial and temporal constraints for the remaining three strategies, identifying the necessary human and technical resources for each operational configuration (e.g. distance traveled, number and type of vehicles and facilities). These estimates were obtained through open surveys of logistics professionals, yielding approximate values within a defined tolerance range for the four criteria. To ensure accuracy, these preliminary figures, derived from real data provided by the 3PL supplier and complemented by professional surveys, were refined using additional data and academic information presented in subsequent sections.

3.2.1 Costs. Accurate cost data is inherently difficult to obtain due to companies' strong inclination to safeguard this information, which often makes estimation techniques necessary. In this study, total costs were calculated as the sum of transportation and handling costs (including facility rental fees). The following cost information was used as a proxy to define the variation boundaries for the variables and criteria across the four strategies. Urban area costs were estimated in this study based on preliminary data provided by the 3PL company and subsequently refined using insights from academic and professional sources. Regarding transportation costs, the establishment of cost-efficient urban depots for delivery and collection operations is constrained by high rental prices. This explains why most strategies minimize infrastructure in inner-city areas, positioning depots in less expensive peripheral locations. Transportation costs are estimated based on distance traveled and vehicle type within the city. Additionally, for the return strategies (microhub and 3PL), the calculated distance will increase within the limits obtained from academic and professional sources in the different simulated scenarios to reflect the adverse effect of unsuccessful attempts. To provide insight into cost structures and establish reference benchmarks for each strategy, this section synthesizes data and guidelines from various sources to construct a comprehensive overview of the scenario.

It is widely assumed that the cost of collecting products from customers accounts for a large proportion of RL costs (El Korchi and Millet, 2011). According to some estimates, online retailers pay for between 50% and 75% of these returns, rather than customers (Lowe and Rigby, 2014; Oracle, 2016). This reflects the impact of price and service level on customer retention, as well as the focus on sales rather than profitability (Allen *et al.*, 2018). In this vein, a 2016 survey of 360 online retailers found that 59% charged less than £5 for delivery if the free delivery threshold was not met (Oracle, 2016). In a trial carried out in London by Allen *et al.*

(2018), which serves as a practical reference in our research, a 3.5-tonne van was used. Operational figures showed a total driving time of 1.77 h and a total parking time of 6.05 h (including time spent loading/unloading, walking to customer facilities and obtaining proof of delivery). There were also 35 parking stops. A total of 119 items were handled (collections were interspersed with deliveries). The total round duration was 7.82 h and the round distance was 6.7 km (excluding stem mileage to and from the depot at the start and end of the round). This equates to an average of 4.1 min per customer.

Another relevant reference for the 3PL strategy is the work of Durand *et al*. (2013), which provided insight into delivery operations, such as the average length of a delivery round (45 km), comprising 30 km outbound and 15 km in the inner city. A total of 72 parcels were delivered in the morning over a period of eight hours. This work also provided data on the average operating cost of a delivery round, estimated at €250 net. This equates to an average of 1.05 parcels per delivery (90% to households and 10% to businesses), costing €4.52 per parcel and with a delivery rate of nine parcels per hour (6.6 min per customer).

Masteguim and Cunha (2022) reported that using pick-up points can reduce average costs by up to 53% compared to attended home delivery services when comparing different strategies. Similarly, Milewski and Milewski (2021) found reductions in fuel consumption per order of between 74% and 87%. Several authors have also highlighted that lockers generate significant cost savings by avoiding undelivered orders, which impact costs and CO_2 emissions (Meuter *et al*., 2005; Alcock and Millard, 2006).

Beyond academic references, some additional information was sourced to serve as benchmarks for validating and refining academic results, thereby strengthening the robustness and accuracy of the simulations. For instance, data source for 3PL may be found in "What You Pay for 3PL Fulfillment Services" (https://www.warehousingandfulfillment.com/resources/fulfillment-services-costs-and-pricing/), where costs for returned items, including inspection and restocking, are estimated at around €3.86 per return.

3.2.2 CO_2 emissions. The environmental implications of online returns are strongly influenced by both parcel carriers' return policies and consumers' preferred habits (Edwards *et al*., 2009). This divergence in results is one of the disadvantages when seeking general conclusions in a scenario with divergent results. To deal with this challenge, our research adopted the following approach and assumptions: firstly, CO_2 emissions are quantified as the aggregate emissions generated within the defined urban boundaries, explicitly excluding any emissions occurring beyond city limits. Secondly, our estimation encompasses two primary sources: (1) emissions produced by the retailer or third party during RL operations and (2) emissions attributable to customers when returning products to drop-off points. In the case of C&C and locker-based returns, both sources occur within the same process, as customers deliver items to collection points while retailers or logistics operators subsequently consolidate and transport these items to distribution centers outside the city. Specifically, for customer-related emissions at collection points, the analysis incorporates modal split (the percentage of returns performed on foot, by private car, or by other motorized vehicles) and the average travel distance between the customer's origin (residential or business address) and the drop-off location.

This approach aligns with internationally recognized standards for greenhouse gas accounting, such as the Greenhouse Gas Protocol and the European standard EN 16258, which establish principles for system boundaries, activity-based allocation and emission factor application to ensure consistency and comparability across studies on urban logistics and transport emissions. Additionally, other research sources were used as complementary guidelines to enhance calculations, such as one based on a 3PL strategy where two-thirds of vehicles used by postal operators were diesel or petrol-powered light commercial vehicles (LCV) with emissions of 0.3194 kg per km and the remainders were electric LCV with CO_2 emissions of 0.05 kg (Durand *et al*., 2013). In the aforementioned study, four of the 14 delivery rounds are also carried out using electric LCVs with CO_2 emissions of 0.05 kg per km and 0.246 kgs of CO_2 per parcel.

In our work, formula [1] to calculate CO_2 emissions extracted from (Misni *et al.*, 2021) has been utilized.

$$CO_2\ emissions = d(km) \times w(kg) \times EF \times p \tag{1}$$

Where:

1. d is the distance traveled.
2. w the package weight.
3. EF of the chosen vehicle(s) in $(\mathrm{kg\,CO_2/km})$.
4. p for a proration (allocation) factor accounting for package weight share and truck load factor

For reviews of e-commerce CO_2 emissions that have supported our research, see (Rotem-Mindali and Salomon, 2007; Edwards *et al.*, 2009; Edwards *et al.*, 2010; Durand *et al.*, 2013; Misni *et al.*, 2021; Fahim *et al.*, 2025).

