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Integrating customer preferences into operational decision-making for prioritizing emerging technologies in last-mile delivery

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ABSTRACT

The rapid expansion of e-commerce has positioned last-mile delivery as the most critical and resource-intensive stage of modern supply chains. Firms must balance multiple and often conflicting objectives: reducing costs, minimizing environmental impacts, and meeting growing customer expectations for speed, reliability, and personalization. While previous research has focused on operational efficiency and routing optimization, limited attention has been given to frameworks that integrate customer preferences with technology-enabled decision-making. This study develops a hybrid decision support model by extending the classical Simple Weight Calculation (SIWEC) method with grey numbers (G-SIWEC), capable of handling uncertainty in subjective judgments to generate robust criterion weights. These weights are incorporated into a multi-objective optimization model, solved using the Weighted Sum Scalarization Method (WSSM), to minimize delivery costs and emissions while maximizing service quality. The model explicitly considers emerging delivery technologies, including drone, Autonomous Vehicle (AV), and bicycle (e-bike), to explore innovative, sustainable, and customer-centric delivery strategies. Findings highlight technology-specific patterns: drone and bicycle excel in lightweight, eco-friendly deliveries, AV dominates mid-range logistics, and conventional truck remains indispensable for heavy loads. By linking customer preferences to technology-driven operational decisions, this work provides practical insights for managers and policymakers seeking to design efficient, sustainable, and innovative last-mile delivery systems for e-commerce. These implications should be interpreted within the context of the numerical experiment conducted in this study.

1. Introduction

e-commerce has been profoundly reshaped by the rapid growth of digital platforms and the widespread adoption (Cao et al., 2025; Lucas et al., 2023). Over the past two decades, cross-border online transactions have become a cornerstone of global economic integration, enabling companies of all sizes to reach international markets with unprecedented ease (Le, 2025). This transformation has redefined consumer expectations, as customers are no longer confined to local suppliers but instead evaluate and compare global alternatives. The expansion of e-commerce has therefore generated both opportunities and challenges for logistics systems, as the efficiency of cross-border supply chains is increasingly judged by the quality and reliability of their final stage, the last-mile (Tabim et al., 2024). In this sense, last-mile delivery is not merely a local logistical task, but a decisive factor in the competitiveness of international trade, as the customer's final experience determines the perceived value of the entire global supply chain (Agboyi, 2025). The last-mile stage of logistics possesses distinctive characteristics that render it one of the most challenging and resource-intensive phases within the supply chain (Shaklab et al., 2023; Wang et al., 2023). In contrast to upstream transportation stages, which typically benefit from economies of scale and standardized processes, last-mile delivery is characterized by fragmentation, context-specific conditions, and strong

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Nomenclature

ARAS	Additive Ratio Assessment
AV	Autonomous Vehicle
BWM	Best-Worst Method
DEMATEL	Decision Making Trial and Evaluation Laboratory
DM	Decision-Maker
EDAS	Evaluation Based on Distance from Average Solution
EI	Edge Intelligence
G-AHP	Grey Analytic Hierarchy Process
G-BWM	Grey Best-Worst Method
G-COBRA	Grey Comprehensive Distance-Based Ranking
G-DEMATEL	Grey Decision Making Trial and Evaluation Laboratory
G-EDAS	Grey Evaluation Based on Distance from Average Solution
G-MARCOS	Measurement of Alternatives and Ranking According to the Compromise Solution
G-MAUT	Grey Multi-Attribute Utility Theory
G-MOORA	Grey Multi-Objective Optimization on the basis of Ratio Analysis
G-SIWEC	Grey Simple Weight Calculation
GIDA	Grey Integrated Decision Analytics
GPSI	Grey Preference Selection Index
GPIV	Grey Proximity Indexed Value
IT	Information Technology
LCA	Life Cycle Assessment
LCCA	Life Cycle Cost Analysis
LBWA	Level-Based Weight Assessment
MCDM	Multi-Criteria Decision-Making
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
PLS-SEM	Partial Least Squares-Structural Equation Modeling
SIWEC	Simple Weight Calculation
SOR	Stimulus Organism Response
WSSM	Weighted Sum Scalarization Method

customer orientation. Modern consumers increasingly demand delivery services that are not only fast and affordable but also flexible and environmentally sustainable (Gutierrez-Franco et al., 2021). At the same time, companies are required to balance these customer expectations with cost efficiency, operational feasibility, and adherence to sustainability standards. In practice, a variety of delivery modes coexist, including conventional ground vehicles, autonomous delivery systems, drones, bicycles, and robotic couriers, each offering specific advantages while also presenting inherent limitations (Shuaibu et al., 2025). For instance, conventional trucks provide high capacity and reliability but are associated with substantial emissions, whereas drones and bicycles offer greater sustainability and flexibility but remain constrained by limited payload capacity and range (Chen et al., 2024). These trade-offs highlight the multidimensional character of last-mile delivery, where decision-making must account for multiple, often conflicting, criteria rather than relying on a single factor.

In recent years, both researchers and practitioners have increasingly acknowledged that last-mile delivery represents not only an operational challenge but also a strategic decision-making problem. Nevertheless, the majority of existing studies have primarily focused on route optimization, reduction of delivery times, and enhancement of vehicle utilization through mathematical optimization techniques (Sembiring et al., 2025; Stanković et al., 2023). Although these contributions are valuable, they predominantly address the issue from a provider- or system-level perspective, thereby overlooking customer preferences. However, in the context of global e-commerce, the effectiveness of last-mile strategies increasingly depends on the extent to which firms can align their operational decisions with the diverse expectations of end-users (Sorooshian et al., 2022). Customers assess delivery performance not solely in terms of cost, but also with regard to environmental sustainability, service reliability, and overall convenience (Rajendran and Harper, 2021). Consequently, there is an increasing need for decision support systems that can integrate these heterogeneous criteria into a coherent framework, thereby guiding both providers and consumers in making informed last-mile delivery choices.

Multi-Criteria Decision-Making (MCDM) provides a promising approach to addressing this complexity. By simultaneously accounting for multiple and often conflicting criteria, MCDM methods facilitate the systematic and transparent evaluation of alternative solutions (Madanchian and Taherdoost, 2025; Tomić et al., 2014). Nevertheless, a persistent challenge in applying MCDM to last-mile logistics lies in the inherent uncertainty and subjectivity of customer preferences. Customers may attribute varying degrees of importance to factors such as cost, emissions, or service quality, and these preferences are not always readily quantifiable in precise numerical terms (Wygonik and Goodchild, 2011). To address this challenge, the present study proposes an integrated methodology that combines Grey Simple Weight Calculation (G-SIWEC) with a multi-objective mathematical model. G-SIWEC is particularly well-suited to this context, as it enables Decision-Makers (DMs) to express their preferences using interval grey numbers, thereby capturing uncertainty and variability in human judgment while deriving accurate and practically applicable weights for subsequent analytical steps (Puška et al., 2024).

In this study, the result of the G-SIWEC method is incorporated into the proposed mathematical model in order to efficiently minimize delivery costs and emissions while maximizing customer satisfaction, thereby ensuring a systematic balance between economic efficiency, environmental responsibility, and service quality. To treat the contradictions between these objectives, the Weighted Sum Scalarization Method (WSSM) is utilized. The weights required by the WSSM are adopted from the output of the G-SIWEC method. This methodological framework is depicted in Fig. 1.

The originality of this research is based on its dual focus on customer-centric decision-making analysis and mathematical optimization. Unlike classic approaches that prioritize fleet efficiency or cost minimization, the proposed framework explicitly connects customer preferences to operational constraints, providing a more comprehensive view of last-mile delivery. In doing so, this work not only contributes to the academic literature on logistics and decision sciences but also offers practical insights for managers who must decide which emerging technologies to adopt and how to allocate resources across different delivery modes. The results demonstrate how emerging technologies such as drone, bicycle (e-bike), and Autonomous Vehicles (AVs) can complement conventional fleets in a diversified system, highlighting threshold effects across weight categories and the trade-offs between sustainability and cost. Against this information, the study is guided by the following Research Questions (RQs):

*RQ*1: How can customer preferences regarding cost, environment, and service quality be effectively integrated into last-mile delivery mode selection?

*RQ*2: To what extent does the G-SIWEC method improve decision-making robustness in uncertain last-mile logistics environments?

*RQ*3: How do emerging delivery technologies perform across varying load segments when evaluated under a multi-objective framework?

