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Research paper

The evolution of consumer preferences in last-mile delivery methods and the impact on urban logistics—A simulation study in the Rotterdam-The Hague region

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ABSTRACT

The growing demand for parcel delivery contributes to traffic congestion, high emissions, and rising costs of freight logistics, particularly in urban areas. To address these issues, new and sustainable last-mile delivery methods must be implemented. However, estimating the impact of different logistics systems is complex, as it depends heavily on consumer adoption of these new delivery methods.

This paper presents a simulation model that captures and explores the interconnections between multiple last-mile delivery methods and corresponding consumer preferences. Two key factors affecting consumer preferences are simulated: (1) consumers' response to the performance and availability of delivery methods, and (2) the sharing of knowledge through word of mouth and familiarisation. System dynamics is applied at the aggregate level to simulate the evolution of consumer preferences for last-mile delivery across multiple methods. At the disaggregate level, an agent-based model simulates the operational performance of these delivery methods, which in turn influences consumer preferences in the system dynamics model. This integrated approach allows for the observation of the evolving interaction between urban logistics supply and demand, providing key performance indicators on consumer preferences and the delivery method operations at consecutive time points.

The developed simulation model is applied to a case study in the Rotterdam-The Hague region, a highly urbanised region in The Netherlands. Results show that consumer preferences strongly depend on the carriers' ability to fulfil the demand. The dynamic interaction between supply and demand creates a reinforcing feedback loop, where the adaptability of carriers is crucial for the long-term success of a delivery method. Additionally, the spatial results reveal that there are zonal differences in the performance of the delivery methods. Further findings indicate that, while total vehicle kilometres and CO_2 emissions will rise due to increasing parcel demand in all scenarios, the average number of van kilometres and CO_2 emissions per parcel will decrease as demand grows.

1. Introduction

The last-mile of parcel delivery is recognised as a critical point in urban logistics, where rising parcel volumes (Statista, 2022), sustainability concerns and consumer expectations converge (International Transport Forum, 2022; Na, Kweon, & Park, 2022). While the logistics sector is innovating with emerging delivery methods, new delivery locations, and automation (Joerss, Jürgen, Neuhaus, Klink and Mann, 2016), their success depends not only on technical feasibility but also on consumer acceptance (Buldeo Rai, Verlinde, & Macharis, 2019). Yet, empirical insights into how consumer preferences evolve in response to these innovations remain limited.

This paper addresses that gap by introducing a hybrid simulation model that simulates consumer behaviour influenced by a synthetic delivery experience. An agent-based (AB) urban freight transport model is used to simulate parcel delivery by multiple carriers. The novelty lies in combining such an AB model with a system dynamics (SD) model that simulates future consumer preferences over time. By doing so, it is possible to capture feedback loops and the delay between parcel delivery supply and demand. The key factors influencing consumer

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preferences development are discussed and modelled, with the added uniqueness of gathering empirical data on the direction and magnitude of these factors at multiple time points. Furthermore, the evolution of the supply side of delivery methods is modelled. This approach allows for the exploration of the complex last-mile system, where multiple delivery methods compete and complement each other, in a way that cannot be achieved with conventional stated or revealed preference studies.

In a case study, the parcel freight logistics of the Rotterdam-The Hague region in the Netherlands are simulated over a five-year forecast horizon to test the methodology and create insights about the interactions in the parcel delivery last-mile system. The base scenario consists of van delivery to consumers' homes and to pick-up points, while two additional scenarios include crowdshipping and drone delivery.

The paper is further structured as follows. Section 2 provides a literature review on last-mile parcel delivery, the delivery methods, the theories to describe consumer preferences, and system dynamics. Section 3 elaborates on the methodology, and Section 4 discusses the case study. Conclusions and recommendations are presented in Section 5.

2. Literature review

In this literature review, four topics are discussed that are used in the methodology. First, the parcel last-mile is explained. Next, different parcel delivery methods are described. The third section elaborates on several theories that describe consumer preference evolution. And lastly, System Dynamics is discussed.

2.1. Last-mile logistics

Buldeo Rai et al. (2019) define last-mile delivery as the final transport segment of the supply chain, extending from the last distribution centre, consolidation point or warehouse to the consumer. Thus, the last-mile begins after long-haul transportation and ends when the parcel successfully reaches the consumer's preferred destination (Boysen, Fedtke, & Schwerdfeger, 2021). Due to inefficiencies, as attended home deliveries and consumer density, the last-mile is further characterised as inefficient, which contributes to high costs and emissions (Gevaers, Van de Voorde, Vanelslander, et al., 2009). According to a literature review of Higgs et al. (2022), the average CO_2 emission per parcel in Europe is estimated at 194 g.

The demand for last-mile parcel delivery is increasing due to factors such as urbanisation (Na et al., 2022) and the growth of e-commerce (Statista, 2025). Additionally, Cauwelier, Macharis, and Mommens (2023) observed a significant shift in online parcel order frequency, from once every few months to monthly and even weekly. This growing demand worsens congestion and emissions, particularly in inner cities (Deloison et al., 2020). As a result, there is increasing focus on sustainable and environmentally friendly operations, driven by consumer awareness and governmental legislation. Moreover, many delivery companies now offer fast delivery, raising consumer expectations. This trend towards shorter delivery times complicates efficient routing and consolidation efforts (Buldeo Rai et al., 2019). With logistics networks nearing capacity limits, delivery firms must innovate and develop new delivery methods (Asdecker, 2020).

2.2. Delivery methods of last-mile logistics

Parcel last-mile delivery to consumers is predominantly performed using human-driven vans (Boysen et al., 2021). While vans are widely used, they have significant disadvantages, such as low efficiency, dependency on consumers being at home, and contributing to traffic congestion. Despite these drawbacks, other delivery methods have yet to disrupt the last-mile environment. Electrification is used to reduce the environmental impact of vans (Buldeo Rai, Verlinde, & Macharis, 2021). Likewise, cargo bikes are becoming an increasingly popular and environmentally friendly alternative to vans in urban areas. In Europe, pick-up points are a well-established alternative for home delivery (ACM, 2020), and the addition of automated lockers further increases consumer flexibility (Boysen et al., 2021). However, only 18% of the parcels in the Netherlands are delivered to self-collection points (ACM, 2020).

New delivery methods are under development, with pilot projects involving drones and droids (Boysen et al., 2021). These delivery methods use automation to reduce the operational costs of the carrier. It is predicted that drones and droids will provide fast, flexible, and convenient delivery for consumers (Leon, Chen, & Ratcliffe, 2023). Drones, in particular, offer new possibilities since they are not dependent on road infrastructure. However, both delivery methods face technical challenges and especially regulatory barriers. Another limitation is their low capacity, which means consolidation centres will often be necessary (Mohammad, Nazih Diab, Elomri, & Triki, 2023).

Crowdshipping is another innovation that can ease the transport burden on carriers by utilising the crowd to move or deliver parcels during their own travel (Gatta, Marcucci, Nigro, Patella, & Serafini, 2018; Punel, Ermagun, & Stathopoulos, 2018). Crowdshippers are compensated for their work/effort (Buldeo Rai et al., 2021), offering carriers a highly flexible and scalable workforce. In this case, drawbacks could be inducing traffic, safety concerns, and the dependency on the willingness to act as a crowdshipper (Tapia, Kourounioti, Thoen, de Bok, & Tavasszy, 2023). New innovations are also introduced for unattended home delivery, which eliminates the problem of consumers not being at home (Boysen et al., 2021).

2.3. Evolution of consumer preferences

Various theories can be used to explain how consumer preferences evolve. One concept is perceived service quality, which helps assess consumers satisfaction (Shabbir, Malik, & Janjua, 2017). This satisfaction can be used to predict delivery preferences at future time points. The theory suggests that consumers evaluate their satisfaction by comparing their expectation with their actual experience. The experienced service includes soft elements like reliability and communication, as well as hard elements such as product/service quality and proof of performance (Hepp, 2018).

The diffusion of innovation (DOI) theory posits a direct relationship between the perceived characteristics of an innovation and the consumer's adoption decision (Grawe, 2009; Wang, Yuen, Wong, & Teo, 2020). Thus, it can be used to link the perceived service quality to consumer behaviour. DOI stems from marketing, where it is used for the analysis and evaluation of life cycle dynamics (De La Torre, Gruchmann, Kamath, Melkonyan, & Krumme, 2019), and additionally, it is applied for demand forecasting of new products. The DOI theory is often complemented by attitude theories. Instead of a direct relationship, attitude theories suggest that attitude is included as a mediator between beliefs and adoption intention.

The logistics innovation theory argues that a firm's market share can increase through more effective logistics operations (Grawe, 2009). When firms identify a disadvantage relative to competitors due to innovation, they often adopt similar innovations to remain competitive (Wang et al., 2020). In this way, innovations spread within the sector. Moreover, logistics innovations frequently enhance customer value. The evolution of radical innovations typically follows an S-curve: consumer benefits grow slowly at first, then increase substantially as the innovation matures, before slowing down again as the innovation reaches full adoption.

Word of mouth (WoM) is another important concept for understanding how consumers evaluate services or products and share their experiences with others (De La Torre et al., 2019). It is reported that when adopting new businesses or services, consumers heavily rely on the experiences and opinions of other consumers in their decision-making process (Buldeo Rai et al., 2019; Vakulenko, Shams, Hellström, & Hjort, 2019). WoM affects factors such as satisfaction, loyalty, service level, and trust. It is particularly relevant when a population is heterogeneous or when the interactions between individuals are complex. The Bass diffusion model is a frequently used construct describing that a consumer's initial purchase is related to the number of previous users. According to this model, sales of new products grow to a peak and then level to a value lower than that peak (Bass, 2004). This behaviour results from the expanding group of people spreading WoM due to their experience and the shrinking group of consumers that can still adopt the service. The Bass diffusion model suggests that an innovation is adopted by two groups: innovators, who make decisions independently, and imitators, who base their decisions on the social system around them.