3.2.3 Cycle time. Cycle time analysis shows that online customers are increasingly demanding rapid delivery. Consequently, despite not fully recouping costs, retailers offer faster services, often embedding these expenses into product prices. Between 2013 and 2015, next-day non-food deliveries increased by 50%, while the proportion of consumers willing to wait 3–5 days dropped by 10% (Allen *et al.*, 2018). This forced businesses to adapt their logistics structures.

Regarding delivery windows, providers offer various time-guaranteed services. By 2016, 32% of orders utilized next-day delivery, while ‘economy’ services declined (IMRG and Metapack, 2017). Furthermore, the proportion of UK retailers offering six or more delivery options increased from 3% to 10% between 2015 and 2016, while the proportion offering only one or two options fell from 55% to 35% (Oracle, 2016). This shift towards shorter delivery windows puts pressure on the entire reverse SC (SC) to reduce cycle times.

Despite these trends, comparative data on the four return strategies remains scarce in academic and commercial literature. Consequently, this research uses primary data from local retailers and logistics providers, with specific studies acting as benchmarks to monitor potential deviations (Quak *et al.*, 2014).

3.2.4 Expected customer utility (ECU). Studies by Melo *et al.* (2022) and Wang *et al.* (2024) have examined consumer preferences regarding parcel delivery, with a particular focus on the physical and social effort involved. However, it remains difficult to assess utility in theoretical RL due to the lack of direct post-experience data. To address this issue, we adopt a behavioral approach based on consumer logistics theory (Granzin and Bahn, 1989), which suggests that satisfaction with self-service channels arises from the alignment between consumers’ willingness to contribute resources and the specific demands of the channel.

In this study, ECU is evaluated using empirical findings from Wang *et al.* (2024) concerning three dimensions of consumer effort: physical, social and attentive. We interpret their regression coefficients (odds ratios) as theoretical proxies for perceived utility, where higher values indicate a stronger alignment between consumer preferences and the required return strategy. Crucially, these external coefficients measure universal drivers of consumer friction – specifically the physical travel burden and temporal constraints. Consequently, these effort-based metrics are highly transferable to our operational context. The fundamental mechanics of spatial friction in urban last-mile logistics remain behaviorally consistent across contemporary metropolitan areas, thereby providing a valid and robust baseline for our simulation.

To account for consumer heterogeneity, we apply variable weight intervals to these dimensions: physical (0.4–0.6), social (0.2–0.4) and attentive (0.1–0.3). This methodology, supported by Govindan *et al.* (2015) and Munier *et al.* (2019), enables us to capture the diversity of consumer profiles rather than relying on a single, static average.

We calculate the estimated ECU range (0–100) for each strategy by normalizing the coefficients from Wang *et al.* (2024) against the maximum observed value and aggregating them through the following utility function:

$$ECU = \sum \frac{Exp(B)_i}{Max_i} \times 100 \times \mathrm{w_i} \tag{2}$$

Where:

(1) i represents the dimension of effort (physical, social, attentive)

(2) Exp $(\mathrm{B})_\mathrm{i}$ is the preference coefficient for the specific strategy derived from Wang *et al.* (2024).

(3) $\mathrm{Max_i}$ is the highest coefficient observed across all strategies for dimension i (representing the “ideal” fit).

(4) $\mathrm{w_i}$ is the weight assigned to the dimension within the defined sensitivity intervals

By applying combinations of weights within defined intervals, we compute minimum and maximum scores for each alternative, capturing the sensitivity of satisfaction estimates to weight variation. The application of this methodology yields score ranges from 0 to 100 (where 100 denotes maximum ECU) for each alternative, as presented in the last column of Table 1.

The results indicate that strategies facilitating consumer autonomy, such as Lockers and C&C, achieve the highest potential satisfaction. This aligns with Wang *et al.* (2024), who found that omni-channel consumers increasingly perceive physical participation as value-adding when it offers flexibility. Conversely, the 3PL strategy shows comparatively lower scores, as it limits consumer control and requires passive waiting, which negatively impacts the utility for autonomy-focused shoppers (Kawa, 2021).

3.2.5 Initial results and refinement. The reliability of the simulation heavily depends on the validity of its underlying assumptions. For the parameterization of CO_2 emissions and travel distances, the model assumes a critical behavioral divergence between commercial logistics vehicles and end-consumers. While home collections (3PL and Microhubs) are assigned dedicated logistics routing with standard commercial vehicle emission factors, configurations requiring consumer effort (Lockers and C&C) assume ‘trip-chaining’ behavior. Consequently, the marginal emission burden and distance allocated to the consumer’s return trip are calculated using established coefficients that align with empirical data on multi-purpose urban trips, rather than assuming theoretical dedicated journeys. Furthermore, to model the inherent uncertainty in the operations, specific probability distributions were applied to the baseline data. Uniform distributions were selected to accurately reflect the daily volatility of urban

Table 1. Criteria tolerance for the four strategies

	Driven distance (km) by		Vehicle type					
Strategy	Business	Customer	Business	Customer	Cost (€/order)	Cycle time (Days)	Kg of CO_2 per order	ECU (0–100)
C&C	10	3	VANS	CAR (45%)	2.8–3.45	2–4	0.031–0.891	89.0–92.6
Microhubs	11	0	VANS/LV	0	3.05–3.8	2–3	0.000–0.011	93.0–96.5
3PL	15	0	VANS	0	3.85–4.75	2–5	0.003–0.018	91.4–94.1
Lockers	10	1.2	VANS	CAR (27%)	2.50–3.10	2–3	0.000–0.483	94.8–95.6

Source(s): Authors’ own work

traffic congestion, fluctuating fuel prices and variable vehicle load factors, ensuring the simulation captures realistic operational extremes.

The initial results based on the operational baselines provided by the experiment were refined and calibrated to reflect real-world uncertainty, and specific probability distributions informed by academic data provided in former sections were applied to the four criteria:

(1) Total cost (€) and CO_2 emissions (kg): A uniform distribution with a fluctuation range of ±12.5% around the baseline was applied. This tolerance interval (ranging between 10% and 15%) accounts for daily variations in fuel prices, traffic congestion, vehicle load factors, etc., as well as obvious deviation for undertaking an experiment at a local level.

(2) Cycle time (Days): Modeled as a discrete uniform distribution within the minimum and maximum days observed in the empirical data.

(3) ECU: Modeled as a continuous uniform distribution within the specific score ranges identified for each strategy.

The resulting large dataset comprises 4,000 unique return scenarios, providing a robust statistical foundation for the subsequent MCDM analysis. As a result, Table 1 summarizes the variability range for each criterion and strategy involved in the collection of 66 returned orders within a small to medium-sized city. These figures reflect the outcomes of the experiment and the subsequent refinement of results based on academic literature and professional insights.