Despite the growing interest in technology-enabled last-mile delivery, existing studies exhibit three crucial limitations. First, few works integrate customer preferences with a mathematically rigorous multi-objective optimization model simultaneously. Most studies treat last-

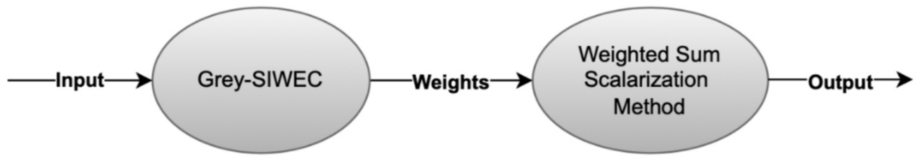

Fig. 1. Proposed methodology.

mile delivery either as a routing problem (Gu et al., 2024; Moradi et al., 2023; Tiwari and Sharma, 2023) or as a stand-alone MCDM evaluation (Simić et al., 2021; Wang et al., 2021). Second, while grey MCDM methods are increasingly used for dealing with uncertainty, current approaches like Grey Analytic Hierarchy Process (G-AHP) or Grey Best-Worst Method (G-BWM) require extensive pairwise comparisons, hence being less practical when DMs provide subjective but imprecise assessments. Third, customer satisfaction is rarely incorporated directly into optimization models. Most existing studies address the last-mile delivery problem from the provider's standpoint, focusing on fleet utilization and cost reduction, leaving a methodological gap in linking customer utilities with operational constraints. This research addresses these gaps by developing an integrated framework that captures customer preferences through G-SIWEC and takes customer satisfaction into account through lateness penalties in the multi-objective mathematical model.

Such a framework can render useful academic insights and guide managers toward building efficient, sustainable, and customer-focused last-mile systems in a global e-commerce world.

2. Literature review

Last-mile delivery mode selection is crucial for logistics operations in many industries. A detailed scientific literature review was conducted to develop the study. Therefore, the literature section of the study was examined under two main headings.

2.1. Last-Mile delivery studies

Last-mile delivery has become a prominent research domain as digital commerce transforms consumer expectations and urban distribution systems. The earlier stream of research typically examined urban logistics challenges and system-level inefficiencies. For example, Dell'Amico and Hadjidimitriou (2012) pointed to congestion, noise, and environmental strain as key challenges in urban logistics, and demonstrated with the CityLog project that two-tier and modular systems can significantly reduce traffic and emission. Cardenas et al. (2017) clarified the concept of city logistics by organizing current approaches and proposing a typology that explains its geographical and functional aspects. Frehe et al. (2017) extended this understanding by examining crowd logistics business models and, through a design science approach supported by expert interviews, developing a sustainability-focused framework. Galkin et al. (2019) examined how demand patterns and consumer behavior influence distribution costs and urban traffic externalities, and proposed a practical framework that incorporates end-customer effects into urban logistics planning. All in all, these studies spotlight that early last-mile research primarily focused on system constraints, operational challenges, and macro-level logistical implications, rather than decision-making at the customer or mode-selection level.

A second wave of studies shifted toward transitional, hybrid, and technology-augmented delivery systems. Guo et al. (2019) examined e-commerce's rapid expansion from a socio-technical perspective, showing with discrete event simulations that hybrid crowd-conventional networks can reduce costs if participation levels are adequate. Yu et al. (2020) applied a multi-objective model to understand how temporary reverse logistics networks can better manage the sudden surge of medical waste during epidemic outbreaks. The authors investigated the COVID-19 case study in Wuhan and optimized the location of temporary incinerators, reducing risks. Sun et al. (2021) employed a simulation-based model to explore how COVID-19 vaccines can be delivered more efficiently through cold chain logistics. Their findings showed that routing decisions, fleet size, and vehicle choices strongly shape service levels and costs. Perboli et al. (2021) introduced a bin-packing-inspired mixed-integer programming model to optimize two-tier city logistics with real-world data from Turin. Andoh and Yu (2023) employed a two-stage decision support framework that combines route optimization and advanced simulation to address the complex, sustainability-driven challenges of last-mile COVID-19 vaccine cold chain logistics. The authors applied this model to a real case in Norway and demonstrated that logistics network structure and fleet composition critically influence service levels, transportation costs, and CO_2 emissions.

Using the Stimulus Organism Response (SOR) theory and Partial Least Squares-Structural Equation Modeling (PLS-SEM), Ngah et al. (2024) demonstrated that environmental attitudes, technology anxiety, and safety concerns shape drone delivery adoption. Zhao et al. (2024) addressed outsourcing strategies in service parts logistics with the help of mixed-integer programming and adaptive large neighborhood search algorithm. It was revealed that cost efficiencies depend strongly on network dispersion and demand uncertainty. Reis (2025) examined Edge Intelligence (EI) in last-mile delivery, concluding via systematic review and Delphi evaluation that EI can enhance routing accuracy and customer service continuity despite high implementation costs.

These studies also reveal that technology acceptance, digital integration, and advanced decision systems increasingly guide last-mile innovation. However, most of this literature has evaluated emerging technologies in isolation or from a provider-centric viewpoint. Bao et al (2025) employed a mathematical model, Life Cycle Assessment (LCA), and Life Cycle Cost Analysis (LCCA) to demonstrate how drone-truck parallel operations can reduce emissions and noise while remaining cost-effective. Kumar et al. (2025) developed a Mixed-Integer Nonlinear Programming (MINLP) model supported by a two-phase heuristic to optimize drone deployment under energy and revenue constraints. Franco et al. (2025) reformulated multi-agent drone routing under collision-avoidance constraints as a Mixed-Integer Linear Programming (MILP) and confirmed via heuristic comparison that efficient solutions are feasible even in dense urban settings.

All in all, it is obvious that emerging technologies can improve environmental performance and operational flexibility, yet they largely overlook how customers value cost, sustainability, timeliness, and service quality when selecting among delivery modes.

2.2. Grey MCDM methods

Grey theory has become an increasingly influential tool in decision-making research, particularly in environments characterized by ambiguity, incomplete information, and subjective human judgment. Over time, scholars have shifted from standalone grey models toward integrated grey MCDM frameworks, reflecting a growing demand for hybrid approaches capable of capturing both uncertainty and multi-criteria complexity. This evolution is evident across several application domains.

Early applications focused on logistics and facility-related decisions, where ambiguity in expert judgments often complicates evaluation processes. Ulutaş et al. (2021) demonstrated this by examining warehouse location selection using a hybrid framework that combined the Grey Preference Selection Index (GPSI) and Grey Proximity Indexed Value (GPIV). Their results showed that GPIV yields stable rankings while remaining sensitive to weight variations, highlighting the robustness of grey-based evaluation in logistics settings. Similarly, Adali et al. (2022) assessed the smartness levels of European cities using a Grey Level-Based Weight Assessment (LBWA)-Evaluation Based on Distance from Average Solution (EDAS) model, revealing that grey extensions of classical MCDM methods can handle complex urban performance indicators more reliably than crisp approaches.

A second group of studies includes alternative selection and ranking problems under uncertainty, where grey numbers support impartial weighting and robust scoring. Krstić et al. (2023) extended this reasoning to governance models for intermodal terminals by integrating G-BWM and Grey Comprehensive Distance-Based Ranking (G-COBRA), identifying high-performing governance structures across multiple performance criteria. Genç et al. (2024) applied G-AHP, Grey Multi-Objective Optimization on the basis of Ratio Analysis (G-MOORA), and Grey Multi-Attribute Utility Theory (G-MAUT) in a personnel performance evaluation context, showing consistent results across methods and highlighting communication and experience as key determinants. Grey theory has increasingly been applied in managerial and organizational decision-making, especially when the relationships among criteria are interdependent. Nguyen et al. (2024) combined grey theory with Delphi and Decision Making Trial and Evaluation Laboratory (DEMATEL) to analyze innovation drivers in Vietnam's Information Technology (IT) sector. The results indicated that visionary leadership and risk-taking cultures are central to improving innovation capability. Similarly, Demir and Moslem (2025) employed Grey DEMATEL (G-DEMATEL) to evaluate barriers to smart transportation, identifying critical challenges such as infrastructure constraints and privacy concerns. Their findings highlighted the effectiveness of G-DEMATEL in revealing causal relationships within highly uncertain socio-technical systems.

More advanced hybrid models have emerged in recent years, illustrating how grey systems can be embedded within fuzzy, spherical, and integrated analytics frameworks. Radovanović et al. (2025) adopted a hybrid spherical fuzzy AHP-Grey Measurement of Alternatives and Ranking According to the Compromise Solution (G-MARCOS) approach for professor evaluation. They utilized spherical memberships and grey interval scoring for weight estimation and ranking, respectively. Rajesh (2025) introduced the Grey Integrated Decision Analytics (GIDA) model, which provides a flexible framework for generating composite decision scores under varying attribute conditions. In the context of healthcare procurement, Hayati et al. (2025) integrated BWM and Additive Ratio Assessment (ARAS) with grey forecasting to support sustainable supplier selection. It was proved that grey-based predictive modeling can enhance long-term decision reliability.

These studies demonstrate that grey MCDM frameworks have evolved into a robust set of tools for addressing uncertainty across logistics, governance, personnel evaluation, innovation, and sustainability. The literature shows that grey extensions enhance robustness, enable decision-makers to express subjective judgments without forced precision, and improve the quality of sensitivity analyses. Even with this progress, the literature reveals a clear gap. Grey MCDM methods are largely used for ranking and weighting, with limited efforts to embed grey-based weights into optimization models, particularly in dynamic and data-driven contexts like last-mile logistics. In addition, existing work rarely links grey-based preference elicitation to operational decision variables within multi-objective frameworks. Addressing this gap, the present study directly incorporates G-SIWEC weights into a mathematical optimization model.