Familiarity is defined in Fandos Herrera and Flavián Blanco (2011) as "the number of product related experiences that the consumer has accumulated". It reflects a consumer's understanding of a product and its characteristics by a consumer, and the consumer's ability to assess the quality of a product. Greater familiarity with a product tends to make consumers more trusting and loyal to that product. Additionally, the introductory experience with a new service is essential for the future perception and expectation of that service (Vakulenko et al., 2019). However, consumers also self-educate over time, which can ease initial mistrust or concerns. The familiarity theory can be used to model the resistance or inertia of consumers to choose an unknown delivery method.

2.4. System dynamics

System dynamics (SD), developed by J. W. Forrester at MIT in the 1950s and 1960s, links qualitative and quantitative models through a causal loop approach (Shepherd, 2014). It is based on the assumption that the behaviour of a system is primarily determined by its internal structure (Pruyt, 2013). SD is applied in various domains, such as health policy, resource scarcity, and supply chain management.

The objective of SD is to explore the effects of decisions within dynamically complex systems, supporting the simulation and analysis of non-linear feedback structures and functions (Thaller, Clausen, & Kampmann, 2016). This is achieved by connecting different system components and linking those connections with mathematical models. Angerhofer and Angelides (2000) explain that the key principle of SD is that feedback and delay cause the behaviour of systems.

SD describes a system at the aggregate level. It is a frequently chosen representation of the internal process of entities (Martin & Schlüter, 2015), which could be an individual or a group. One advantage of this method is its ability to visualise interdependencies between different parts of the system in a clear and transparent way (Thaller et al., 2016). SD models are commonly used for medium- and long-term forecasting, trend analysis and impact assessments. Another benefit of this method is the relative low data requirement due to its high level of aggregation. Additionally, SD models can integrate algorithms from multiple fields, like economics and transport modelling.

However, SD has several drawbacks, particularly relevant to this paper. First, because of the high level of aggregation, homogeneity among agents is assumed and SD models are typically not precise. Furthermore, validation can be challenging due to the increasing complexity as more relationships are introduced. Representing spatial components and performing point-in-time forecasts are also difficult. To address these limitations, SD is combined with other modelling approaches in various cases.

Agent-based modelling (ABM) offers an alternative to system dynamics (SD) by disaggregating a system into individual components (Crooks & Heppenstall, 2011), following a bottom-up approach (Macal, 2010). These components, known as agents, each have their own characteristics and behaviour rules. Agents interact with and influence one another, adapting their behaviour based on their experiences and environment. ABM helps explain emergent patterns at the system level while accounting for the heterogeneity of entities, spatial and temporal heterogeneity, and stochasticity (Martin & Schlüter, 2015). For this reason, ABM is regularly used to study adaptive systems characterised by self-organisation, emergence, and adaptation. Additionally, ABM is well-suited for spatial models, as it can handle geographical components in a heterogeneous manner.

However, these capabilities come with high data requirements to accurately model systems at the micro-level (Martin & Schlüter, 2015). Moreover, it can be difficult to quantify or calibrate systems where agents, for example, express irrational or subjective behaviour (Crooks & Heppenstall, 2011). Interpreting simulation outputs can also pose challenges. Furthermore, ABM is sensitive to initial conditions and small variations in agent rules, making it a challenging to use ABM for forecasting.

SD has been previously combined with other modelling methods to simulate the last-mile environment, also with a focus on consumer behaviour. For example, Rabe, Chicaiza-Vaca, and Gonzalez-Feliu (2020) developed a model for the adoption of automated parcel lockers (APLs) within the last-mile delivery system. This study combined SD with a facility location optimisation model to explore potential APL locations in the city of Dortmund. By integrating these two models, Rabe et al. (2020) were able to incorporate a spatial component into the SD model.

Another study, conducted by De La Torre et al. (2019), used an SD modelling technique to develop strategies and recommendations for the last-mile food industry. The study identified that the number of new customers is influenced by multiple inputs, including a reinforcing loop involving word of mouth (WoM) and customers leaving, which adds to the pool of potential customers. This concept was used to model how a company's good performance can drive higher demand, potentially exceeding its capacities. When that occurs, the company's offer becomes less attractive, and the model reflects this dynamic. The study demonstrated that maintaining a constant service level eventually led to market saturation and a decline in customers, as people left the company and fewer new customers were attracted.

A third relevant study is Melkonyan, Gruchmann, Lohmar, Kamath, and Spinler (2020), which compared three distribution channel options for a local food and logistics provider. The sustainability aspects of each option were quantified using an SD model, and a multi-criteria decision analysis was employed to rank the most sustainable distribution options. In this model, new customers were acquired through WoM, advertisement and relative attractiveness of the delivery model. Rather than simulating the delivery service directly, the model adapted the service level based on a service improvement rate.

3. Methodology

To simulate the evolution of consumer preferences and the operational fulfilment of the deliveries, a hybrid model is proposed, that combines system dynamics (SD) modelling and agent-based modelling (ABM). The SD model captures the preference evolution of consumers over time, while the ABM simulates the carriers delivering the parcel from the depot to the receiver and the evolution of performance characteristics of each delivery method in a specific urban network. Fig. 1 illustrates the proposed hybrid model.

This conceptual model consists of a feedback loop, in which the SD model and the ABM interact in two key ways. First, there is an interaction between the delivery operations, where carriers (agents) perform parcel deliveries, and the evolving consumer preferences at the system level, which results in a new demand for the carriers. The second interaction specifies that carriers can adapt their operations for each delivery method based on the demand for that method. Each loop of this model represents a time step where parcel demand and aggregate delivery preferences are established, and the corresponding

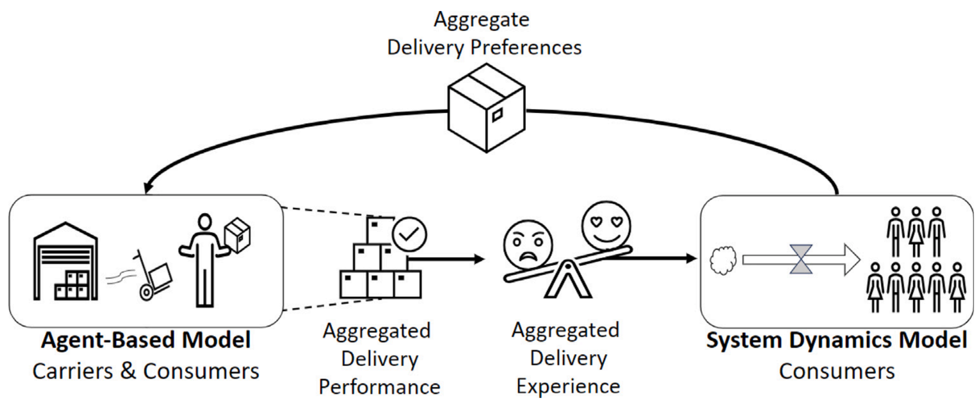


Fig. 1. Schematic overview of the conceptual model.

delivery services are calculated. From this, new delivery preferences are estimated.

An advantage of this structure is that data on consumer preferences and delivery method operations can be obtained at multiple time points. Furthermore, the ABM accounts for stochasticity in the delivery operations, which enables the modelling of consumer responses to changes in the upfront chosen delivery.

In this section, the chosen delivery methods for the study and the attributes describing these methods are presented. Next, the SD model component of the conceptual model is described with a causal loop diagram, see Fig. 2, which simulates the relations between various factors in this consumer-centred, last-mile environment. Thirdly the parcel delivery assignment is explained. Then, the ABM is described and finally the warm-up period is discussed.

3.1. The delivery methods

Since this study focuses on consumer preferences, the delivery methods offering distinctive services from the consumer's perspective are considered. Therefore, this study will simulate van delivery, self-collection, crowdshipping, and drone delivery. Self-collection includes both pick-up points and automated lockers, a simplification that is justifiable as consumers tend to view these options similarly (Molin, Kosicki, & van Duin, 2022). Crowdshipping provides a unique delivery experience, as parcels are not handled by dedicated carrier personnel but rely on the crowds' willingness to ship them. Both drones and droids offer consumers automated delivery with short delivery times. Among these, drone delivery is selected to explore the potential of a delivery method that is independent of road infrastructure. Since drones represent a new technology, it is assumed that within the simulation time, this delivery method is improved due to innovations, which could enhance the operational performance.

An underlying assumption in this methodology is that while carriers make the final decisions regarding delivery methods, they do so in response to consumer expectations on the delivery experience. This approach allows us to capture the market-driven nature of last-mile delivery, where operators adjust their choices to remain competitive and use last-mile delivery as a key differentiator (Joerss, Neuhaus and Schröder, 2016). Therefore, it is assumed that operators follow the preferences of their consumers.