For clarity, the following text explains how certain inputs presented in Table 2 were calculated: Driven distance: Total distance traveled by the retailer or logistics company (business) within the city to collect 66 return orders. For lockers and C&C, CO_2 calculations also include customer trips to drop points. Based on literature and professional insights, 27% of locker returns are made by car, with an average driven distance of 1.2 km and 73% on foot; for C&C, 45% by car (3 km round trip). The 3PL provider covers 15 km within the city in 8 h. For other strategies, distances are shorter due to consolidated returns; typically, 4–5 points must be visited, depending on the strategy, to collect the 66 orders. Shorter driven distances also have a direct impact on petrol costs. Vehicle type: for the lockers, C&C and 3PL, the entire driving distance is covered by light vans. For Microhubs,

Table 2. Descriptive statistics of simulated RL strategies

Strategy	Metric	Mean	Std. dev. (SD)
3PL	Total Cost (€)	4.29	0.26
	Cycle Time (days)	3.60	1.43
	CO_2 Emissions (kg)	0.0102	0.0076
	ECU (0–100)	92.75	0.80
Click and Collect	Total Cost (€)	3.13	0.19
	Cycle Time (days)	3.01	1.01
	CO_2 Emissions (kg)	0.4614	0.43
	ECU (0–100)	90.83	1.04
Lockers	Total Cost (€)	2.80	0.18
	Cycle Time (days)	2.78	0.31
	CO_2 Emissions (kg)	0.2027	0.28
	ECU (0–100)	95.19	0.23
Microhubs	Total Cost (€)	3.42	0.21
	Cycle Time (days)	2.48	0.52
	CO_2 Emissions (kg)	0.005	0.0062
	ECU (0–100)	94.77	1.02

Source(s): Authors' own work

64% of the distance is covered by light vans and 36% by environmentally-friendly vehicles such as cargo bikes (with or without electric assistance).

3.3 Design of the synthetic database

In Phase 4, and to address the lack of standardized primary data in RL research, this study employs a simulation-based methodology to generate a synthetic database. To this end, a stochastic model was designed to replicate the operational variability of the four RL process configurations. This model, used for simulation, was executed using Python, generating $N = 1{,}000$ independent cases for each strategy. To ensure feasible results, for the same case, each strategy is evaluated with the same item size (weight and volume), varying the values of each criterion within its respective interval (see Table 1).

Because of the simulation run in Python, a large synthetic database was obtained, enabling the TOPSIS method to identify the best strategy.

3.4 Selecting the best strategy: TOPSIS

TOPSIS (Hwang and Yoon, 1981) simultaneously considers the distance to the ideal solution for each alternative and selects the closest relative to the ideal solution as the best alternative. It has been applied to solve a variety of applications, like the selection of RL providers (Kannan *et al*., 2009) or for the selection of a facility location (Chu, 2002), among others. For a comprehensive application of the TOPSIS method, see Behzadian *et al.* (2012).

For the TOPSIS application, values corresponding to the same case and criteria across each strategy were first normalized. Since the TOPSIS method requires assigning relative weights to each criterion, an equal weight of 25% was initially allocated to all four dimensions. This equiproportional weighting was purposely designed to establish a strictly neutral baseline, intending to demonstrate the mathematical mechanics of the DSF without introducing subjective author bias into the initial feasibility mapping. However, it is explicitly acknowledged that in real-world operations, corporate priorities are rarely distributed equally across all performance metrics and a strictly neutral baseline does not fully capture the dynamic nature of managerial decision-making. Because the proposed methodology is highly adaptable, it empowers e-commerce retailers and 3PL providers to replace this baseline, enabling stakeholders to define their own parameter ranges and apply asymmetrical weighting profiles that align with their specific strategic objectives (See Section 4.3).

3.5 Sensitivity analysis incorporating undelivered collections

In Phase 6 of the proposed methodology, the logistical drawback associated with uncollected returns in the 3PL and microhub strategies will be incorporated to evaluate its impact on cost-related criteria and CO_2 emissions. To assess this impact, three additional scenarios were defined, each reflecting different uncollection rates. The base scenario corresponds to the baseline presented in the previous section, for which no failed deliveries were considered. For the sensitivity analysis, the first scenario assumes a 15% uncollection rate, meaning that during the first try, 15% of the deliveries failed but were successfully delivered on the second try. The remaining scenarios consider uncollection rates of 30% and 45%, aligned with values identified in the literature review and discussed in earlier sections.

4. Results and discussion

4.1 Baseline case

Table 2 summarizes the performance metrics obtained from the 1,000 simulations per strategy. The results highlight distinct operational trade-offs across the dimensions of cost, sustainability, cycle time and customer experience.

From an economic perspective, the conventional 3PL model incurs the highest mean cost, at €4.29 per return. Microhubs and C&C reduce this considerably to €3.42 and €3.13, respectively, while lockers provide the lowest overall cost at €2.80. Small standard deviations suggest stable outcomes under simulated conditions, though the 3PL model and Microhubs show slightly higher dispersion than collection-point options.

Cycle time results further differentiate service responsiveness. Microhubs achieve the shortest average cycle time (2.48 days), followed by lockers (2.78 days) and C&C (3.01 days). The 3PL model exhibits the longest mean cycle time (3.60 days) and higher variability, indicating less predictability than the standardized performance of Microhubs and lockers.

Environmental performance reveals a stark contrast between operator-centric and customer-involved strategies. While 3PL yields low average emissions (0.0102 kg CO_2/return), Microhubs are the most sustainable option at 0.0051 kg CO_2. Conversely, strategies requiring customer travel generate emissions that are orders of magnitude higher: 0.2027 kg for lockers and 0.4614 kg for C&C. The high dispersion for these options reflects the significant impact of variability in customer travel distances and modes of travel.

ECU patterns favor drop-off solutions, with lockers achieving the highest score (95.19), followed closely by Microhubs (94.77). 3PL records intermediate satisfaction (92.7), while C&C performs the worst (90.83). The low standard deviation for lockers indicates consistent satisfaction, whereas Microhubs and C&C show greater sensitivity to specific scenarios.

When the criteria are combined with equal weighting (25% each), the multi-criteria evaluation favors strategies with balanced performance. In the feasibility analysis, Microhubs were selected as the optimal choice in 59.3% of the 1,000 simulated cases, followed by lockers (24.6%). 3PL (8.2%) and C&C (7.9%) were chosen significantly less frequently, as illustrated in Figure 2.

It's worth noting that from a BPM perspective, the TOPSIS "closeness coefficient" should not be interpreted merely as a static ranking of universal superiority. Instead, under conditions of operational uncertainty – such as fluctuating failed collection rates and variable urban congestion – being "closest to the ideal solution" operationally translates to achieving maximum systemic resilience.