2.3. Research gap

Despite the increasing attention devoted to last-mile delivery in recent years, significant gaps persist in the academic literature. Most existing studies have predominantly focused on operational issues, such as routing efficiency (Wang et al., 2014), vehicle utilization (Lal et al., 2023), and cost minimization (Ranieri et al., 2018), frequently emphasizing the perspective of logistics providers rather than that of end customers. Although these studies have provided valuable insights, they do not fully capture the complexity of customer preferences, which are increasingly decisive for competitiveness in international e-commerce markets. Efforts to incorporate environmental considerations have also often been fragmented, frequently isolating sustainability from other critical factors such as cost and service quality. Concurrently, the adoption of grey systems and MCDM techniques has expanded in logistics research; however, their application to last-mile delivery mode selection, particularly in a manner that integrates subjective customer priorities with rigorous mathematical optimization, remains limited. This highlights a clear need for research that develops a holistic and transparent decision support framework capable of simultaneously balancing economic efficiency, environmental sustainability, and customer satisfaction.

2.4. Motivation

While the literature has made notable progress in routing efficiency, cost minimization, and new delivery technologies, it has yet to offer an integrated framework that incorporates customer preferences into uncertain multi-objective optimization settings (Boysen et al., 2021; Ranieri et al., 2018; Shuaibu et al., 2025). Existing studies often consider cost, sustainability, and service quality as separate concerns, rather than as interconnected dimensions shaped by human judgment (Olsson et al., 2019). This gap reflects the absence of an integrated last-mile delivery framework capable of jointly addressing customer expectations, environmental priorities, and operational constraints (Escudero-Santana et al., 2022; Lal et al., 2023).

To address this gap, we develop a hybrid decision support approach that combines the G-SIWEC method with a multi-objective mathematical model, translating uncertain and imprecise customer evaluations into robust criterion weights, which are then embedded in a structured mode-selection model.

By linking grey-based preference weighting with an optimization framework, this research provides an efficient data-driven approach for evaluating delivery modes across conflicting objectives. In doing so, it closes a key gap by connecting subjective customer assessments with quantitative logistics performance modeling. The practices listed in Table 1 was examined in detail during the development of this study. Therefore, they are among the motivational sources for the study.

3. Proposed framework

This section provides the developed MCDM method with the developed multi-objective model.

3.1. Problem Definition

In the rapidly evolving e-commerce landscape, customers increasingly expect efficient, reliable, and eco-friendly delivery services. The "last-mile" phase, where products are transported from a local distribution center to the end customer, often proves to be the most challenging and resource-intensive stage in the logistics chain. Traditionally, logistics providers offer multiple delivery modes (e.g., standard ground delivery, express shipping, drone or bike couriers, pickup lockers), each with distinct attributes relating to cost, speed, environmental impact, and overall service experience (He et al., 2011; Li et al., 2020; Ranieri et al., 2018).

Table 1
A summary of the previous last-mile delivery models and methods.

Reference	Subject	Method
(Dell'Amico and Hadjidimitriou, 2012)	Addressing urban goods distribution challenges (congestion, noise, emissions) with CityLog two-tier system	Two-tier logistics model (freight buses, eco-vans, Modular BentoBox), case project application
(Frehe et al., 2017)	Development of sustainable crowd logistics business models	Design Science approach, expert interviews, document analysis
(Galkin et al., 2019)	Impact of distribution costs and consumer expenses on urban traffic and logistics efficiency	Quantitative analysis, framework for integrating consumer effects
(Guo et al., 2019)	Transition of urban last-mile logistics under e-commerce growth	Socio-technical transition theory, discrete event simulation
(Perboli et al., 2021)	Role of two-tier city logistics systems in freight operations	Mixed-integer programming, heuristic methods, real data validation
(Ngah et al., 2024)	Determinants of online shoppers' intention to adopt drones	Survey, PLS-SEM
(Zhao et al., 2024)	Outsourcing strategies for two-echelon last-mile systems with dispersed demand	Mixed-integer programming, adaptive large neighborhood search
(Bao et al., 2025)	Integration of drones and trucks for sustainable last-mile logistics	LCA, LCCA, sensitivity analysis

When placing an order online, a customer is typically presented with a set of delivery mode options. Each mode might differ in price, time-to-delivery, and associated environmental footprint (He et al., 2011; Li et al., 2020; Yan and Zhang, 2015). Beyond these operational characteristics, the customer's perceived satisfaction and convenience also play critical roles in the decision-making process. The complexity emerges from the need to consider multiple, often conflicting criteria simultaneously. An eco-friendlier option may cost more or take longer, while a cheaper alternative might not align well with the customer's environmental values or desired delivery speed (Escudero-Santana et al., 2022; Wang, 2019).

From the customer's perspective, selecting the most appropriate delivery mode is an MCDM challenge. Given a set of available delivery modes, each characterized by different performance levels across criteria such as cost, environmental impact, and quality of service (customer satisfaction), the customer faces the question: Which delivery mode should I choose to meet my individual preferences and priorities best(Boysen et al., 2021; Meyer, 1999).

Customer satisfaction is operationalized through lateness, as timely delivery is constantly found to be the most critical determinant of perceived service quality in last-mile logistics (Vrhovac et al., 2024). Other factors, such as friendliness, package condition, or convenience, are relevant but hard to include in a mathematical model because of their qualitative nature and large variability across customers. Lateness, by contrast, is (*i*) directly measurable, (*ii*) universally relevant across delivery contexts, and (*iii*) incorporated into optimization models through penalty costs. Using lateness as a proxy for customer satisfaction allows the model to maintain theoretical soundness while embedding customer considerations directly into operational decisions. This approach is consistent with prior work where on-time performance is the dominant quantitative indicator of delivery satisfaction.

The primary objective is to provide a systematic and transparent decision support framework that assists customers in identifying the "best" delivery mode according to their specific importance weights assigned to key criteria. This approach aims to:

Integrate multiple decision-making criteria (e.g., cost, environmental factors, customer satisfaction) into a single decision support model (He et al., 2011; Ranieri et al., 2018).
Balance potentially conflicting objectives, enabling the customer to see the trade-offs clearly (Yan and Zhang, 2015).
Utilize MCDM methods to rank or score delivery modes (Wang, 2019).
Incorporate mathematical modeling techniques to quantify criteria, enabling a more objective and robust evaluation (Boysen et al., 2021; Escudero-Santana et al., 2022).

3.2. Mathematical model

The multi-objective optimization model developed in this study relies on a number of fundamental assumptions when determining customer-transportation mode matching. First, each customer is assumed to be served by only one transportation system using a single mode; thus, partial shipments or multimodal use are not allowed. Capacity limitations of transportation systems are defined deterministically, and the selected transportation mode is assumed to have adequate capacity to cover customer demand. The model is treated as deterministic by assuming that transit times, setup times, and emission-cost coefficients are fixed and known, while traffic, weather, and other operational uncertainties are not considered. Since customer satisfaction is related to on-time delivery, the quantity of delays is subject to a linear penalty, and delay is modeled linearly, with a constant cost applied per unit of time.

Now, the proposed mathematical model is described as follows:

- **Indices**

$j \in J$: Index of demand points (customers),
$k \in K$: Index of transportation system mode.

- **Parameters**

c_{jk}: Unit transportation cost to serve customer j with transportation system mode k,
t_{jk}: Delivery time (transportation time) of transportation system mode k to serve customer j,
a_k: Available time of transportation system mode k (minute),
e_{jk}: Unit amount of emission (negative environmental impact) imposed by transportation system mode k to serve customer j,
d_j: Demand of customer j (kg),
Q_k: Capacity of transportation system mode k (kg),
p_j: Unit penalty cost for the lateness to serve customer j (currency/minute),
b_j: Latest acceptable delivery time for customer j.

- **Decision variable**

$$y_{jk}: \begin{cases} 1, & \text{if transportation system mode } k \text{ is selected to serve customer } j, \\ 0, & \text{otherwise}, \end{cases}$$

f_j: Finish time of service to customer j,
l_j: Amount of lateness to serve customer j,
z_{jk}: Amount of delay to serve customer j with transportation system mode k.