3.2. Attributes in consumer preferences

Key attributes describing consumer parcel delivery choices and/or preferences have been identified in Buldeo Rai et al. (2019), Caspersen and Navrud (2021), de Oliveira, Morganti, Dablanc, and de Oliveira (2017), Gatta et al. (2018), Gatta, Marcucci, Nigro, and Serafini (2019), Ignat and Chankov (2020), Maltese, Le Pira, Marcucci, Gatta, and Evangelinos (2021) and Nguyen, De Leeuw, Dullaert, and Foubert (2019). Four attributes are selected for this study: delivery speed, costs, reliability, and pick-up distance. Delivery speed and costs are commonly used in stated preference studies. Reliability reflects whether the delivery is performed as expected. This attribute is rarely used, as failed deliveries are often not accounted for. Offering consumers a time slot choice is a commonly used attribute that relates to reliability. However, this still disregards the possibility of unsuccessful or disturbed operations. Pick-up distance is only applied to self-collection and refers for the distance a consumer needs to travel from their home to pick up a parcel.

3.3. The system dynamics model

The SD model is used to simulate the evolution of consumer preferences. In Fig. 2, the principal factors and their interactions are displayed in a causal loop diagram (CLD). Since the proposed simulation model is hybrid, the SD model receives input from the ABM, with each hexagon in the diagram representing an output from the ABM.

The centre of the causal loop diagram (CLD) is the *Delivery Preference Method i*, which, according to the DOI theory, influences *Delivery Choice Method i* and, ultimately, the demand for each delivery method. Consumer preferences for a delivery method are estimated based on operational performance, WoM and the familiarity effect. Operational performance is defined by the reliability, costs, speed and pick-up distance specified per delivery method. The dynamic interactions within multiple loops (reinforcing (+) and balancing (-) with delays) create a complex system, making simulation necessary to fully understand these interactions.

A key step in the SD model is the estimation of consumer preferences. These preferences are expressed as an aggregate probability distribution across the available delivery methods. From that probability distribution, a preference is randomly drawn for each parcel in the ABM.

To provide consumers with feedback on their chosen delivery option, the characteristics of the performed delivery are estimated by calculating a performance score for each delivery method at each time step. This score quantitatively represents the perceived service quality from the consumer's perspective and the preferences of consumers towards different attributes. The performance score of each delivery method i is calculated by:

$$S_{it} = -\left(\beta_s * \mu S_{it} + \beta_c * \mu C_{it} + \beta_r * \mu R_{it} + \beta_d * \mu D_{it}\right) \quad \forall \quad i \in N \qquad (1)$$

where μS_{it} is the average normalised delivery speed score at time step t, μC_{it} the average normalised delivery cost score at time step t, μR_{it} the average normalised reliability score at time step t, μD_{it} the average normalised distance score for the consumer to pick-up their parcel at time step t. A score of zero indicates a very good delivery service, while scores below zero reflect worsening delivery experiences. The weights of the attributes are denoted by $\beta_s, \beta_c, \beta_r, \beta_d$. The value of the attribute

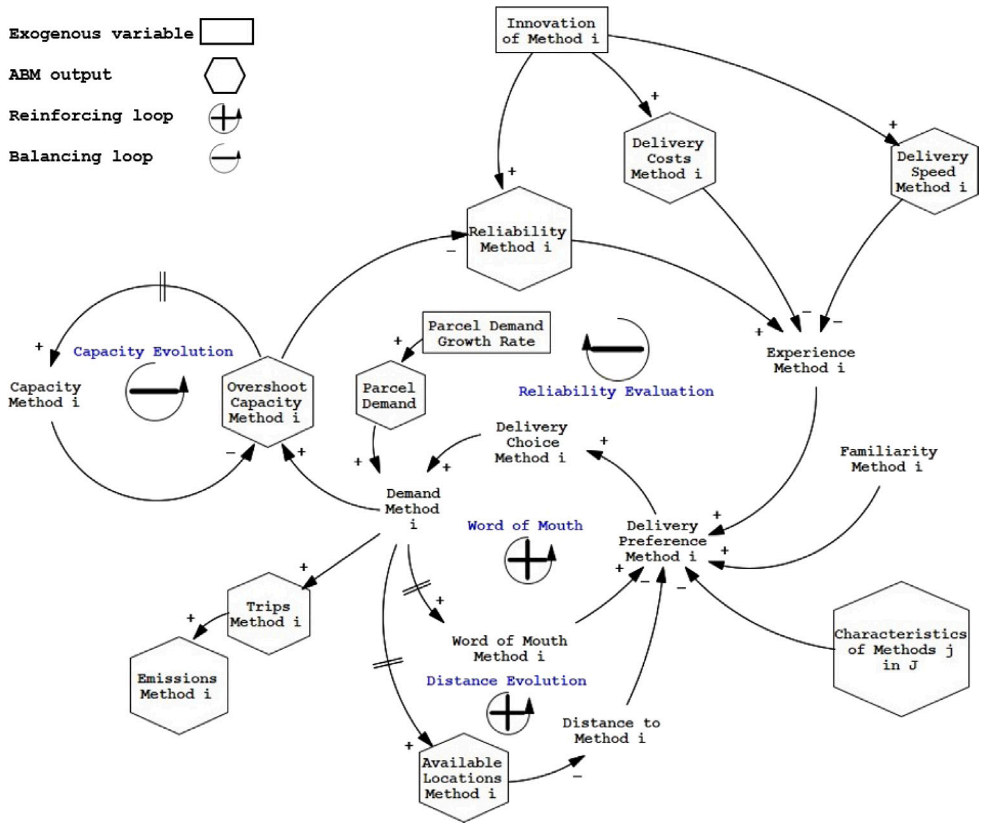


Fig. 2. The SD causal loop diagram.

Table 1
Attribute levels.

Attribute	Levels	Description	Normalised performance score
Delivery speed	0	Several hours	0
	1	Same-day	0.04
	2	1-day	0.2
	3	2-days or more	1
Delivery costs	0	Free delivery	0
	1	Costs < 2 euro	0.33
	2	Costs < 5 euro	0.66
	3	Costs > 5 euro	1
Delivery reliability	0	As expected	0
	1	Delayed delivery and/or other delivery method	0.33
	2	Unsuccessful delivery	1
Pick-up distance	0	Distance < 100 m	0
	1	Distance < 300 m	0.387
	2	Distance < 500 m	0.613
	3	Distance < 1000 m	0.774
	4	Distance < 2000 m	0.898
	5	Distance > 2000 m	1

levels and beta weights are based on previous studies, see Tables 1 and A.1.

To calculate the delivery method probability the performance of each method must be linked with the probability of using the method. A prominent method to estimate discrete choices is a utility-based logit formula, with the Random Utility Model (RUM) the most generally applied version (Walker & Ben-Akiva, 2002). This theory describes that an individual derives utility by choosing an alternative, like a product or service, where it is assumed that the alternatives are independent. Thereby, it is theorised that each individual wants to opt for the alternative that provides them with the maximum utility. The utility is calculated with observable variables, in this case, the attributes delivery speed, costs reliability & pick-up distance, and an error term that accounts for unobserved variables, often called disturbances. With the utility of each alternative, the logit formulation provides an elegant way to estimate the probability of an individual choosing each method.

In Eq. (2) the multinomial logit (MNL) function, that uses S_{it} from Eq. (1), can be seen. ASC_i is an alternative specific constant (ASC) that captures the average effects of factors not included in Eq. (1). An ASC of 1 is assigned to van delivery, while an ASC of 0 is applied to self-collection, crowdshipping and drones. There is no random error component included in this formulation.

$$P_i(t+1) = \frac{e^{\left(S_{it}+ASC_i\right)}}{\sum_{i=0}^{N} e^{\left(S_{it}+ASC_i\right)}} \quad \forall \quad i \in N \tag{2}$$

It is expected that self-collection and drone delivery methods will grow or decline based on the evolving preferences of consumers. The distribution of self-collection points and the number of drones per depot can adjust over time, depending on the previous demand-supply ratio. In contrast, van delivery and crowdshipping will not evolve because van delivery has an unlimited supply, and crowdshipping depends on the availability of crowdshippers, which is assumed to be constant due to a lack of more detailed information.

To model the effect of WoM, the Bass diffusion model is applied, which estimates the power of the WoM effect (Bass, 2004). In this model, an extension is made that takes into account the relative performance of an alternative (Mahajan, Muller, & Bass, 1990; Wong & Sheng, 2012). The relative performance of a delivery method scales the magnitude and determines whether the WoM is positive or negative. A relatively good performance increases the probability of preferring delivery method i, while poor performance reduces that probability. Eq. (3) presents the formula used in the model.

$$P_i(t+1) = P_i(t) + \frac{q\left(\frac{nP_i(t)}{\sum_{j=0}^{N} nP_i(t)}\right)\left(\left[\sum_{j=0}^{N} nP_i(t)\right] - nP_i(t)\right)\left(\frac{\sum_{i=0}^{N} -S_{it}}{N} + S_{it}\right)}{\sum_{j=0}^{N} nP_i(t)} \quad \text{if } P_i(t) \neq 0 \quad \forall \quad i \in N \tag{3}$$

where q is the coefficient of imitation, and nP_i is the number of parcels delivered by method i. Mahajan et al. (1990) provide a general advised value of 0.38 for the coefficient of imitation. Although not explicitly shown in this equation, the preference for each delivery method is normalised by dividing it by the sum of all preferences, ensuring that the total preference sums to 100%. If a delivery method is new, as in the case of drone delivery, consumers may adopt it based on its potential performance. In such cases, the choice probability is initially set to 3%, reflecting the percentage of innovators (Bass, 2004; Mahajan et al., 1990).