4.2 Sensitivity analysis

To enhance the realism and robustness of the baseline simulation, a sensitivity analysis was conducted by introducing uncollection rates ranging from 0% to 45%, in line with values reported in the literature. Uncollection events were applied exclusively to home-based return strategies, 3PL and Microhubs, as these depend on customer presence for successful pickup. In contrast, non-home-based strategies (Lockers and C&C) are unaffected by uncollection, since they transfer responsibility to the customer and inherently eliminate failed pickup attempts.

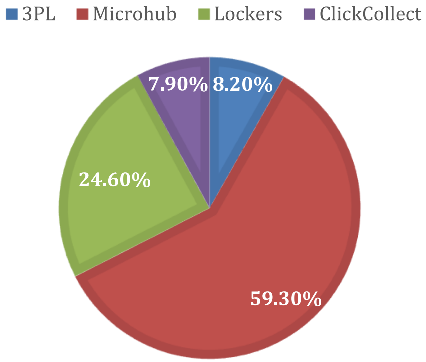

Figure 2. Percentage of best-performing strategy across the 1,000 cases. Source: Authors' own work

When an uncollection event occurs, the return is assumed to be completed successfully on a second attempt. However, this entails a 75% increase in return costs to account for additional routing, labor and operational complexity. Moreover, a proportional increase in CO_2 emissions is incorporated to reflect the environmental burden of the additional delivery attempt.

The sensitivity analysis evaluates how increasing uncollection rates affect (1) the relative feasibility of each return strategy and (2) their performance across cost, cycle time, environmental impact and ECU.

4.2.1 Scenario 1: low uncollection rate (15%). Introducing a 15% uncollection rate leads to a moderate redistribution of feasibility across strategies. Microhubs remain the most frequently selected option, although their share decreases to 52.6%. Lockers gain relevance, increasing their feasibility share to 27.2%, while 3PL and C&C account for 11.0% and 9.2%, respectively.

Cost penalties begin to materialize for home-based strategies. The average cost of Microhubs increases to €3.87, while 3PL rises more sharply to €4.79. Despite this increase, Microhubs continue to outperform 3PL in cycle time (2.65 vs 3.74 days) and emissions (0.0059 vs 0.0105 kg CO_2). Lockers remain cost-efficient (€2.80) and maintain the highest ECU (95.2), reinforcing their role as a stable alternative when mild operational frictions are introduced.

4.2.2 Scenario 2: medium uncollection rate (30%). At a 30% uncollection rate, the sensitivity of home-based strategies becomes more pronounced. The feasibility share of Microhubs declines further to 48.8%, while Lockers continue to gain ground, being selected in 29.7% of simulations. The relevance of 3PL and C&C increases slightly, reaching 12.0% and 9.5%, respectively.

Cost escalation intensifies for home-based returns: the average cost of 3PL increases to €5.21, and Microhubs to €4.27. Nevertheless, Microhubs retain clear advantages over 3PL in cycle time (2.53 vs 3.58 days) and emissions (0.0046 vs 0.0088 kg CO_2). Lockers continue to display robust performance, combining stable costs (€2.80), high ECU (95.21) and operational resilience, which explains their growing competitiveness under increased uncertainty.

4.2.3 Scenario 3: high uncollection rate (45%). Under severe operational stress (45% uncollection), the dominance of Microhubs erodes substantially. Although they remain the most frequently selected strategy, their feasibility share falls to 37.9%. Lockers nearly match this performance, increasing their share to 39.0%, effectively becoming co-dominant. In contrast, 3PL and C&C remain secondary, at 11.9% and 11.2%, respectively.

At this level, the average cost of Microhubs rises to €4.63, narrowing the gap with alternative strategies. Their cycle time also deteriorates (2.97 days), though emissions remain comparatively low (0.0070 kg CO_2). Lockers, by contrast, exhibit remarkable stability: costs remain virtually unchanged (€2.79), cycle time stays constant (2.80 days) and ECU remains consistently high (95.20). This stability under high uncertainty significantly strengthens their relative attractiveness.

Figure 3 illustrates how the relative feasibility of return strategies evolves as uncollection rates increase from the baseline to 45%. Under baseline conditions, Microhubs clearly dominate, being selected as the most feasible option in nearly 60% of the simulations, followed by Lockers at approximately 25%. Home-based 3PL and C&C remain marginal alternatives.

As uncollection rates increase, a systematic shift in feasibility is observed. The dominance of Microhubs progressively declines, falling to approximately 38% at a 45% uncollection rate. In contrast, Lockers exhibit a steady and pronounced increase in feasibility, ultimately becoming the most frequently selected strategy under high operational stress. This trend highlights the structural robustness of non-home-based strategies, which are unaffected by failed pickup attempts. Meanwhile, 3PL and C&C show only modest increases in feasibility and remain secondary options across all scenarios. Overall, Figure 3 confirms that operational uncertainty reshapes strategic attractiveness, favoring solutions that decouple return success from customer availability.

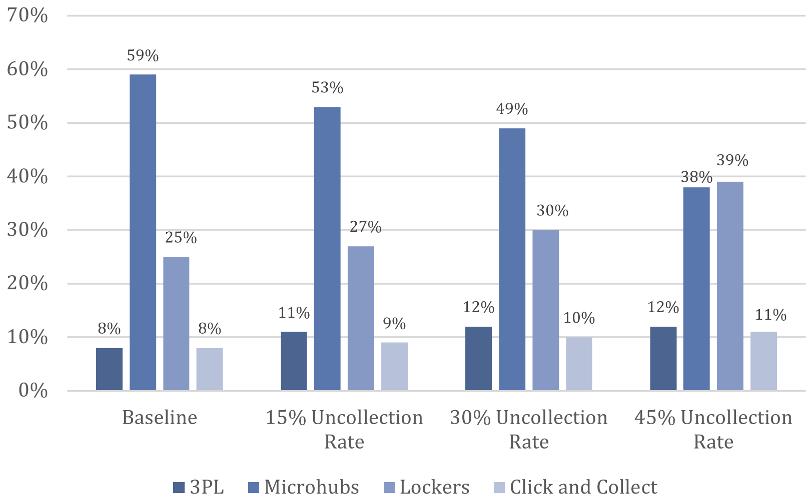

Figure 3. Feasibility by uncollection rate. Source: Authors' own work

Table 3 reports the operational performance of the two home-based strategies (3PL and Microhubs) across uncollection scenarios, focusing on cost, cycle time and environmental impact.