- **Objective functions**

The first objective function (1) minimizes the total cost of delivery:

$$\text{minimize}\, C = \sum_{j \in J} \sum_{k \in K} c_{jk} y_{jk} \tag{1}$$

The second objective function (2) minimizes total emission, contributing to sustainable development:

$$\text{minimize}\, E = \sum_{j \in J} \sum_{k \in K} e_{jk}\, y_{jk} \tag{2}$$

The third objective function (3) is designed to enhance customer satisfaction by factors like on-time delivery and service quality. In the context of the model, customer satisfaction is often associated with timely deliveries. Late deliveries can lead to customer dissatisfaction, so the model aims to minimize late deliveries or the penalties associated with them.

$$\text{minimize}\, T = \sum_{j \in J} \sum_{k \in K} p_j\, l_j\, y_{jk} \tag{3}$$

- **Constraints**

$$\sum_{k \in k} y_{jk} = 1 \quad \forall j \in J, \tag{4}$$

$$\sum_{k \in K} d_j y_{jk} \le Q_k \quad \forall j \in J, \tag{5}$$

$$l_j = \max\left\{0, f_j - b_j\right\} \quad \forall j \in J, \tag{6}$$

$$f_j = \sum_{k \in K} (a_k + t_{jk}) y_{jk} \quad \forall j \in J, \tag{7}$$

$$y_{jk} \in \{0, 1\};\; l_j,\; f_j \ge 0 \quad \forall k \in K, j \in J. \tag{8}$$

Eq. (4) ensures that each customer is served. Constraint (5) represents the capacity limitation of each transportation system. Eq. (6) calculates the lateness to serve each customer. Eq. (7) computes the finish time of delivery to each customer. Constraint (8) displays the types of variables.

3.3. Linearization

Since Eqs. (3) and (6) lead to non-linearity of the model, we can make it linear as follows:

$$l_j \ge 0 \quad \forall j \in J, \tag{9}$$

$$l_j \ge f_j - b_j \quad \forall j \in J, \tag{10}$$

$$z_{jk} \le M\, y_{jk} \quad \forall j \in J,\; k \in K, \tag{11}$$

$$z_{jk} \le l_j \quad \forall j \in J,\; k \in K, \tag{12}$$

$$z_{jk} \ge l_j - M\left(1 - y_{jk}\right) \quad \forall j \in J,\; k \in K, \tag{13}$$

$$z_{jk} \ge 0 \quad \forall j \in J,\; k \in K. \tag{14}$$

Therefore, we just replace Eq. (6) with Constraint (10) and Eq. (3) with Constraints (11)-(13), since Constraints (9) and (14) are already included in Constraint (8).

3.4. Weighted Sum Scalarization method

The WSSM is the most well-known technique for multi-objective decision-making problems (Kasimbeyli et al., 2019). It combines multiple, typically conflicting, objective functions into a single objective function by multiplying each of them by predetermined weights and then summing them. Weights are subjective and express the relative importance given by the DM to each objective. Its greatest advantage is ease of implementation and the ability to express all the objectives on a common scale. In this study, the WSSM approach is used for trading off between criteria such as cost, environmental impact (emission), and delay penalties on customer satisfaction. By adjusting the weight of each criterion, the most suitable mode of transport is determined for various scenarios.

To do so, we first normalize the individual objective functions as follows:

$$C_{\text{norm}} = \frac{C - C_{\min}}{C_{\max} - C_{\min}}, \tag{15}$$

$$E_{\text{norm}} = \frac{E - E_{\min}}{E_{\max} - E_{\min}}, \tag{16}$$

$$T_{\text{norm}} = \frac{T - T_{\min}}{T_{\max} - T_{\min}}, \tag{17}$$

where C_{norm}, E_{norm}, and T_{norm} stand for the normalized objective functions (1), (2), (3), respectively. Moreover, $C_{\min}$ and $C_{\max}$, $E_{\min}$ and $E_{\max}$, and $T_{\min}$ and $T_{\max}$ represent the minimum and maximum possible values for objective functions (1), (2), (3), respectively. These values are obtained by minimizing and maximizing the individual objective functions.

Finally, the single objective function (Z_{WSSM}) is built up as Eq. (18):

$$\text{minimize}\, Z_{\text{WSSM}} = w_C \times C_{\text{norm}} + w_E \times E_{\text{norm}} + w_T \times T_{\text{norm}}), \tag{18}$$

where w_c, w_E, and w_T display the weights assigned to the objective functions (1), (2), (3), respectively.

3.5. Grey numbers

A grey number can be indicated as $\otimes x = [\underline{x}, \overline{x}]$ and the $\underline{x}$ and $\overline{x}$ are lower and upper limits of a grey number. These numbers are frequently referred to as interval grey numbers. The interval grey numbers are selected in the application part of this study. Assume that two interval grey numbers are $\otimes x_1 = [\underline{x_1}, \overline{x_1}]$ and $\otimes x_2 = [\underline{x_2}, \overline{x_2}]$. Some basic operations of these two grey numbers are presented as follows (Adali et al., 2022; Kaviani et al., 2020; Stanujkic et al., 2017):

$$\otimes x_1 + \otimes x_2 = \left[\underline{x_1} + \underline{x_2}, \overline{x_1} + \overline{x_2}\right], \tag{19}$$

$$\otimes x_1 - \otimes x_2 = \left[\underline{x_1} - \overline{x_2}, \overline{x_1} - \underline{x_2}\right], \tag{20}$$

$$\otimes x_1 \times \otimes x_2 = \left[\min\left(\underline{x_1} \times \underline{x_2}, \underline{x_1} \times \overline{x_2}, \underline{x_2} \times \overline{x_1}, \overline{x_1} \times \overline{x_2}\right), \max\left(\underline{x_1} \times \underline{x_2}, \underline{x_1} \times \overline{x_2}, \underline{x_2} \times \overline{x_1}, \overline{x_1} \times \overline{x_2}\right)\right], \tag{21}$$

$$\frac{\otimes x_1}{\otimes x_2} = \left[\underline{x_1}, \overline{x_1}\right] \times \frac{1}{\overline{x_2}}; \ \frac{1}{\underline{x_2}} \notin \otimes x_2, \tag{22}$$

$$k \times \otimes x_1 = k \times \left[\underline{x_1}, \overline{x_1}\right] = \left[k \times \underline{x_1}, k \times \overline{x_1}\right]. \tag{23}$$

Whitenization of grey numbers is as follows (Adali et al., 2022):

$$x_\lambda = (1 - \lambda) \times \underline{x} + \lambda \times \overline{x}, \tag{24}$$

where λ is the whitening coefficient ($\lambda \in [0, 1]$) representing the preference or risk attitude of the DM. If $\lambda < 0.5$, it indicates a pessimistic (conservative) attitude, and $\lambda > 0.5$ indicates an optimistic attitude. In this study, we take $\lambda = 0.5$ to keep a neutral attitude toward risk, giving equal weight to both the lower and upper bounds of the interval of uncertainty. This value will be taken 0.5 at the application part.

3.6. Grey Simple weight Calculation

One of the most recent methods for obtaining the weights of criteria is the SIWEC method, which was developed by Puška et al. (2024). The main argument behind the SIWEC method is simplifying the calculation process with the help of measuring variation across the different criteria using the standard deviation.

G-SIWEC is developed because it offers clear advantages over existing grey-based weighting methods. Unlike G-AHP or G-BWM, it avoids large pairwise-comparison matrices and iterative consistency checks, thereby reducing cognitive burden and the risk of inconsistency among experts. In contrast to distance-based grey approaches, such as G-EDAS or G-MOORA, G-SIWEC is variance-driven and captures the dispersion of expert judgments through grey standard deviations, allowing the weighting process to reflect both central tendency and uncertainty. Its computational structure is simple, transparent, and scalable, and is particularly suited to contexts where DMs outline their preferences using broad grey intervals instead of inputs in precise numerical form. These features make G-SIWEC well suited to customer-driven last-mile logistics, where preferences are inherently subjective and often ambiguous or variable.

Table 2
Linguistic scale for evaluation of criteria.

Definition	Interval Grey numbers
Low	[0,0.2]
Less than moderate	[0.2,0.4]
Moderate	[0.4,0.6]
More than moderate	[0.6,0.8]
High	[0.8,1.0]

This section discusses the extension of grey numbers within the context of the SIWEC method. The decision-making problem covers n criteria $(C_j : j = 1, 2, \cdots, n)$ and m DMs $(DM_i : i = 1, 2, \cdots, m)$.

Step 1: In this step, DMs evaluate the importance of each criterion with interval grey numbers; they give the highest score to the criterion they find most important.

Step 2: The initial decision matrix is established based on the expert assessment conducted by the invited DMs. The initial decision matrix is constructed using the interval grey linguistic scale presented in Table 2.

Step 3: A decision matrix where each value $\otimes f_{ij}$ (the assessment value of DM i based on of criterion j) is a grey number, denoted as $\otimes f_{ij} = \left[\underline{f_{ij}}, \overline{f_{ij}}\right]$. The representation of $\otimes f_{ij}$ is given in Eq. (21):

$$f = \begin{bmatrix} \otimes f_{11} & \otimes f_{12} & \cdots & \otimes f_{1n} \\ \otimes f_{21} & \otimes f_{22} & & \otimes f_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes f_{m1} & \otimes f_{m2} & \cdots & \otimes f_{mn} \end{bmatrix}. \tag{25}$$

Step 4: The grey decision matrix is used to create a grey normalized matrix $\otimes r_i$. The initial decision matrix is normalized in the way given by Eq. (26):

$$\otimes r_{ij} = \frac{\otimes f_{ij}}{x_{\max}}; \otimes r_{ij} = \left[\underline{r_{ij}}, \overline{r_{ij}}\right] = \left[\frac{\underline{f_{ij}}}{\overline{x_{\max}}}, \frac{\overline{f_{ij}}}{\underline{x_{\max}}}\right], \tag{26}$$

where $x_{\max} = \max_{i,j} \otimes f_{ij}$ represents the maximum value in the matrix.