The familiarity effect is expressed in Eq. (4). It calculates the average likelihood that a consumer has never used a particular delivery method before, and thus accounts for the resistance consumers may have to trying that delivery method (Fandos Herrera & Flavián Blanco, 2011; Vakulenko et al., 2019).

$$P_i(t+1) = \frac{P_i(t) * \left(1 - \left(\prod_{P_i t=0}^{t} 1 - P_i(t)\right) * \Omega_{chance}\right)}{\sum_{i=0}^{N}\left[P_i(t) * \left(1 - \left(\prod_{P_i t=0}^{t} 1 - P_i(t)\right) * \Omega_{chance}\right)\right]} \quad \forall \quad i \in N \tag{4}$$

In the SD model the carriers have to opportunity to adapt their self-collection and drone services based on previous demand. This is represented by the distance evolution loop and the capacity evolution loop in Fig. 2.

Firstly, the self-collection supply can be adapted each year on the basis of the following methodology. If the average yearly demand for a self-collection point is lower than 25% of its capacity, a point is removed from that zone. A self-collection point can be added to a zone if the zonal demand is 50% higher than the capacity. The growth of the total number of points is limited to 20% per year. The priority for new self-collection points is based on the sum of the demand times the distance to a point.

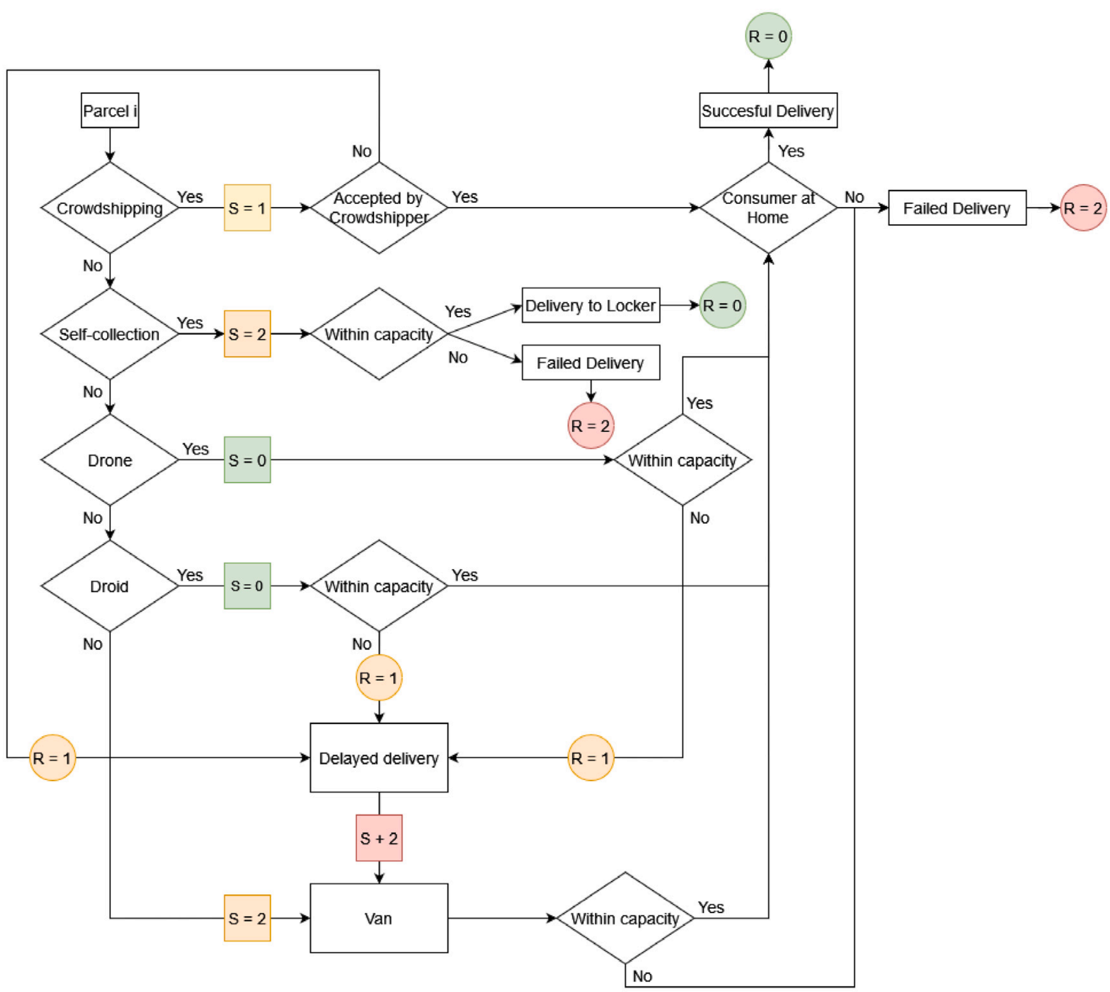


Fig. 3. Delivery assignment flow diagram with Speed Score (S) and Reliability Score (R).

Drones are limited to a capacity of one parcel, however, depots can buy or sell drones based on the demand. This can be done on a six-month basis, thus every two iterations. If the difference between the demand and the offered capacity is at least 25% higher than the average number of parcels a drone delivers per day, an additional drone is bought by a depot. If this difference is negative and larger than 25% a drone is sold.

Van delivery and crowdshipping will not evolve, as it is assumed that van delivery has an unlimited supply and that the availability of crowdshippers is constant.

3.4. Delivery assignment

The demand for parcel deliveries by specific methods is converted into an assignment of delivery methods for each parcel. Not every parcel can or will be delivered with the preferred delivery method of the consumer because there could be no capacity, no crowdshipper can be found, or the delivery location is outside the drone range. In Fig. 3, a flow diagram is shown that represents the assignment procedure in this module. The diagram represents filtering a parcel to its preferred delivery method. That method comes with a predefined level of the delivery speed, see Table 1 for the description of each level. After filtering it is checked if the parcel can be delivery with the preferred delivery method. If this is the case, the delivery receives a delivery score of 0. When the initial delivery cannot be performed successfully, a penalty is given to the reliability and speed score.

Subsequently, the parcel carrier for each parcel is determined based on observed market shares (de Bok, Tavasszy, Thoen, Eggers, & Kourounioti, 2025). After the assignment to a parcel carrier, the parcel is placed at the nearest depot of that carrier with respect to the delivery location. Then, trips will be scheduled that combine the delivery of parcels with the same mode.

3.5. The agent-based model

The ABM is an existing agent-based model for urban freight transport: The Multi-Agent Simulation System for Goods Transport (MASS-GT) (de Bok et al., 2025). MASS-GT simulates the transportation activities of conventional commodity demand and parcel demand. In this paper only the parcel delivery part of MASS-GT is used, which consist of two modules: a parcel demand module and a delivery tour formation module. The parcel demand module estimates the parcel demand by households (B2C) and businesses (B2B). This paper only considers B2C parcels and B2B are thus not simulated. The household parcel demand is estimated with an ordered logit model on a household travel survey of Mobility Panel Nederland (MPN) with the explanatory variables: age, income and degree of urbanisation.

The resulting parcel demand is multiplied by a delivery success factor to correct for previous non-deliveries. Subsequently, each parcel is allocated to a carrier based on observed market shares in the Netherlands and to a depot of that carrier. It is assumed that each carrier performs the delivery from the depot nearest to the delivery location.

Parcel delivery with vans is already modelled in MASS-GT. Tour formation is based on capacity and time constraints, and tours originate and terminate at the same carrier depot (Thoen, Tavasszy, de Bok, Correia and van Duin, 2020).

For a successful delivery, consumers need to be at home when the postman is at its destination. A successful delivery rate of 75% is used (Buldeo Rai et al., 2019). Of all parcels that are delivered via these methods, 25% will be randomly chosen as a failed delivery. The number of vans per depot is unconstrained.

MASS-GT groups parcels on geographical proximity and provides a plausible set of tours (de Bok et al., 2025). After the cluster forming delivery tours are scheduled, hereby, the nearest neighbour approach is used to minimise the tour distance. For van delivery, the scheduled tours are converted into trip matrices, which are assigned to a congested road network (de Bok et al., 2025). This assignment is based on an all-or-nothing shortest path assignment with generalised transportation costs of congested travel times. With those routes, the emissions for each used link are calculated using emission factors. A distinction in road type (urban, rural, highway) is used for these calculations and full and empty vehicles (Thoen, de Bok and Tavasszy, 2020) with linear interpolation across the tour. The route calculations in MASS-GT estimate the route distance between the origin and destination zone. However, within each zone, multiple parcels can be delivered, for which additional kilometres must be driven. The in-zone drop-off location for each parcel request is unknown. Therefore, it is assumed that an additional distance is made by vans, which is twice the average Manhattan distance from the centroid to the average Euclidean intrazonal distance.

The initial distribution of the self-collection points is based on the Dutch average number of inhabitants per self-collection point, and for each zone, the distance to the nearest self-collection point is calculated. Parcels for zones without a self-collection point are placed in the closest neighbour zone. If the demand for a self-collection point exceeds its capacity, parcels will be randomly removed until the capacity is reached. The removed parcels are not delivered, which is reflected in the delivery score in Eq. (1). Lastly, the assigned parcels for self-collection are assigned within the van tour formation.

MASS-GT already comes with a module for crowdshipping for this study area in the version used for the HARMONY study (de Bok et al., 2021). For each crowdshipping request, the model allocates a crowdshipper that performs the delivery (Tapia et al., 2023). In that allocation, preferences from the sender (the carrier) are not taken into account, as they are assumed to be indifferent to the crowdshippers. The group of available crowdshippers is estimated based on the V-MRDH model (MRDH, 2022). The output of this model specifies the origin, destination, travel mode and travel purpose of the potential crowdshippers.