For 3PL, increasing uncollection rates lead to a marked deterioration in performance. Average return costs rise from €4.34 at baseline to €5.72 at a 45% uncollection rate, accompanied by an increase in cycle time from 3.61 to 4.12 days. CO_2 emissions also increase, indicating a higher environmental burden due to repeated delivery attempts. These results confirm the high sensitivity of traditional home-based returns to operational disruptions.

In contrast, Microhubs display greater resilience. Although costs increase with uncollection (from €3.46 to €4.63), cycle times remain relatively stable up to the 30% scenario and only increase noticeably at 45%. Importantly, Microhubs maintain consistently low CO_2 emissions across all scenarios, reflecting more efficient routing and consolidation effects. This performance stability explains why Microhubs remains the most feasible strategy across most scenarios despite growing uncertainty. Taken together, Table 3 demonstrates that while both home-based strategies are negatively affected by uncollection, Microhubs experience a substantially lower performance degradation, reinforcing their role as a robust intermediate solution between fully home-based and fully customer-driven return strategies.

Table 3. Operational performance across uncollection scenarios (0–45%)

Strategy	Cost (€)	Cycle (days)	CO_2 (kg)
3PL – Baseline	4.34	3.61	0.0089
3PL – 15% Uncollection rate	4.79	3.74	0.0105
3PL – 30% Uncollection rate	5.21	3.58	0.0088
3PL – 45% Uncollection rate	5.72	4.12	0.013
Microhub – Baseline	3.46	2.53	0.0047
Microhub – 15% Uncollection rate	3.87	2.65	0.0059
Microhub – 30% Uncollection rate	4.27	2.53	0.0046
Microhub – 45% Uncollection rate	4.63	2.97	0.007

Source(s): Authors' own work

4.3 Scenario analysis based on strategic profiles

While the baseline evaluation provides an unweighted mapping of the operational configurations, contemporary BPM requires decision-making tools to adapt to specific corporate strategies. Therefore, a scenario analysis was conducted by recalculating the TOPSIS rankings under three distinct, asymmetrical weighting profiles, serving as a robustness check for the framework.

1. Cost-Driven Profile: Allocates a dominant weight to economic efficiency (Cost 60%), distributing the remainder equally among the other criteria. This mirrors a highly competitive market strategy focused on margin protection.
2. Green-Driven Profile: Prioritizes environmental impact (CO_2 Emissions 60%), reflecting corporate sustainability mandates or adaptation to stringent urban emission regulations.
3. Customer-Centric Profile: Focuses on service excellence (ECU 60%), aligning with strategies aimed at maximizing brand loyalty and minimizing friction in the return process.

As illustrated in Figure 4, shifting from an equiproportional baseline to asymmetrical profiles drastically alters the strategic hierarchy. Under the Green-Driven profile, Microhubs dominate, being identified as the optimal solution in 64.0% of the simulated scenarios. Conversely, when the overarching priority shifts to strict margin protection (Cost-Driven), Lockers emerge as the clear optimal strategy (57.8%), completely marginalizing the traditional 3PL model, which falls to a 0.0% feasibility rate. Interestingly, under a Customer-Centric profile, Microhubs reclaim dominance (61.7%) due to their strong balance of rapid cycle times and high utility scores, with Lockers serving as a robust secondary alternative (25.6%).

For an operations decision-maker, the optimal configuration is the one that best absorbs process exceptions (i.e. minimizing the exponential cost and emission penalties associated with delivery re-attempts) while remaining strictly aligned with the firm's defined strategic weighting profile (Cost-Driven, Green-Driven, or Customer-Centric). Consequently,

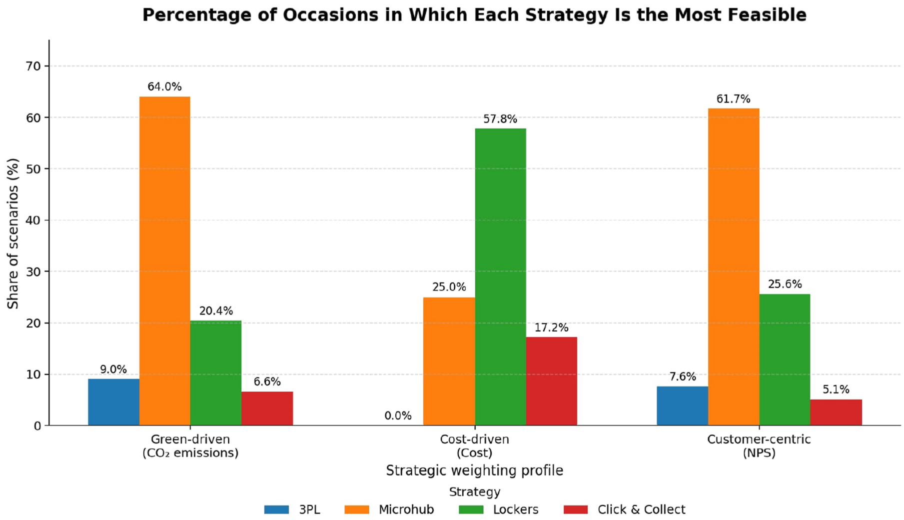

Figure 4. Relative feasibility distribution of return strategies across distinct strategic weighting profiles.
Source: Authors' own work

managers should read the TOPSIS ranking as a dynamic risk-mitigation compass: the highest-ranked strategy represents the workflow configuration that introduces the lowest operational friction and maximum efficiency under their specific, localized environmental constraints.

5. Conclusions and limitations

This study makes an academic contribution by proposing an integrated DSF that evaluates the operational and environmental performance of RL. Using a robust simulation approach, the research compares Lockers, Click & Collect, Microhubs and 3PLs across four critical dimensions: cost, CO_2 emissions, cycle time and ECU. The findings reveal that lockers are the most financially efficient configuration (€2.79 per return) and yield high ECU scores. Conversely, Microhubs represent the most sustainable option, reducing average CO_2 emissions by almost 50% compared to 3PL, corroborating foundational urban consolidation research (e.g. Katsela *et al.*, 2022; Browne *et al.*, 2005).

Managerial Implications: From a managerial standpoint, e-commerce SC managers should shift from homogeneous 3PL solutions toward adaptive logistics networks under a unified BPM lens. However, the primary research and practical value of this paper resides in highlighting the necessity to systematically analyze operational trade-offs rather than prescribing a definitive or static ranking. To operationalize this mature, vendor-neutral framework, the following conditional guidance applies: managers should prioritize unattended configurations (e.g. Lockers) in urban zones where uncollection rates exceed 20% to mitigate re-attempt costs. Microhubs are recommended for sustainability-led strategies under moderate uncollection rates (below 15%). If maximizing consumer utility is the primary strategic objective, traditional 3PL remains viable, provided profit margins can absorb the systemic inefficiencies associated with failed home pickups.