Step 5: Consistent with the SIWEC rationale, criteria whose evaluations exhibit greater dispersion across DMs are assigned higher weights. In G-SIWEC, this dispersion is captured via a grey standard deviation for each criterion j. $\otimes r_{ij} = \left[\underline{r_{ij}}, \overline{r_{ij}}\right]$ be the normalized evaluation of DM i for criterion j. The mean lower and upper bounds of criterion j across the m DMs are denoted by $\underline{r_j} = \frac{1}{m}\sum_{i=1}^{m} \underline{r_{ij}}$ and $\overline{r_j} = \frac{1}{m}\sum_{i=1}^{m} \overline{r_{ij}}$, respectively.

The grey standard deviation for criterion j is thus defined as the interval $\otimes\sigma_j = \left[\underline{\sigma_j}, \overline{\sigma_j}\right]$. The sample standard deviations of the lower and upper bounds are then calculated by $\underline{\sigma_j} = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(\underline{r_{ij}} - \underline{r_j}\right)^2}$ and $\overline{\sigma_j} = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(\overline{r_{ij}} - \overline{r_j}\right)^2}$, respectively.

Step 6: The normalized grades are multiplied by the standard deviations as given in Eq. (27):

$$\otimes v_{ij} = \otimes r_{ij} \times \otimes \sigma_{ij}. \tag{27}$$

Step 7: The values obtained by multiplying the criteria grades by the standard deviations are collected, as denoted by Eq. (28):

$$\otimes s_j = \sum_{i=1}^{m} \otimes v_{ij}. \tag{28}$$

Step 8: In this step, each $\otimes s_j$ value is divided by the total $\otimes s_j$ value so that the sum of the weights of the criteria is one, as given in Eq. (29):

$$\otimes w_j = \frac{\otimes s_j}{\sum_{j=1}^{n} \otimes s_j}. \tag{29}$$

Step 9: The grey weight values for all criteria are transformed into crisp numbers using Eq. (24). The outcome is a crisp criterion weight value (w_j), which represents the final weights of the criteria.

4. Numerical experiment

In this section, the data structure, findings, and analyses in the experimental design of the study are expressed in detail.

4.1. Data structure

Because the problem addressed in this study was solved in two distinct stages, the data have also been generated differently. In the first stage of the study, the data used in the G-SIWEC method consist of DM opinions. In the second stage, the mathematical model parameters reflect the data used.

4.1.1. Data for the MCDM model

Three fundamental requirements assume prime importance for any orders, either individual or corporate, while choosing a last-mile mode of delivery: cost, air emissions, and customer satisfaction. Cost is the most critical among these, and it is the clincher here, just as it is in almost all decision-making situations. The cost of delivery matters significantly to both individual buyers and companies. Cheaper deliveries can result in enormous long-term gains, especially to those who order very frequently. The second criterion is air emissions. As the effects of global warming and the environment become increasingly prevalent, green practices are becoming increasingly prevalent. This directly affects consumer and business decisions. For example, alternatives like bicycle delivery or electric car delivery that utilize fewer carbon emissions become more appealing to environmentally conscious individuals. This alternative not only helps the environment but also allows the individual or company to knowingly demonstrate their effort towards sustainability. The final one is customer satisfaction. This refers to the extent to which aspects such as speed, reliability, flexibility, and quality of service meet user needs during the delivery process. Efficient and seamless delivery is core to the user experience. Delays or communication failures during the delivery process can affect individual user satisfaction and organizations significantly. A delivery mechanism that is equal to or above expectations, therefore, has high usability value for users.

Table 3
Parameters related to the customers.

Parameters	Lower	Upper
d_j	1	110
p_j	3	10
b_j	60	120

The technologies used in last-mile delivery have diversified and, with emerging technologies, moved out of the conventional framework. Conventional delivery remains a prevalent practice, typically conducted using cargo company vehicles and human labor. This mode is widely preferred due to its reliability and adherence to routine operational processes. In contrast, AVs represent emerging technologies capable of performing deliveries independently. They can yield time and energy savings due to their efficiency in traffic, speed, and route planning. Bike delivery is an extremely short-range and environmentally friendly option. Its ability to reduce air emissions and move with pace in city traffic makes it a tangible means of sustainability. Drone delivery has been a trendy idea over the last few years and is popular primarily among businesses and technology-savvy individuals. Its advantage lies in fast delivery time, the ability to access hard-to-reach geographies, and minimal human capital requirements. It could be limited by weather or regulatory factors, though. Unlike the typical AVs, Postomate is a compact autonomous robot that can navigate pedestrian walkways and deliver packages to customers' doorsteps. They are used for short distances and operate at slow speeds, with safety being their priority. Being electric, they are environmentally friendly and can cut operational expenses by avoiding human labor. The criteria and alternatives are given in Fig. 2.

4.1.2. Data for the mathematical model

Test data were generated using a uniform distribution; i.e., ~U(min, max), as real data for the problem addressed in this study are not available. Some of these test data values were generated in an appropriate control, while others were found in the literature. The lower and

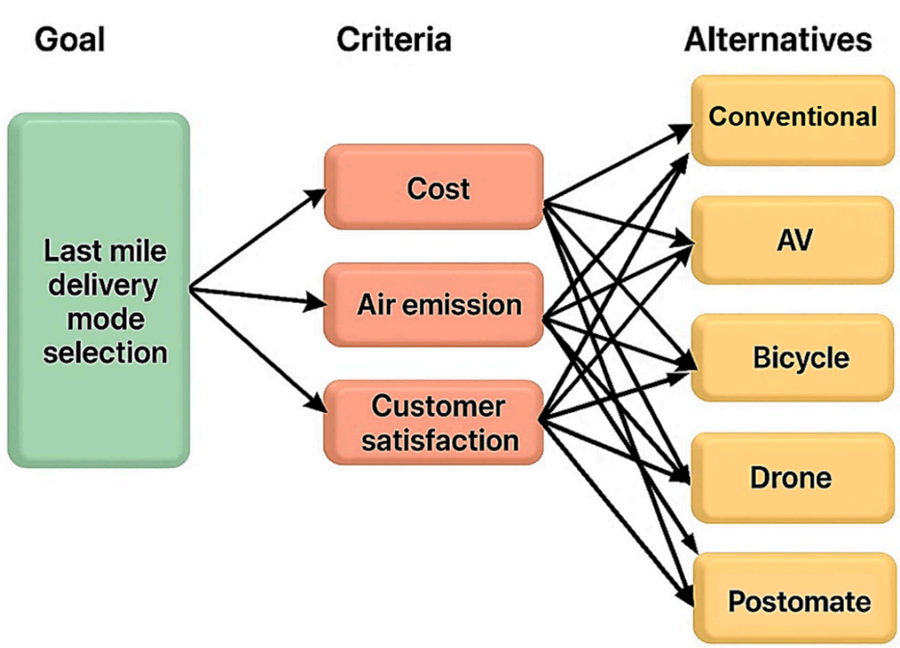

Fig. 2. Representation of the last-mile delivery mode selection problem.

Table 4
Parameters related to the customers and vehicles.

Modes	Q_k		a_k		c_{jk}		t_{jk}		e_{jk}	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Conventional	100	110	10	15	20	30	30	90	6	10
AV	60	100	10	15	18	28	25	70	2	5
Bicycle	10	15	1	3	5	15	15	40	0	0.2
Drone	20	25	1	3	10	20	10	30	0.25	1.5
Postomate	20	25	1	3	10	20	20	60	0.5	2

Table 5
Initial decision matrix.

	C_1	C_2	C_3
DM1	MM	LM	H
DM2	H	L	M
DM3	M	LM	H

L: Low, LM: Less than moderate, M: Moderate, MM: More than moderate, H: High.

Table 6
Initial decision matrix.

	C_1	C_2	C_3
DM1	[0.6, 0.8]	[0.2, 0.4]	[0.8, 1.0]
DM2	[0.8, 1.0]	[0.0, 0.2]	[0.4, 0.6]
DM3	[0.4, 0.6]	[0.2, 0.4]	[0.8, 1.0]

upper bound values of the data are given in Tables 3 and 4.