Subsequently, the willingness to work as a crowdshipper is analysed for each parcel. This is simulated by an utility function for working as a crowdshipper, see Eq. (5), and by a utility function for the regular trip, see Eq. (6). Herein, remuneration is paid out to a crowdshipper to create an attractive utility for acting as a crowdshipper. The value of this remuneration is estimated with a natural logarithm between €1,50 and €3,35, with the last value being the average price for parcel delivery from business to consumer (B2C) in 2020 (Berendschot, 2021).

$$U_{pickup} = \beta_{TravelCost} * (Cost - Remuneration) + \beta_{TravelTime} * Time + \eta_{pickup} \quad (5)$$

$$U_{currenttrip} = \beta_{TravelCost} * Cost_{trip} + \beta_{TravelTime} * Time_{trip} + \eta_{trip} \quad (6)$$

The consumer delivery fee is the remuneration plus a profit margin of 15%. That percentage reflects the commission across existing crowdship platforms like Nimber. With both utility functions, the most suitable parcel is allocated to the most suitable crowdshipper. The process ends when all parcels are allocated to the crowd or when crowdshippers with a higher utility for acting as a crowdshipper than for performing the regular trip are no longer available.

Crowdshippers travel via the same road network as vans, and they make a detour from their original travel plans to pick-up and deliver a parcel. This detour distance is summed to gather the vehicle kilometres for crowdshipping. Furthermore, the MASS-GT model considers crowdshipping via car and bike. Because of that, the CO_2 emissions are estimated by multiplying the emission factors (g/km) for cars times the detour distance of car crowdshipping. From 2013 the average CO_2 emission of new passenger cars in the Netherlands dropped from 110 to 95.1 g/km in 2021 (ACEA, 2022; Carlier, 2023), therefore the emission factor for car crowdshipping is set to 100 g/km. Also, for crowdshipping, a delivery success rate of 75% is assumed.

Drones have a capacity of one parcel, therefore they repeatedly fly from a depot to a consumer and back to the same depot. The delivery potential of a parcel depot via drones depends on the fleet size of that depot and on the delivery time per parcel. For this reason the delivery time for each parcel is estimated with Eq. (7). V_{TT} represents the time that it takes to reach a safe flight height which is estimated at 60 s, as the Amazon Prime Air flies at least 100 m (Sudbury & Hutchinson, 2016). As drones do not rely on the road infrastructure the flight distance is calculated by the Euclidean distance between the depot location and the centroid of the requested zone. Accordingly, D_{di} is the distance between depot d and the centroid of zone i, v is the average flight speed of a drone, which is roughly 45 km/h (D'Andrea, 2014). A drop-off time of 120 s per parcel is assumed, which is also considered as the time to reload a drone at the depot.

$$DT = 2 * V_{TT} + 2 * \frac{D_{di}}{v} + 2 * DropTime \tag{7}$$

Drone deliveries are scheduled as follows: a delivery request is randomly drawn from the drone demand of a depot. The delivery time of that request is calculated and added to the total flight time of a drone. Each drone is estimated to operate for 18 h per day, from 6:00 to 24:00. For example, recharging and maintenance time is not considered. When the total flight time overreaches this time constraint, the remaining parcels will not be delivered via drone. Additionally, a flight range of 10 kilometres is assumed (D'Andrea, 2014). The fee for drone delivery is €0.10 per kilometre (D'Andrea, 2014), multiplied with a profit margin of 15%.

3.6. Warm-up period

The current parcel market is quite stable without big changes on a day-to-day basis. To reflect this, a warm-up period is implemented in the model. In this warm-up period the number of parcels to be delivered and the delivery methods, for example the number of self-collection points, stay constant. Also the WoM and familiarity effect are inactive. By doing this the model can reach an initial stable market shares. A warm-up period of four time steps ($t = 4$) is used.

4. Case study

The developed simulation model has been applied in a case study in the Rotterdam-The Hague region (RMTH), part of the province of South Holland. The RMTH region is a highly urbanised region containing multiple large cities and the seaport of Rotterdam; Fig. 4 shows a map of the area. In dark blue the study area is shown, and in light blue and grey the influence area (the province of South Holland) and the external zones. The total province has a population of 3.6 million, 50 municipalities and a surface area of 3.403 km^2. Both Rotterdam and The Hague are highly urbanised areas, yet most other zones are still quite densely populated and cannot be called rural. South Holland has a well-developed transport network with various high-capacity roads and highways. In total, there are 29 carrier parcel depots in and near South Holland. In 2020 a total of 388 million business-to-consumer (B2C) parcels were transported in the Netherlands (ACM, 2022). As there are about 2.2 million inhabitants in the RMTH region, (the study area) roughly 100,000 to 150,000 parcels must be delivered each day.

4.1. Simulation scenarios

With the presented model, the parcel freight logistics of the RTMH region is simulated for three different scenarios with a simulation horizon of five years. Each loop inside a simulation run represents a time step of a quarter of a year. Thus, each simulation consist of 20 time steps to represent the evolution over five years. A constant yearly growth rate of 21.6% for the parcel demand is implemented, which is the average growth rate in the Netherlands form 2017 till 2021 (ACM, 2022). The population and its distribution are considered constant. The following delivery scenarios are simulated:

1. Current State: Van and self-collection delivery. The self-collection points can evolve in number and capacity.
2. Crowdshipping: As crowdshipping has to overcome fewer regulatory and technological barriers than drones, it is expected that crowdshipping will be the first delivery innovation that will be implemented in the Netherlands. This scenario simulates the coexistence of van, self-collection and crowdshipping in the study area.
3. Full Innovation: Drones are added to the crowdshipping scenario.

4.2. Validation and verification

To verify and validate the proposed approach, three tests are performed: (1) Test for face validity; (2) Test for various input parameters; (3) Compare model predictions with the performance of the actual system or with predictions from other studies (Sargent, 2010).

A thorough sensitivity analysis is performed for various estimated model parameters. In all cases, irrespective of the sensitivity, the model output changes in a logical manner that corresponds to the theory. Only in the case of an extreme value for the beta coefficient of reliability the model showed unstable behaviour; see the example of Fig. A.1. The choice probability of all delivery methods becomes very unstable. This is caused by the highly alternating performance scores (Eq. (1)) of self-collection and drone delivery. Both performance scores fluctuate strongly as the demand overshoots the capacity in one run. Subsequently, the preference shifts to other delivery methods, which results in a high performance of self-collection and drone. Hence, the demand rises and overshoots the capacity. As all results are explainable and the developed model functions appropriately, the model can be used to evaluate the interactions within the system. Furthermore, a time horizon test is carried out, in which the model behaviour is consistent and explainable.

To validate the model, the model output is compared with real-world results and other research. In Table 2, the market shares, as estimated by the model and as presented in literature are compared. The literature values for van delivery are the currently operation percentages in the Netherlands. The market shares for self-collection, crowdshipping and drone are estimation results based on stated preference studies. The market shares in Scenario 1, Current State, have a proper match with the current shares for van and self-collection delivery in the Netherlands. As this modelling approach is highly novel and with the addition of more delivery methods the uncertainty increases, validation of Scenario 2 and 3 is complicated. The results for crowdshipping are quite low compared with literature and the margin of the market share for drone delivery is large. Despite these uncertainties the model can be used to analyse the last-mile system, but it cannot be considered as an exact forecasting model.

4.3. Results

Table 3 presents the results of the three simulation scenarios. For each scenario, the simulation is performed five times. The table presents the averages of these five runs. The top row shows the total parcel demand per day. Van tours deliver both parcels to consumers' homes and self-collection points. Within these tours 20% of the trips consists of trips to a self-collection point at $t = 0$, at $t = 20$ this shifts to just 4% in all scenarios. It is assumed that crowdshippers and drones can only deliver one parcel each time, therefore, the number of tours is equal to the number of parcels that are delivered with these delivery methods. The vehicle kilometres show the distance travelled by the delivery vans, detour routes of crowdshippers and the flight distance of drones. The CO_2 emissions of crowdshipping are much lower per kilometre, partly because cars have lower emissions than vans and partly because crowdshipping can be performed by bike. In