Limitations and Future Research: Despite offering a robust quantitative framework, the empirical generalizability of these findings is limited. The specific strategic hierarchy and numerical results presented in this study are based on a synthetic database and a local experimental baseline anchored in a medium-sized Spanish city. Therefore, these numerical findings must be interpreted strictly as illustrative and exploratory, rather than as evidence of operational superiority across markets or diverse urban contexts. Furthermore, while the proposed framework integrates customer experience as a core decision variable, its operationalization presents a methodological limitation. Because the DSF is an *ex ante* simulation tool, customer satisfaction could not be measured directly. Instead, the model employs an indirectly constructed variable – *Expected Customer Utility* – acting as a theoretical proxy based on effort coefficients derived from extant literature (e.g. Wang *et al.*, 2024).

Beyond its immediate managerial applications, this study contributes a replicable methodological workflow. Future research must prioritize validating the stochastic model with large-scale, firm-level empirical datasets across diverse geographical configurations (e.g., comparing highly dense urban centers with dispersed suburban areas). Modifying criteria weighting structures and incorporating additional socio-economic variables – such as social impact, labor constraints, service fairness and finite urban street space (Jiménez *et al.*, 2025)would further enhance the multi-criteria model. Ultimately, the insights generated by this framework can directly inform urban logistics planning, guiding targeted investments in sustainable infrastructure to mitigate urban emissions.

References

Ahmad, A., Ikram, A., Rehan, M.F. and Ahmad, A. (2022), “Going green: impact of green supply chain management practices on sustainability performance”, *Frontiers in Psychology*, Vol. 13, 973676, doi: 10.3389/fpsyg.2022.973676.

Alcock, T. and Millard, N. (2006), “Self-service — but is it good to talk?”, *BT Technology Journal*, Vol. 24 No. 1, pp. 70-78, doi: 10.1007/S10550-006-0022-0.

Allen, J., Browne, M., Woodburn, A. and Leonardi, J. (2012), “The role of Urban consolidation centres in sustainable freight transport”, *Transport Reviews*, Vol. 32 No. 4, pp. 473-490, doi: 10.1080/01441647.2012.688074.

Allen, J., Piecyk, M. and Piotrowska, M. (2017), “An analysis of online shopping and home delivery in the UK”, available at: https://share.google/ysE9LZgXIWMRn7H3F

Allen, J., Piecyk, M., Piotrowska, M., McLeod, F., Cherrett, T., Ghali, K., Nguyen, T., Bektas, T., Bates, O., Friday, A., Wise, S. and Austwick, M. (2018), “Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: the case of London”, *Transportation Research Part D: Transport and Environment*, Vol. 61, pp. 325-338, doi: 10.1016/J.TRD.2017.07.020.

Amini, M.M., Retzlaff-Roberts, D. and Bienstock, C.C. (2005), “Designing a reverse logistics operation for short cycle time repair services”, *International Journal of Production Economics*, Vol. 96 No. 3, pp. 367-380, doi: 10.1016/j.ijpe.2004.05.010.

Arslan, Y. (2026), “E-shopper innovativeness and parcel locker adoption: mediating roles of social influence and trust, and the moderating impact of transaction costs”, *Research in Transportation Business and Management*, Vol. 64, 101550, doi: 10.1016/J.RTBM.2025.101550.

Ballare, S. and Lin, J. (2020), “Investigating the use of microhubs and crowdshipping for last mile delivery”, *Transportation Research Procedia*, Vol. 46, pp. 277-284, doi: 10.1016/J.TRPRO.2020.03.191.

Behzadian, M., Otaghsara, S.K., Yazdani, M. and Ignatius, J. (2012), “A state-of the-art survey of TOPSIS applications”, *Expert Systems with Applications*, Vol. 39 No. 17, pp. 13051-13069, doi: 10.1016/j.eswa.2012.05.056.

Boyson, S., Corsi, T., Dresner, M. and Rabinovich, E. (1999), “Managing effective third party logistics relationships: what does it take?”, *Journal of Business Logistics*, Vol. 20 No. 1, p. 73.

Brown, J.R. and Guiffrida, A.L. (2014), “Carbon emissions comparison of last mile delivery versus customer pickup”, *International Journal of Logistics Research and Applications*, Vol. 17 No. 6, pp. 503-521, doi: 10.1080/13675567.2014.907397.

Browne, M., Sweet, M., Woodburn, A.G. and Allen, J. (2005), *Urban Freight Consolidation Centres*, Department for Transport, London, available at: https://westminsterresearch.westminster.ac.uk/item/9286y/urban-freight-consolidation-centres-final-report

Buldeo Rai, H., Touami, S. and Dablanc, L. (2022), “Not all e-commerce emits equally: systematic quantitative review of online and store purchases’ carbon footprint”, *Environmental Science and Technology*, Vol. 57 No. 1, pp. 708-718, doi: 10.1021/acs.est.2c00299.

Cahyono, B.T., Pawar, A., Indrati, K. and Loupias, H. (2020), “Synthesizing the influences of green supply chain management towards organisational outcomes”, *International Journal of Supply Chain Management*, Vol. 9 No. 3, pp. 730-740, available at: https://ojs.excelingtech.co.uk/index.php/IJSCM/article/view/4985/2488

Capistrano, B.J.O. and Buluran, R.N. (2021), “Improving cycle time of returnable packaging logistics management in a Philippine automotive manufacturing plant”, *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 830-838, available at: https://www.ieomsociety.org/brazil2020/papers/490.pdf

Choo, C. (2016), “Impact of a delivery point network for Urban e-commerce deliveries”, (Doctoral dissertation, Singapore University of Technology and Design), available at: https://repository.sutd.edu.sg/esploro/outputs/graduate/Impact-of-a-Delivery-Point-Network/9910595409846

Chu, T.C. (2002), “Facility location selection using fuzzy TOPSIS under group decisions”, *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, Vol. 10 No. 06, pp. 687-701, doi: 10.1142/S0218488502001739.

Das, D., Kumar, R. and Rajak, M. (2020), “Designing a reverse logistics network for an e-commerce firm: a case study”, *Operations and Supply Chain Management: An International Journal*, Vol. 13 No. 1, pp. 48-63, doi: 10.31387/OSCM0400252.

Daugherty, P.J., Autry, C.W. and Ellinger, A.E. (2001), “Reverse logistics: the relationship between resource commitment and program performance”, *Journal of Business Logistics*, Vol. 22 No. 1, pp. 107-123, doi: 10.1002/j.2158-1592.2001.tb00162.x.