Table 3 illustrates lower and upper limits for customer-based parameters. The.

parameter d_j in this case represents the quantity of product ordered to be delivered by a customer, ranging from 1 to 110 units. The value is determined based on vehicle capacity. The penalty coefficient e_j, whose value is to be utilized for the customer in case of tardiness, lies between 3 and 10 currency units per minute. In addition, the parameter b_j, the most recent time window in which every customer will be able to receive their order, ranges between 60 and 120 min. These parameter values were set to simulate various customer types and service sensitivities so that the model would react realistically to client demand. Table 4 has the lower and upper limits of the operating capacity and performance levels of every mode of transport. While conventional cars possess a huge carrying capacity of 100–110 units, new but capacity-restricted modes of transport like drones are limited to carrying 1–10 units. All modes of transport are independently defined for parameters such as initial availability (a_k), transport cost (c_{jk}), travel time (t_{jk}), and carbon emissions (e_{jk}). The value of (e_{jk}) specifically was determined according to the literature (Raghunatha et al., 2023).

4.2. Results of the MCDM: G-SIWEC

In the G-SIWEC method; firstly, the evaluations of the criteria were taken from the DMs as given in Table 5, and accordingly, the initial decision matrix given in Table 6 was created.

Let $\otimes f_{ij} = \left[\underline{f_{ij}}, \overline{f_{ij}}\right]$ denote the interval grey evaluation given by DM i for criterion j, where $\underline{f_{ij}}$ and $\overline{f_{ij}}$ represent the lower and upper bounds of the corresponding grey number. The initial grey decision matrix $f = \left[f_{ij}\right]$ is obtained by mapping the linguistic terms in Table 5 to the interval grey numbers in Table 2 (see Table 6 for the resulting matrix).

Table 7
Normalized decision matrix.

	C_1	C_2	C_3
DM1	[0.6, 1.0]	[0.2, 0.5]	[0.8, 1.25]
DM2	[0.8, 1.25]	[0.0, 0.25]	[0.4, 0.75]
DM3	[0.4, 0.75]	[0.2, 0.5]	[0.8, 1.25]

Table 8
Results that are multiplied by the standard deviations.

	C_1	C_2	C_3
DM1	[0.345, 0.6225]	[0.011, 0.311]	[0.046, 0.778]
DM2	[0.046, 0.7781]	[0.0, 0.155]	[0.023, 0.466]
DM3	[0.023, 0.466]	[0.0115, 0.311]	[0.046, 0.778]

Step 1 (Initial Assessment): To ensure the reproducibility of the results, we present the step-by-step calculation for criterion one (C_1) using the data from Table 6.

The DMs assigned the following importance intervals to C_1:

DM1: $[0.6, 1.0]$, DM2: $[0.8, 1.25]$, DM3: $[0.4, 0.75]$.

Step 2 (Normalization): To bring all interval grey evaluations onto a comparable scale, we first compute the maximum lower bound across the entire matrix $x_{\max} = \max_{i,j} \otimes f_{ij}$.

In our case, $x_{\max} = [0.8, 1]$. Each grey number $\otimes f_{ij}$ is then normalized as $\otimes r_{ij} = \left[\underline{r_{ij}}, \overline{r_{ij}}\right] = \left[\frac{\underline{f_{ij}}}{\overline{x_{\max}}}, \frac{\overline{f_{ij}}}{\underline{x_{\max}}}\right]$.

Applying the interval division rule with the denominator $[0.8, 1]$, we obtain the normalized grey evaluations for C_1:

$$\text{DM1:}\left[\frac{0.6}{1}, \frac{0.8}{0.8}\right] = [0.6, 1.0],$$

$$\text{DM2:}\left[\frac{0.8}{1}, \frac{1}{0.8}\right] = [0.8, 1.25],$$

$$\text{DM3:}\left[\frac{0.4}{1}, \frac{0.6}{0.8}\right] = [0.4, 0.75].$$

So, the initial decision matrix is then normalized in accordance with Eq. (25) as given in Table 7.

Step 3 (Grey standard deviation): Using the normalized intervals, we compute the mean lower and upper bounds for C_1; $\underline{r_1} = \frac{0.6+0.2+0.8}{3} = 0.53, \overline{r_1} = \frac{1.0+0.5+1.25}{3} = 0.92$.

Substituting these into the standard deviation formulas (Eq. (25)) yields the grey standard deviation as $\sigma_1 = \left[\underline{\sigma_1}, \overline{\sigma_1}\right] = [0.06, 0.62]$.

Step 4 (Weighted grey values and aggregation): Using interval multiplication, we compute the weighted grey values; $v_{i1} = r_{i1} \otimes \sigma_1$, which yields; for example:

$$\text{DM1:} v_{11} = \left[\min\begin{pmatrix} 0.6\times 0.06, \ 0.6\times 0.62, \\ 1\times 0.06, 1\times 0.62 \end{pmatrix}, \max\begin{pmatrix} 0.6\times 0.06, \ 0.6\times 0.62, \\ 1\times 0.06, 1\times 0.62 \end{pmatrix}\right]$$
$$= [0.0345, \ 0.6225].$$

The same calculation is repeated according to Eq. (26), resulting in the

Table 9
Values of s_j and w_j.

	C_1	C_2	C_3
s_j	[0.103, 1.867]	[0.023, 0.778]	[0.115, 2.023]
w_j	[0.025, 8.718]	[0.005, 3.632]	[0.027, 9.445]

Table 10
Scores and weights.

	Scores	Weights
C_1	4.3719	0.4001
C_2	1.8192	0.1665
C_3	4.7366	0.4334

Table 11
Overall system performance per weight range (averages over 30 runs).

Customer ID	Mode	Weight (d_j)	Cost (c_{jk})	Emission (e_{jk})	Lateness
1	AV	55	27.11	4.92	0
2	Conventional	109	22.18	9.31	0
3	AV	56	25.48	3.54	0
4	AV	57	21.64	2.66	0
5	Conventional	109	23.62	8.21	0
6	Conventional	107	26.66	7.43	0
7	AV	57	25.45	2.49	0
8	Bicycle	11	11.01	0.16	0
9	AV	58	23.76	4.34	0
10	Conventional	100	23.20	7.66	0
11	AV	67	18.80	3.99	0
12	Drone	8	10.39	0.61	0
13	AV	40	24.82	**3.05**	0
14	Drone	13	12.34	0.39	0
15	Postomate	17	18.14	1.27	0
16	Drone	16	12.75	0.95	0
17	AV	39	23.66	3.39	0
18	AV	55	19.56	2.89	0
19	Drone	12	11.66	0.79	0
20	Conventional	71	28.68	9.19	0

weighted matrix shown in Table 8.

The aggregated grey score for each criterion is then obtained by summing across all DMs. Therefore, s_j and w_j values are calculated with Eqs. (27) and (28) as given in Table 9.

Lastly, the scores and weights of all criteria are calculated using Eq. (24), where the results are outlined in Table 10.

4.3. Results of the mathematical Model: Optimization

The second stage of this study consists of solving the mathematical model. The method used here is WSSM. The weights determined by the MCDM method are used as the objective function weights for WSSM. In this study, the mathematical model was developed using the Python programming language, and the Gurobi Optimizer software was used for the solution process.

The values of the parameters entered in the mathematical model solution are crucial because they directly affect the results. Both the results and the decision variables change based on these values. Because the purpose of this study is to investigate the selection of delivery modes in the last-mile delivery process, and because the results vary depending on the data, we have evaluated the results by modifying the data.

All of the alternatives used in the study have unique capabilities. However, when the tests are conducted entirely based on the data provided in Section 4.1.2, the following results are obtained (30 runs were taken for each result, and their averages were calculated).

The mathematical model was solved using the criteria weights determined by the G-SIWEC method. Specifically, the weights for cost, emission, and customer satisfaction are set to 0.4001, 0.1665, and 0.4334, respectively. The combined objective function is therefore structured as minimize $Z_{\mathrm{WSSM}} = 0.4001 \times C_{norm} + 0.1665 \times E_{norm} + 0.4334 \times T_{norm})$.

According to the given parameter values, the example test was made for 20 customers, and the performance per weight range is given in Table 11 and in Fig. 3.

Based on an analysis of 30 different datasets, drone and bicycle were ranked as the most commonly used means for delivering products weighing between 1 and 25 kg. On average, drone account for 66.67% of deliveries of this weight, followed by bicycle for 16.67% and Postomate for 16.67% (see Table 12).

The findings illustrated in Fig. 4 suggest that quick and sustainable modes (e.g., bicycle and drone) are preferable to conventional autonomous freight robots for the transportation of lightweight parcels.