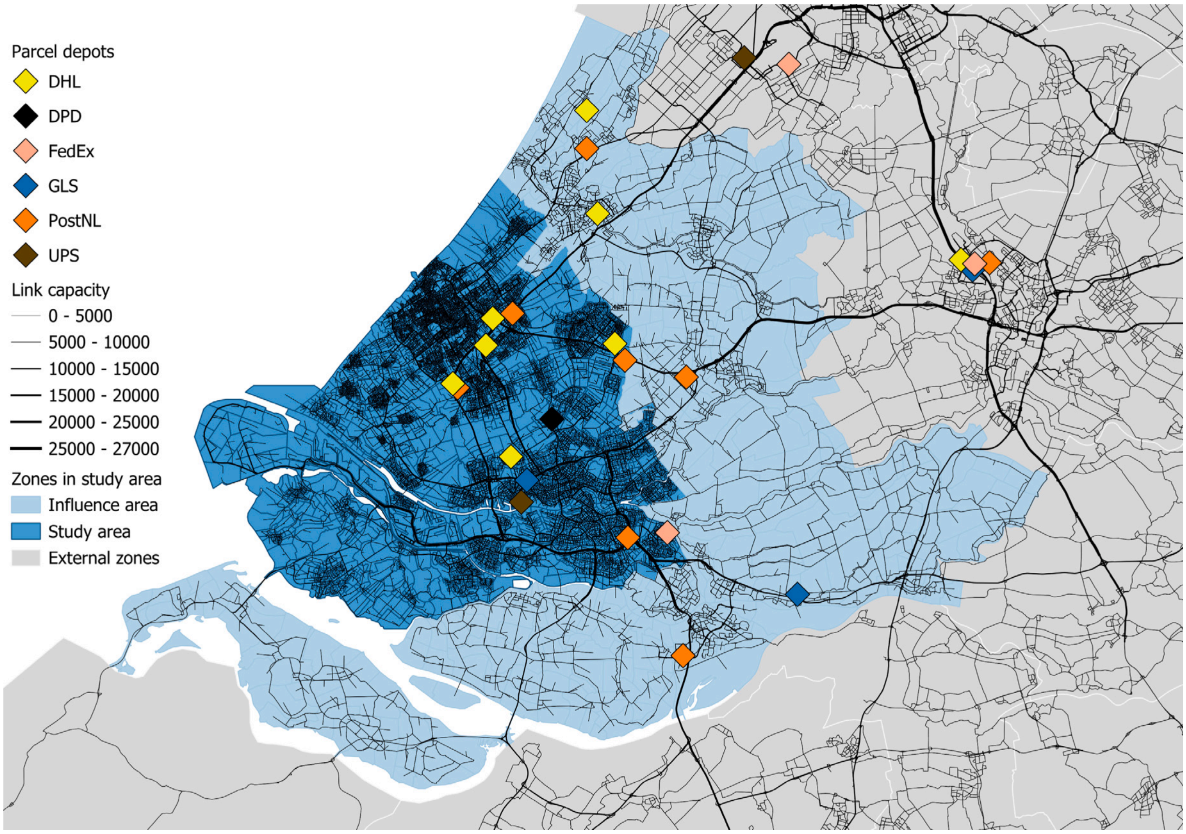


Fig. 4. The study area of MASS-GT with the road network, zonal distinction and carrier depot locations (de Bok et al., 2025).

Table 2
Market share model estimation versus literature.

Market share	Scenario t = 20 [quarter] 1: Current state	2: Crowdshipping	3: Full innovation	Literature value	Source
Van	82%	73%	61%	79.5–81.5%	ACM (2022) and ACM (2021)
Self-collection	18%	17%	14%	18%–29%	Molin et al. (2022) and Niemeijer and Buijs (2023)
Crowdshipping		10%	8%	21%–27%	Buldeo Rai et al. (2021)
Drone			17%	7.18%–53%	Kim (2020) and Merkert, Bliemer, and Fayyaz (2022)

Table 3
KPIs scenarios per day.

Indicator	Method	Scenario t = 0 [quarter] 1: Current state	2: Crowd-shipping	3: Full innovation	Scenario t = 20 [quarter] 1: Current state	2: Crowd-shipping	3: Full innovation
Parcel demand [1000 parcels]	Total	116	116	116	223	223	223
Market share	Van	69%	62%	62%	82%	73%	61%
	Self-collect	31%	30%	29%	18%	17%	14%
	Crowdshipping		8%	8%		10%	8%
	Drone			0%			17%
Tours	Van	714	673	671	1164	1068	940
	Crowdshipping		5475	5380		12 877	10 968
	Drone			0			23 527
Vehicle kilometres [1000 km]	Van	99.9	95.7	95.8	129	120	108
	Crowdshipping		12.8	12.7		28.0	24.3
	Drone			0			157.6
CO_2 emissions [ton]	Van	20.2	19.3	19.3	27.1	25.1	22.4
	Crowdshipping		0.9	0.8		1.9	1.6
	Drone			0			0
Number of self-collection points		3012	3012	3012	1631	1516	1200
Total capacity self-collection points		60 240	60 240	60 240	32 620	30 324	23 996
Number of drones				29			573

Table 4
Scenario comparison.

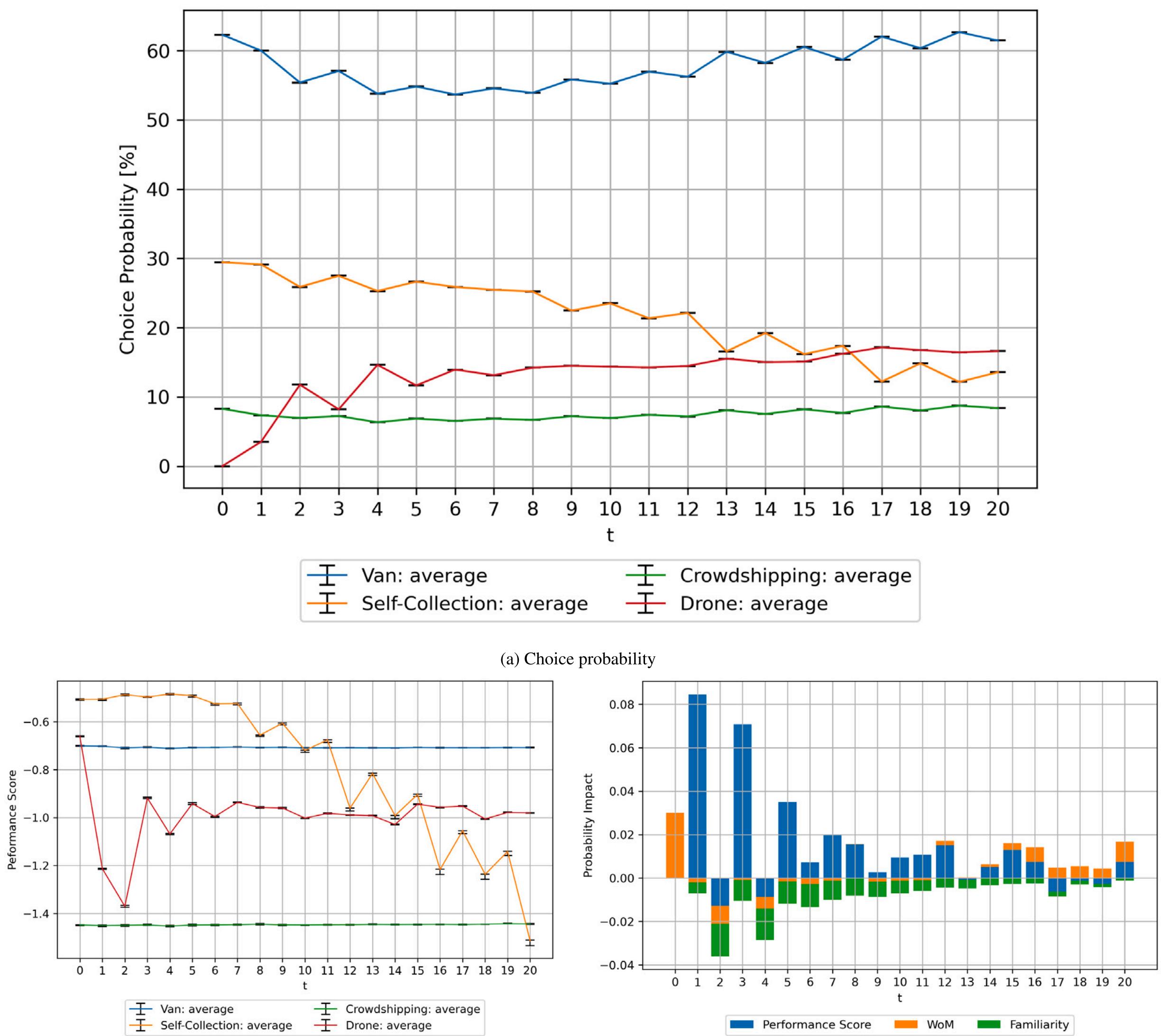
Indicator	Scenario t = 0 [quarter]			Scenario t = 20 [quarter]		
	1: Current state	2: Crowd-shipping	3: Full innovation	1: Current state	2: Crowd-shipping	3: Full innovation
Parcel demand [1000 parcels]	116	116	116	223	223	223
Vehicle kilometres [1000 km]	99.9	95.7	95.8	129	120	108
CO_2 emissions [ton]	20.2	20.1	20.1	27.1	26.9	24.1

Table 5
Average CO_2 emissions per parcel [kg/parcel] and average kilometres per parcel [km/parcel].

Time	CO_2 [kg/parcel]			Vehicle kilometres [km/parcel]		
	1: Current state	2: Crowd-shipping	3: Full innovation	1: Current state	2: Crowd shipping	3: Full innovation
t = 0	0.174	0.173	0.173	0.861	0.935	0.935
t = 20	0.122	0.121	0.108	0.579	0.664	1.302

Table A.2 the standard deviation for each indicator is shown. In all three scenarios, the stochasticity in the model produces very limited differences in the preference probabilities.