Dennis, M.J. and Kambil, A. (2003), “Service management: building profits after the sales”, *Supply Chain Management Review*, Vol. 7, pp. 42-48.

Dobroselskyi, M., Madleňák, R. and Laitkep, D. (2021), “Analysis of return logistics in e-commerce companies on the example of the Slovak republic”, *Transportation Research Procedia*, Vol. 55, pp. 318-325, doi: 10.1016/j.trpro.2021.06.037.

Ducret, R. (2014), “Parcel deliveries and urban logistics: changes and challenges in the courier express and parcel sector in Europe—the French case”, *Research in Transportation Business and Management*, Vol. 11, pp. 15-22, doi: 10.1016/J.RTBM.2014.06.009.

Durand, B., Mahjoub, S. and Senkel, M.P. (2013), “Delivering to Urban online shoppers: the gains from ‘Last-Mile’ pooling”, *Supply Chain Forum: International Journal*, Vol. 14 No. 4, pp. 22-31, doi: 10.1080/16258312.2013.11517325.

Edwards, J.B., McKinnon, A.C. and Cullinane, S.L. (2009), “Carbon auditing the ‘last mile’: modelling the environmental impacts of conventional and online non-food shopping”, Green Logistics Report, Heriot-Watt University, available at: https://www.abtslogistics.co.uk/green-logistics-resources/ee164c78-74d3-412f-bc2a-024ae2f7fc7e_FINAL%20REPORT%20Online-Conventional%20Comparison%20(Last%20Mile).pdf

Edwards, J., McKinnon, A., Cherrett, T., McLeod, F. and Song, L. (2010), “Carbon dioxide benefits of using collection–delivery points for failed home deliveries in the United Kingdom”, *Transportation Research Record*, Vol. 2191 No. 1, pp. 136-143, doi: 10.3141/2191-17.

El Korchi, A. and Millet, D. (2011), “Designing a sustainable reverse logistics channel: the 18 generic structures framework”, *Journal of Cleaner Production*, Vol. 19 Nos 6-7, pp. 588-597, doi: 10.1016/J.JCLEPRO.2010.11.013.

Fahim, M., Saleh, M., Grida, M. and Abou Gamila, M. (2025), “Greening the route: enhancing sustainability and efficiency in Omni channel retailing”, *Journal of Cleaner Production*, Vol. 500, 145264, doi: 10.1016/J.JCLEPRO.2025.145264.

Farahani, S. (2018), “Optimal decision making for capacitated reverse logistics networks with quality variations”, (Doctoral dissertation, The University of Wisconsin-Milwaukee), available at: http://digital.library.wisc.edu/1793/91668

González-Varona, J.M., Villafáñez, F., Acebes, F., Redondo, A. and Poza, D. (2020), “Reusing newspaper kiosks for last-mile delivery in Urban areas”, *Sustainability*, Vol. 12 No. 22, 9770, doi: 10.3390/SU12229770.

Govindan, K., Soleimani, H. and Kannan, D. (2015), “Reverse logistics and closed-loop supply chain: a comprehensive review to explore the future”, *European Journal of Operational Research*, Vol. 240 No. 3, pp. 603-626, doi: 10.1016/j.ejor.2014.07.012.

Granzin, K.L. and Bahn, K.D. (1989), “Consumer logistics: conceptualization, pertinent issues and a proposed program for research”, *Journal of the Academy of Marketing Science*, Vol. 17 No. 1, pp. 91-101, doi: 10.1007/BF02726358.

Greve, C. and Davis, J. (2015), *Recovering Lost Profits by Improving Reverse Logistics*, available at: https://www.ups.com/media/en/Reverse_Logistics_wp.pdf

Hanbazazah, A.S., Abril, L., Erkoc, M. and Shaikh, N. (2019), “Freight consolidation with divisible shipments, delivery time windows, and piecewise transportation costs”, *European Journal of Operational Research*, Vol. 276 No. 1, pp. 187-201, doi: 10.1016/J.EJOR.2018.12.043.

Huang, X., He, J. and Li, Z. (2023), “Internal incentives for carbon emission reduction in a capital-constrained supply chain: a financial perspective”, *PLOS One*, Vol. 18 No. 7, e0287823, doi: 10.1371/journal.pone.0287823.

Hwang, C.L. and Yoon, K. (1981), "Methods for multiple attribute decision making", in *Multiple Attribute Decision Making: Methods and Applications a state-of-the-art Survey*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 58-191, doi: 10.1007/978-3-642-48318-9_3.

IMRG MetaPack (2017), "IMRG meta pack UK delivery index report, August 2017, IMRG metapack", available at: https://www.metapack.com/wp-content/uploads/2017/08/IMRG_MetaPack_Delivery_Index_August_2017.pdf

Janakiraman, N., Syrdal, H.A. and Freling, R. (2016), "The effect of return policy leniency on consumer purchase and return decisions: a meta-analytic review", *Journal of Retailing*, Vol. 92 No. 2, pp. 226-235, doi: 10.1016/J.JRETAI.2015.11.002.

Janjevic, M. and Ndiaye, A.B. (2014), "Development and application of a transferability framework for micro-consolidation schemes in urban freight transport", *Procedia-Social and Behavioral Sciences*, Vol. 125, pp. 284-296, doi: 10.1016/J.SBSPRO.2014.01.1474.

Jiménez, P., Garrido, L., Gomez, J. and Vassallo, J.M. (2025), "Environmental and operational impact of freight urban delivery: in-store, home and locker", *Transportation Research Part D: Transport and Environment*, Vol. 149, 105026, doi: 10.1016/J.TRD.2025.105026.

Kanagal, A. (1991), "Partnering for total quality: an industry's blueprint to regain and retain competitiveness", *[1991 Proceedings] Eleventh IEEE/CHMT International Electronics Manufacturing Technology Symposium*, IEEE, pp. 48-54, doi: 10.1109/IEMT.1991.279744.

Kannan, G., Pokharel, S. and Kumar, P.S. (2009), "A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider", *Resources, Conservation and Recycling*, Vol. 54 No. 1, pp. 28-36, doi: 10.1016/j.resconrec.2009.06.004.

Katsela, K., Güneş, Ş., Fried, T., Goodchild, A. and Browne, M. (2022), "Defining urban freight microhubs: a case study analysis", *Sustainability*, Vol. 14 No. 1, p. 532, doi: 10.3390/SU14010532.

Kawa, A. (2021), "Fulfilment as logistics support for e-tailers: an empirical studies", *Sustainability*, Vol. 13 No. 11, 5988, doi: 10.3390/SU13115988.