Moreover, the test based on the parameter value was done with 1000 customers, and the results are given in Table 13 and Fig. 5. Table 13 summarizes last-mile delivery mode preference rates by product weight range. One row is used to present the average percentage of delivery modes for each weight range. Overall, the results show that the model is quite good in its behavior. For 1–25 kg, drone (43.36%) and bicycle (42.66%), being eco-friendly and low-capacity vehicles for light loads, are most favored, as expected. Postomate (4.60%) has also been sparingly utilized. AVs (7.80%) and, in particular, conventional truck (1.59%) was practically never favored. This indicates that cost, emissions, and capacity allocation are best allocated for light loads. Small vehicles are phased out in the 26–75 kg category. Autonomous trucks (83.41% and 72.01%) and conventional trucks (16.59% and 27.99%) are employed in the category mainly for delivering loads. This shows cost efficiencies and speed benefits from autonomous trucks for the medium-load segment. Postomate, bicycle, and drone are excluded since they do not have adequate loading capacity. In the 76–110 kg, regular cars completely dominate. Conventional truck was used 72.24% for 76–100 kg, and 100% for 101–110 kg. That demonstrates the conventional module's ability to provide adequate high-capacity transport and effective usage of capacity printers by the model. Therefore,

Table 12
Average vehicle usage (%) for 20 customers.

Modes	**Vehicle Usage**
Bicycle	16.67
Drone	66.67
Postomate	16.67

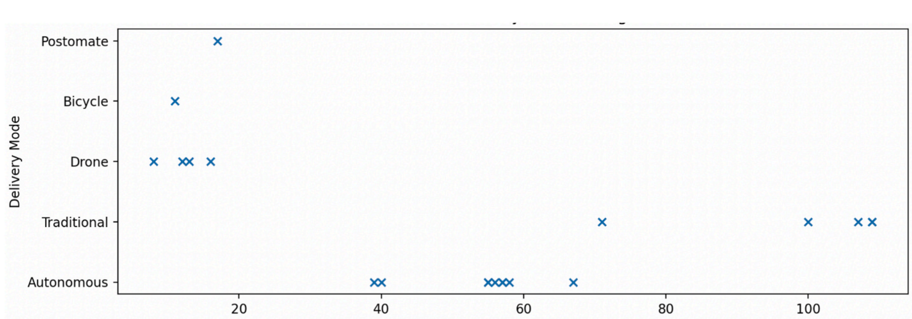

Fig. 3. Delivery mode selection based on the weight of the orders.

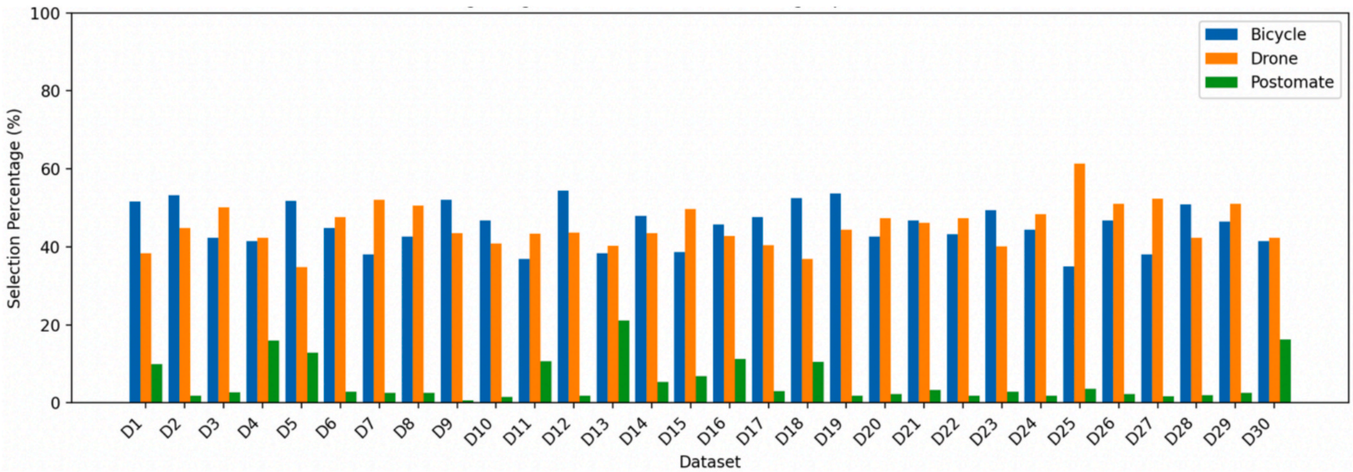

Fig. 4. Delivery mode selection based on the weight of the orders.

Table 13
Average vehicle usage (%) for 1000 customers.

Weight ranges	Conventional	Autonomous	Bicycle	Drone	Postomate
1–25	1.59	7.80	42.66	43.36	4.60
26–50	16.59	83.41	0	0	0
51–75	27.99	72.01	0	0	0
76–100	72.24	27.76	0	0	0
101–110	100.00	0	0	0	0

I. **AVs (Mid-Weight 26–75 kg):** AVs dominate this segment because they represent the "Pareto-optimal" compromise. Unlike drone/bicycle, which are capacity-infeasible for loads weighing more than 25 kg, AVs have sufficient payload capacity. Simultaneously, they operate at significantly lower marginal costs and emission rates compared to conventional trucks. Therefore, the solver selects them to minimize the weighted objective function.

II. **Conventional Trucks (Heavy Loads 76–110 kg):** The dominance of conventional trucks here is dictated by feasibility rather than preference. The mathematical model forces a hard capacity constraint given by Eq. (5). Since the maximum capacity of AV in our model tops out at 100 kg and drone at 25 kg, the conventional truck is often the only available mode for heavy loads; and hence, the higher emissions become irrelevant to the selection process within this specific weight band.

III. **Real-World Consistency:** These results strongly mirror emerging "multi-modal" logistics strategies. Real-world pilots, such as Starship and Nuro, deploy autonomous bots for mid-size grocery runs; at the same time, drones like Wing and Zipline dedicate their resources to lighter items such as medicine and food. Heavy logistics pertaining to furniture and bulky cargo naturally remain the exclusive domain of conventional vans due to the physical limitations in payload capacity.

Table 14
Weights of scenarios.

Change coefficient	C_1	C_2	C_3
10%	0.360	0.148	0.389
20%	0.320	0.132	0.346
30%	0.280	0.115	0.303
40%	0.240	0.099	0.259
50%	0.200	0.082	0.216
60%	0.160	0.066	0.173
70%	0.120	0.049	0.129
80%	0.080	0.033	0.086
90%	0.040	0.016	0.043
100%	0.000	0.000	0.000

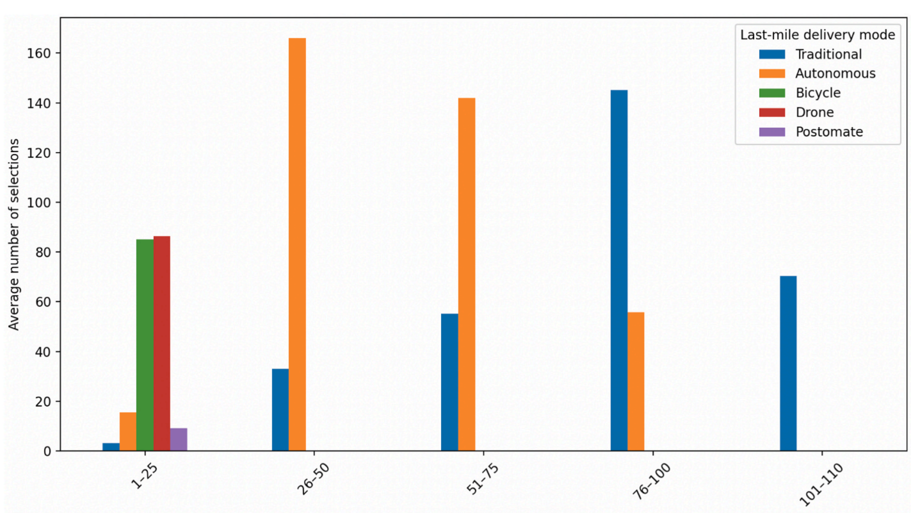

Fig. 5. Results of selecting the delivery mode.