The results in Table 3 indicate that most consumers prefer van delivery in all three scenarios. The number of parcels with delivery method van is expected to increase by roughly 130% in Scenario 1 and 2, and still by 90% in Scenario 3. In the tour formation, parcels for van and self-collection delivery are combined, resulting in growth in the amount of tours by 63%, 59% and 40% for Scenario 1 to 3 respectively. The vehicle kilometres by van increase moderately, with 29%, 25% and

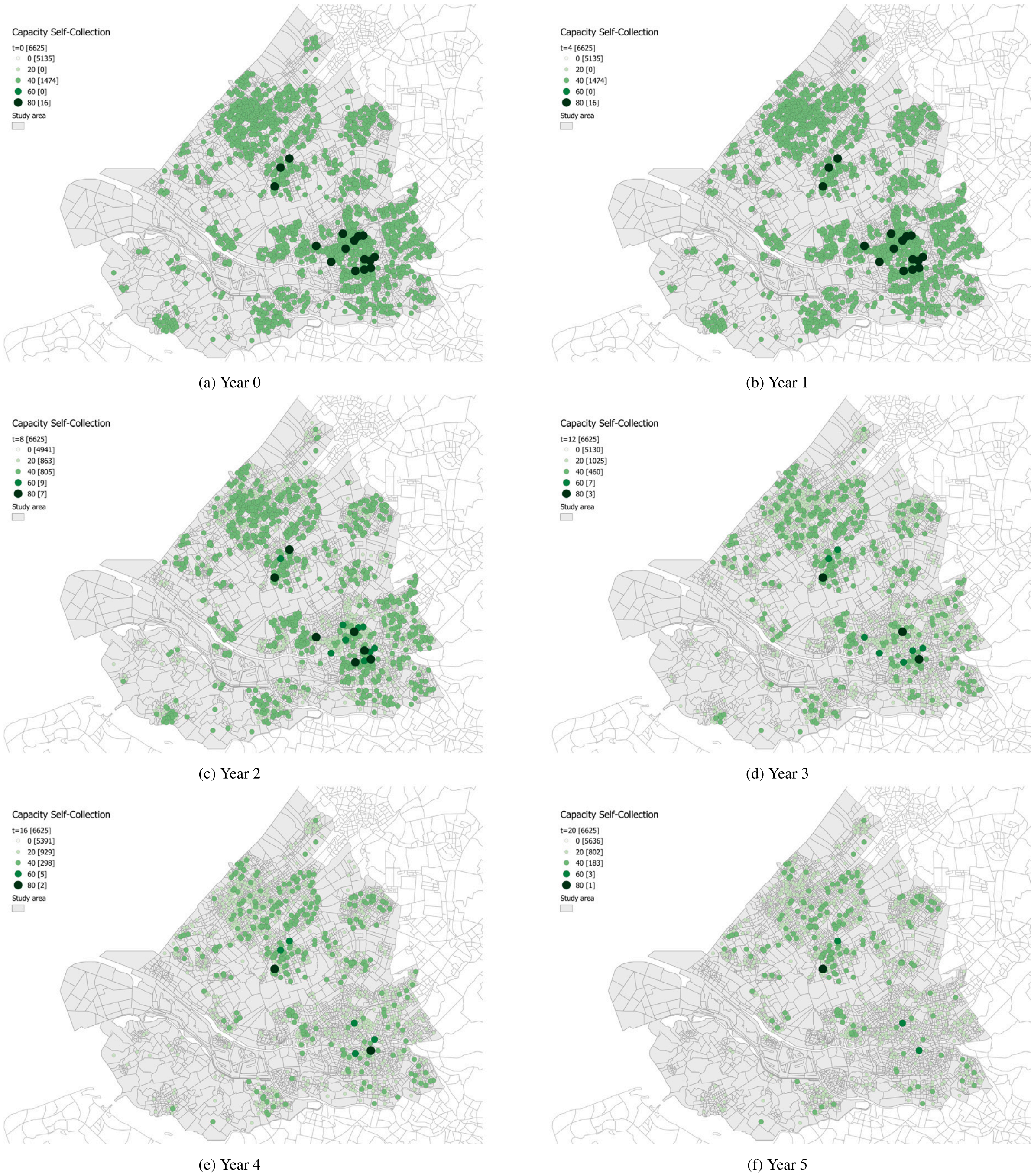


(a) Choice probability

(b) Performance score

(c) Impact on the choice probability of drone

Fig. 5. Evolution over time in Scenario 3: Full Innovation.



(a) Year 0 (b) Year 1 (c) Year 2 (d) Year 3 (e) Year 4 (f) Year 5

Fig. 6. Development of the self-collection capacity in Scenario 3: Full Innovation Run 1.

13%. This results clearly show the benefit of scale of operation. With the increasing demand, more parcels can be delivered in each zone.

In Fig. 5(a), the evolving consumer choice probabilities can be seen for Scenario 3. These probabilities are effectively the market shares in each time step. It can be seen that the probabilities of van and crowd-shipping are constant, while the choice probability of self-collection declines and drone increases. The reason many consumers prefer van delivery is that the performance score of van delivery is constantly high, see Fig. 5(b). From time step 12 it is, on average, outperforming the other delivery methods. The performance of self-collection strongly decreases at the end of the time horizon.

A clear illustration of the interaction between demand and supply occurs with self-collection. Over time, the supply of self-collection points reduces, see Table 3, which can be explained by the demand being below the removal threshold in many zones. In Fig. 6, the capacity of the self-collection points is presented for each simulation year. The diminution of self-collection results in a worsening performance score, see Fig. 5(b), where the reliability mainly decreases due to the number of parcels not fitting in the shrunken capacity. This creates a negative feedback loop between consumer demand and the supply of self-collection. Still, around one-seventh of the consumers are expected to choose self-collection in all scenarios and the spatial results show that self-collection can be a competitive delivery method in dense urban areas, see Fig. 7.

The results show that with the introduction of more delivery methods, fewer consumers will prefer self-collection, see Table 3. Due to these lower demands, the distribution of self-collection becomes scarcer, and the total capacity at $t = 24$, after 5 years, is around 7%

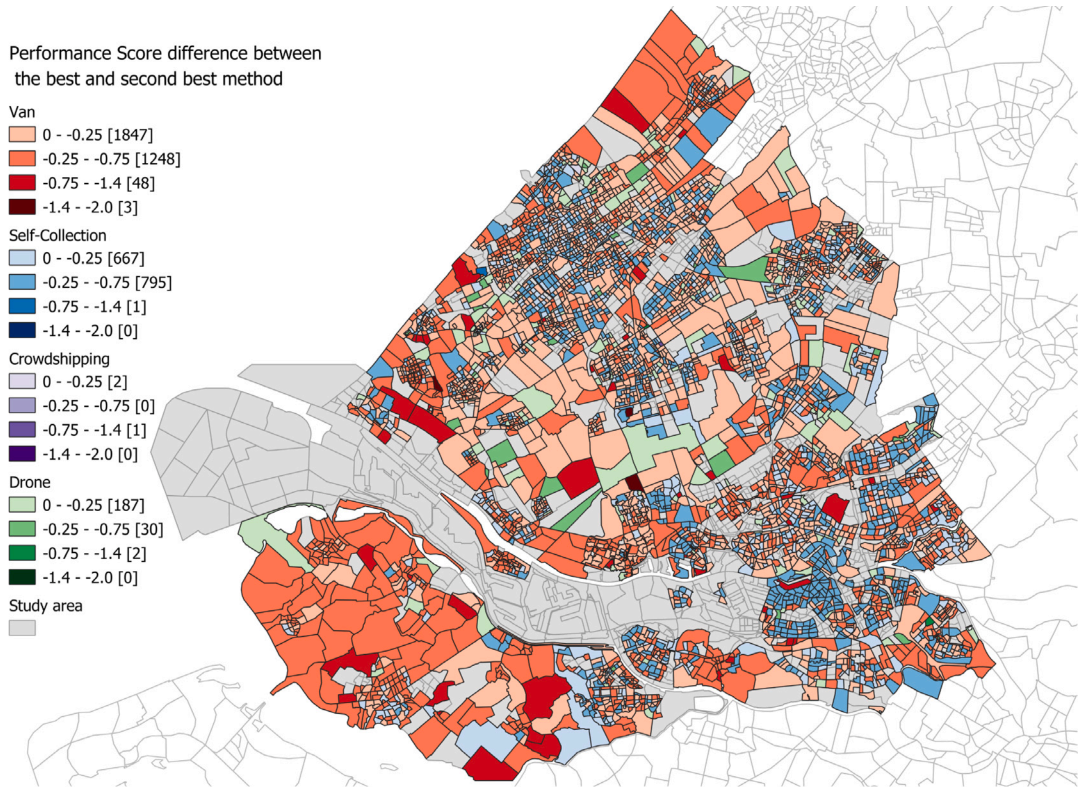


Fig. 7. Zonal distribution of the relative performance of all delivery methods in Scenario 3: Full Innovation Run 1 after 5 years (t = 20). A zone is filled with the colour of the best-performing delivery method. The value is the difference between the performance score of the best and second-best delivery method.

and 27% lower for Scenarios 2 and 3 than in Scenario 1, respectively. Consequently, the performance score of self-collection in Scenario 3 evolves to a slightly worse level than in Scenarios 1 and 2. An interesting effect of the shrinking number of self-collection points is that grouping of self-collection parcels becomes easier, resulting in less trips per day for the same amount of parcels.

Due to the way of modelling, crowdshipping has, like van delivery, a constant performance score, see Fig. 5(b). Additionally, the performance is very consistent across all zones. Because of the stable performance, the evolution of crowdshipping is very comparable between Scenarios 2 and 3. However, in Scenario 3, the competition with drone delivery results in a lower market share.

The introduction of drone delivery has a large impact on the predicted market shares of the other delivery methods, as can be seen in Table 3 by the reduced market shares of the other methods compared with Scenarios 1 and 2. Spatial results show that drones perform well around the depots. However, the performance in the outskirts of the study area is generally low. The development of the flight range makes drone delivery accessible to more consumers. Still, the average performance score does not improve, see Fig. 5(b). This is because the high accessibility effect is cancelled out by the increased delivery costs, which are linked to the flight distance. To fulfil the demand, drones must travel large amounts of vehicle kilometres. In just five years, the drone fleet has to grow from 29 drones in total to almost 600 in order to fulfil the demand. Consequently, there will be three depots that must operate more than 50 drones, with a maximum of 120.