Li, J., Choi, T.M. and Cheng, T.E. (2013), "Mean variance analysis of fast fashion supply chains with returns policy", *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 44 No. 4, pp. 422-434, doi: 10.1109/tsmc.2013.2264934.

Liu, Z., Qian, Q., Hu, B., Shang, W.L., Li, L., Zhao, Y., Zhao, Z. and Han, C. (2022), "Government regulation to promote coordinated emission reduction among enterprises in the green supply chain based on evolutionary game analysis", *Resources, Conservation and Recycling*, Vol. 182, 106290, doi: 10.1016/j.resconrec.2022.106290.

Lowe, R. and Rigby, M. (2014), "The last mile: exploring the online purchasing and delivery journey", *Barclays*, September, available at: https://www.utikad.org.tr/images/BilgiBankasi/thelastmileexploringtheonlinepurchasinganddeliveryjourney-7912.pdf

Macharis, C. and Kin, B. (2017), "The 4 A's of sustainable city distribution: innovative solutions and challenges ahead", *International Journal of Sustainable Transportation*, Vol. 11 No. 2, pp. 59-71, doi: 10.1080/15568318.2016.1196404.

Masteguim, R. and Cunha, C.B. (2022), "An optimization-based approach to evaluate the operational and environmental impacts of pick-up points on E-commerce urban last-mile distribution: a case study in São Paulo, Brazil", *Sustainability*, Vol. 14 No. 14, p. 8521, doi: 10.3390/SU14148521.

Melo, A.C.S., de Nunes, D.R.L., Júnior, A.E.B., de Lima, R.B., Nagata, V.D.M.N. and Martins, V.W.B. (2022), "Analysis of activities that make up reverse logistics processes: proposition of a conceptual framework", *Brazilian Journal of Operations and Production Management*, Vol. 19 No. 2, doi: 10.14488/BJOPM.2022.001.

Meuter, M.L., Bitner, M.J., Ostrom, A.L. and Brown, S.W. (2005), "Choosing among alternative service delivery modes: an investigation of customer trial of self-service technologies", *Journal of Marketing*, Vol. 69 No. 2, pp. 61-83, doi: 10.1509/jmkg.69.2.61.60759.

Milewski, D. and Milewska, B. (2021), "The energy efficiency of the last mile in the e-commerce distribution in the context the COVID-19 pandemic", *Energies*, Vol. 14 No. 23, 7863, doi: 10.3390/en14237863.

Misni, F., Lee, L.S. and Jaini, N.I. (2021), “Multi-objective hybrid harmony search-simulated annealing for location-inventory-routing problem in supply chain network design of reverse logistics with CO2 emission”, *Journal of Physics: Conference Series*, Vol. 1988 No. 1, 012054, doi: 10.1088/1742-6596/1988/1/012054.

Morgan, T.R., Tokman, M., Richey, R.G. and Defee, C. (2018), “Resource commitment and sustainability: a reverse logistics performance process model”, *International Journal of Physical Distribution and Logistics Management*, Vol. 48 No. 2, pp. 164-182, doi: 10.1108/IJPDLM-02-2017-0068.

Munier, N., Hontoria, E. and Jiménez-Sáez, F. (2019), “Sensitivity analysis by SIMUS: the IOSA procedure”, in *Strategic Approach in Multi-Criteria Decision Making: a Practical Guide for Complex Scenarios*, Springer International Publishing, Cham, pp. 159-172, doi: 10.1007/978-3-030-02726-1_8.

Nanayakkara, P.R., Jayalath, M.M., Thibbotuwawa, A. and Perera, H.N. (2022), “A circular reverse logistics framework for handling e-commerce returns”, *Cleaner Logistics and Supply Chain*, Vol. 5, 100080, doi: 10.1016/j.clscn.2022.100080.

Oracle (2016), “Delivering retail 2016 – executive report, oracle”, available at: https://go.oracle.com/LP=39022/?

Pawar, A., Kolte, A., Sangvikar, B.V. and Jain, S. (2024), “Analysis of reverse logistics functions of small and medium enterprises: the evaluation of strategic business operations”, *Global Business Review*, Vol. 25 No. 5, pp. 1129-1149, doi: 10.1177/0972150921996011.

Ponce, D., Contreras, I. and Laporte, G. (2020), “E-commerce shipping through a third-party supply chain”, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 140, 101970, doi: 10.1016/j.tre.2020.101970.

Quak, H., Balm, S. and Posthumus, B. (2014), “Evaluation of city logistics solutions with business model analysis”, *Procedia-Social and Behavioral Sciences*, Vol. 125, pp. 111-124, doi: 10.1016/j.sbspro.2014.01.1460.

Rotem-Mindali, O. and Salomon, I. (2007), “The impacts of E-retail on the choice of shopping trips and delivery: some preliminary findings”, *Transportation Research Part A: Policy and Practice*, Vol. 41 No. 2, pp. 176-189, doi: 10.1016/J.TRA.2006.02.007.

Saleh, K. (2024), *E-commerce Product Return Rate Statistics and Trends (Infographic)*, INVESP, available at: https://www.invespcro.com/blog/ecommerce-product-return-rate-statistics/

Satır, B., Erenay, F.S. and Bookbinder, J.H. (2018), “Shipment consolidation with two demand classes: rationing the dispatch capacity”, *European Journal of Operational Research*, Vol. 270 No. 1, pp. 171-184, doi: 10.1016/j.ejor.2018.03.016.

Stenius, O., Marklund, J. and Axsäter, S. (2018), “Sustainable multi-echelon inventory control with shipment consolidation and volume dependent freight costs”, *European Journal of Operational Research*, Vol. 267 No. 3, pp. 904-916, doi: 10.1016/j.ejor.2017.12.029.

Wang, X., Wong, Y.D., Shi, W. and Yuen, K.F. (2024), “An investigation on consumers’ preferences for parcel deliveries: applying consumer logistics in omni-channel shopping”, *The International Journal of Logistics Management*, Vol. 35 No. 2, pp. 557-576, doi: 10.1108/ijlm-07-2022-0288.

Wurjaningrum, F. and Meirina, E. (2016), “The effect of reverse logistics capabilitiy on cost savings: innovation as moderator variable”, *Proceeding ICOBAME*, available at: https://www.unisbank.ac.id/ojs/index.php/icobame/article/view/4661

Zhang, Q., Vonderembse, M.A. and Lim, J.S. (2005), “Logistics flexibility and its impact on customer satisfaction”, *The International journal of logistics management*, Vol. 16 No. 1, pp. 71-95, doi: 10.1108/09574090510617367.

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