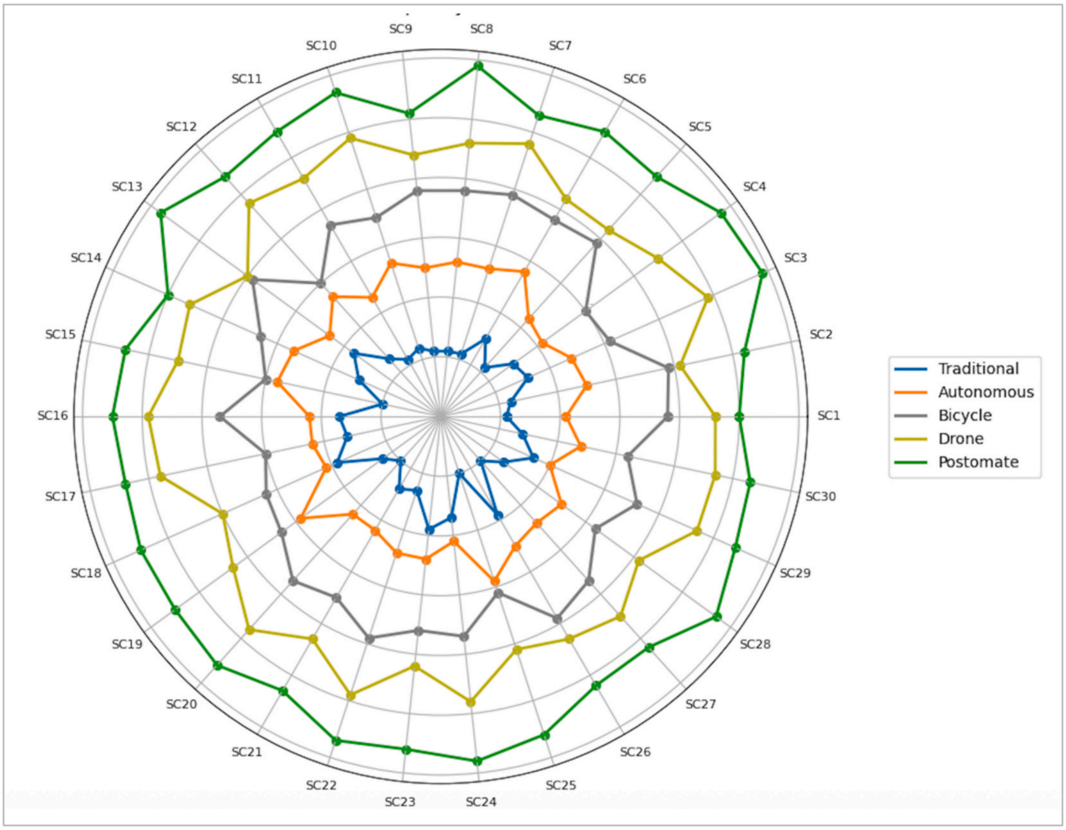

Fig. 6. Sensitivity analysis results.

4.4. Sensitivity analysis

The results are now analyzed using sensitivity analysis and weight changes. The weight changes are shown in Table 14. In the sensitivity analysis, the weight of each criterion was changed by 10%. The weight sums of the remaining factors are adjusted so that they are equal to 1.

Fig. 6 demonstrates the vehicle assignment results in 30 weighting scenarios where the cost, emission, and penalty weights are changed systematically. As can be observed, despite the fact that weighting settings alter, the dominance of certain delivery modes (especially Postomate) is consistent. While there are minimal changes in the ranking for other alternatives, such as drone and bicycle, these changes are restricted. For example, Postomate is selected as the top-performing alternative in nearly all scenarios. On the other hand, Conventional and Autonomous modes are selected much less frequently. These results confirm the robustness and stability of the decision model under varying conditions.

5. Discussion and managerial implications

The proposed framework considers last-mile mode selection as a selection problem from the customer's viewpoint with some system constraints (capacity, availability, time). While most studies treat this selection problem as a VRP optimization model, we developed a new perspective on how customer preferences can convert into feasible decision-making solutions, advancing joint MCDM-optimization modelling for the last-mile. By combining G-SIWEC with a multi-objective mathematical model, the established framework can handle the subjectivity and uncertainty of expert judgments (in terms of grey numbers) as well as produce firm, optimized decisions on delivery mode selection. Application of G-SIWEC for retrieving criterion weights from DM judgments provides a variance-based, efficient avenue to preference elicitation under ambiguity. It abstracts recent weighting approaches in the sense that (*i*) it operates on interval ratings, (*ii*) preserves dispersion information in the form of standard deviation, and (*iii*) gives crisp weights for optimization after whitenization, thereby connecting uncertain preference data to exact solution methods.

Customer satisfaction is quantified through lateness penalties. In the model, satisfaction is operationalized using a penalty function and linearized constraints, providing a reproducible method for incorporating service quality (i.e., on-time delivery) into multi-objective logistics models. Moreover, in the model, since real-world data is not available, all parameters used for model validation were generated by considering operational logic, the physical limitations of transportation modes, and realistic scales of customer demand. When defining parameter ranges, the capacity, speed, cost, and emission characteristics of each transport mode were aligned with its underlying technological and physical features. Similarly, customer demands, delivery time windows, and delay penalties were scaled to feasible levels that could be observed in real systems. This careful scaling ensures that the numbers used are not simply random but designed to represent the actual behavior of the system; hence, it will ensure that the model provides a reliable simulation environment for managerial inference.

Numerical results reveal clear weight-band segmentation: light loads (1–25 kg) tend to use low-emission, small-capacity modes; medium loads (26–75 kg) shift to autonomous delivery; and heavy loads ($\geq$76 kg) revert to conventional vans. These emergent patterns suggest testable hypotheses regarding threshold effects among payloads, the relative importance of emissions, and service penalties, offering valuable insights for theorizing contingent complementarities between multiple criteria.

The outcomes strongly support the use of a diversified and dynamically dispatched fleet. Rather than relying on a single vehicle type, companies can employ a combination of conventional truck, AV, drone, and bicycle. A centralized dispatch platform, guided by a decision support model, can allocate the most suitable vehicle to each order based on factors such as weight and priority, thereby maximizing operational efficiency. For example, a supervisor can set up a system that sorts all orders weighing under 25 kg and directs them automatically to the bicycle and drone fleet, and those that are over 75 kg go to conventional trucks.

The model illustrates the value of investment in emerging technologies. AVs show strong advantages for mid-weight deliveries (26–75 kg), suggesting they could be the workhorses of a future fleet. Drone and Postomate, while capacity-limited, are perfect for low-cost, low-emission, and fast deliveries of small parcels. Managers can use these insights to offer a rationale for strategic investments in the purchase and integration of these novel delivery asset types. This shared objective enables a streamlined dashboard encompassing cost (C), emissions (E), and lateness penalties (P). Managers can conduct what-if analyses; for example, assessing the impact of a 20% reduction in emissions, and evaluating corresponding changes in cost and penalties before making sustainability commitments.

5.1. Contextual Boundaries and limitations of the numerical experiment

Although the findings offer meaningful managerial insights, it is essential to recognize that the implications drawn from the numerical experiment are inherently context dependent. The results are driven by a controlled experimental setup that assumes particular demand patterns, parcel weight distributions, and the operational characteristics of the delivery modes. Accordingly, findings such as the suitability of drones and bicycles for lightweight deliveries and the strong performance of autonomous vehicles in mid-range segments should be interpreted as scenario-specific insights rather than universal prescriptions. Because the dataset was generated under predefined experimental conditions, real-world implementations may exhibit different behavioral dynamics influenced by geographical, regulatory, and operational constraints. This context-specific nature represents a key limitation of the study and represents the need for further empirical validation using real-world industry data.

6. Conclusions and Outlook

This study set out to address the growing complexity of last-mile delivery mode selection in an era of rapidly expanding e-commerce and intensifying sustainability requirements. By integrating G-SIWEC with a multi-objective optimization model, we developed a robust and adaptable framework capable of incorporating customer preferences while simultaneously balancing operational and environmental objectives. Unlike conventional approaches that focus solely on cost or efficiency, the proposed methodology systematically aligns customer expectations with delivery system constraints, thereby enhancing both theoretical insights and practical decision-making in last-mile logistics. The results indicate that delivery mode preferences are strongly segmented by parcel weight. Lightweight shipments are best served by bicycle and drone, which offer a combination of efficiency and low emissions, whereas AVs dominate the mid-weight range due to their cost-effectiveness and reliability. Conventional trucks remain essential for heavy-load deliveries, reflecting their unmatched capacity despite environmental drawbacks. These findings underscore the value of a diversified fleet strategy, in which emerging technologies complement rather than replace conventional delivery modes.

From a managerial perspective, the proposed framework serves as a decision support tool that enables logistics providers to design delivery systems that are customer-oriented, sustainable, and cost-effective. By quantifying trade-offs among cost, emissions, and service quality, the framework allows managers to conduct scenario analyses, guide investments in emerging technologies, and align delivery operations with both regulatory requirements and consumer expectations. Theoretically, this study contributes to the literature by integrating grey systems with multi-objective optimization in last-mile logistics, emphasizing the critical role of customer preferences in operational modeling. Practically, it provides firms with a means to translate sustainability commitments into actionable operational practices while maintaining high levels of service quality.

It is important to clarify that the study's implications stem from a scenario-specific numerical experiment, not from observed real-world data. Therefore, future research could extend this framework by incorporating real-world data from diverse urban contexts, examining dynamic demand patterns, or expanding the model to collaborative and platform-based logistics ecosystems. Moreover, exploring the interactions among regulatory constraints, technological advances, and consumer behavior represents a promising avenue for future research. All in all, this work provides scholars and practitioners with a systematic approach for designing last-mile delivery strategies that are efficient, environmentally responsible, and responsive to the evolving expectations of global e-commerce markets.

CRediT authorship contribution statement

Ahmet Çalık: Writing – original draft, Visualization, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Esra Boz:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sinan Çizmecioğlu:** Writing – review & editing, Validation, Investigation, Formal analysis, Data curation. **Erfan Babaee Tirkolaee:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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