Consumers evolve their preferences because of the performance score, WoM and familiarity. In Fig. 5(c), the impact of these three factors on the choice probability for drone is shown for consecutive time steps. Initially, the only influence comes from the WoM effect because that factor accounts for the adoption of innovators. Based on the operational performance that those innovators experience, the logit model assumes a strong uptake in users in the first quarter after the introduction, $t = 1$. At that time step, the magnitude of WoM is very limited due to the small group of consumers that can spread WoM. On the contrary, the familiarity effect is relatively strong at the start because only a few consumers have used drones, and thus many consumers still need to familiarise themselves with drones. When the performance score of drone delivery stabilises, from Fig. 5(b) around $t = 11$, also the impacts become smaller. In the end, the WoM effect becomes the most important reason for the continued growth of the market share of drones.

Finally, the large yearly growth in parcel demand results in higher vehicle kilometres and CO_2 emissions, regardless of the scenario. In Table 4 three key indicators are presented to compare each scenario, Table A.3 provides the standard deviations of these indicators. In five years the total demand almost doubles. The introduction of crowdshipping reduces the demand for van delivery and self-collection, yet it will result in more vehicle kilometres that need to be made on the same road infrastructure as van delivery. However, crowdshipping produces less CO_2 per kilometre than vans. Therefore, the CO_2 emissions are very comparable with Scenario 1. The high CO_2 emissions in Scenario 2 can be explained by vans becoming more efficient when the demand is higher. With increasing parcel demand, the number of zones that need to be visited increases only slightly, while those transports contribute to the largest share of vehicle kilometres and emissions. Hence, the positive effect of the substitution of van and self-collection delivery by crowdshipping is partly reversed. This can also be seen in Table 5, where the average kg CO_2 emission per parcel is shown. The standard deviation for each indicator are shown in Table A.4. In all scenarios, this number improves. Scenario 3 results in the lowest CO_2 emissions due to drone delivery being emission-free and results in 11% less CO_2 emission than Scenarios 1 and 2. Additionally, the van vehicle kilometres and emissions within zones are much lower than in the other scenarios, which reduces the last-mile burden in urbanised areas and on low-capacity roads.

5. Conclusion and future work

This research develops a hybrid simulation model to estimate consumer preferences and the evolving operation of various parcel delivery methods. By using a system dynamics (SD) model to track consumer preference shifts and an agent-based model (ABM) to simulate delivery operations, the model captures the influence of synthetic delivery experience, word-of-mouth, and familiarity effects on consumer behaviour.

The model's key contributions are threefold. First, by simulating demand and supply interactions in a spatial framework, it enables policymakers and logistics providers to assess delivery strategies and policy impacts on an aggregate to zonal level. This approach allows the exploration of the complex last-mile system where multiple delivery methods compete and complement each other. Second, it accounts for stochasticity in delivery operations, allowing for reliability assessments across different supply–demand levels. This insight is crucial for understanding how reliability influences consumer choice. Third, the model provides insight into the direction and magnitude of various factors that take place, with the added novelty of gathering that empirical data at multiple time points. This is a valuable model feature, as stated preference and especially revealed preference research cannot determine such data.

From the performed case study on the Rotterdam-The Hague region, several recommendations for policymakers can be made. If policymakers or parcel carriers want to reduce the demand for van delivery, providing additional delivery methods could lessen that demand. However, those delivery methods should establish very high service levels, which is not likely and can be costly in many zones. Additionally, the results show that a vast drone network is needed, which comes with many issues as safety, privacy and nuisance. A significant impact could also be realised by reducing the service of van delivery, mainly by introducing a delivery fee, as consumers are cost-sensitive. Furthermore, it is concluded that self-collection is a highly competitive delivery method in dense urban areas. Because of that, highly urbanised municipalities should direct or build a vast network, especially of white-label, automated lockers, while rural areas could better invest in other parcel delivery methods. Finally, as both crowdshipping and drone delivery are new innovations, policymakers have the opportunity to steer regulations such that societal benefits are prioritised.

The simulation model and results can be improved by adding or applying various advancements. First of all, a MNL model is applied to model the choice behaviour of the consumers. This method can be improved by using a latent class logit model (LCLM) or a mixed logit (ML) model. In this way, correlation between alternatives is accounted for, as the delivery methods do not operate entirely independent from each other; and secondly, these models better account for heterogeneity between the decision makers. Additionally, the choice model could be improved by accounting for consumer characteristics (e.g. income, car-ownership). Furthermore, the SD, wherein the MNL model is used, is currently implemented at the aggregate level of the entire study area. This could also be applied at a lower level, e.g. a neighbourhood or municipality, allowing for more precise estimation of the prevalence of delivery methods. In addition, this development allows zonal differentiation in, for example, attribute weights. If a sufficient data source is available, the dynamics within the SD model can be implemented at the individual consumer level allowing for even more heterogeneity.

Secondly, a moving memory can be considered, especially for longer simulation horizons. Furthermore, parcel characteristics like weight and size are disregarded, which overestimates the possibility of especially drone delivery. Furthermore, the estimation of the vehicle kilometres within the zones could be improved. The current estimation adds a fixed distance for each additional delivery in the same zone. Because of this methodology scale of operation does not take place for intrazonal travel, see for example Table A.5. This approach for the intrazonal distance also contributes to the relatively high average tour distance. Lastly, as the period on which the yearly growth rate of the parcel demand is based includes two years that were impacted by COVID-19, a smaller growth rate could also be implemented.

Besides these model improvements, it is recommended that future research and data collection efforts are carried out on consumer preferences for last-mile delivery. Limited data is currently available and general best practices have not been settled. Additionally, future research could implement non-direct performance-related delivery attributes to describe consumer preferences, such as environmental impact.

CRediT authorship contribution statement

J.E. van Vliet: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **M.A. de Bok:** Writing – review & editing, Supervision, Methodology, Conceptualization. **B. Atasoy:** Writing – review & editing, Supervision, Methodology, Conceptualization. **G. Homem de Almeida Correia:** Writing – review & editing, Supervision, Methodology.

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.

Appendix

See Tables A.1–A.5 and Fig. A.1.

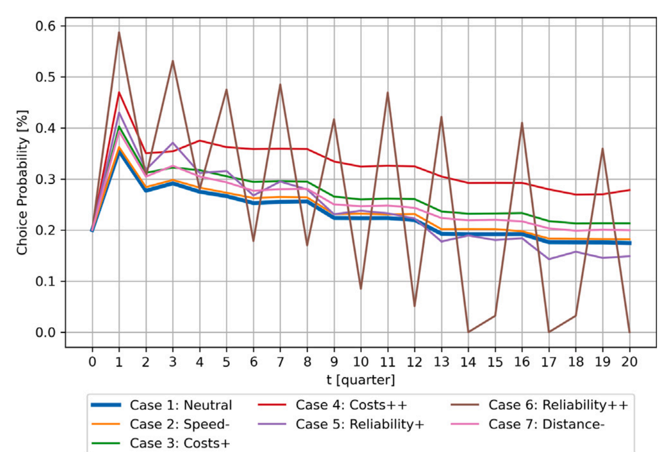


Fig. A.1. Probability self-collection with different beta weights.

Table A.1
Attribute beta weights based on Buldeo Rai et al. (2019), Caspersen and Navrud (2021), de Oliveira et al. (2017), Gatta et al. (2018, 2019), Maltese et al. (2021), Molin et al. (2022) and Nguyen et al. (2019).

Attribute	Weight
β_{Speed}	1
β_{Costs}	2
$\beta_{Reliability}$	2
$\beta_{pick-upDistance}$	1
ASC_{van}	1
$ASC_{self-collection}$	0
$ASC_{crowdshipping}$	0
ASC_{drone}	0

Table A.2
KPIs scenarios: Standard deviation.

Indicator	Method	Scenario t = 0 [quarter]			Scenario t = 20 [quarter]		
		1: Current state	2: Crowd-shipping	3: Full innovation	1: Current state	2: Crowd-shipping	3: Full innovation
Parcel demand [1000 parcels]	Total	0	0	0	0	0	0
Market share	Van	0.136	0.070	0.038	0.076	0.026	0.084
	Self-collect	0.136	0.045	0.047	0.076	0.044	0.251
	Crowdshipping		0.044	0.031		0.027	0.023
	Drone			0			0.173
Tours	Van	1.12	2.23	2.02	1.46	1.98	6.46
	Crowdshipping		75.3	35.8		185.3	110.2
	Drone			0			1.90E3
Vehicle kilometres [1000 km]	Van	557	350	391	439	199	492
	Crowdshipping		244	43.2		345	433
	Drone			0			21 180
CO_2 emissions [ton]	Van	124	94.0	89.0	82.0	34.8	78.8
	Crowdshipping		10.5	26.5		24.4	54.7
	Drone			0			0
Number of self-collection points		0	0	0	18.8	27.0	24.8
Total capacity self-collection points		0	0	0	377	541	497
Number of drones				0			50

Table A.3
Scenario comparison: Standard deviation.

Indicator	Scenario t = 0 [quarter]			Scenario t = 20 [quarter]		
	1: Current state	2: Crowd-shipping	3: Full innovation	1: Current state	2: Crowd-shipping	3: Full innovation
Parcel demand [1000 parcels]	0.000	0.000	0.000	0.000	0.000	0.000
Vehicle kilometres [1000 km]	0.557	0.284	0.354	0.439	0.449	20.9
CO_2 emissions [ton]	0.124	0.094	0.100	0.082	0.024	0.104

Table A.4
Average CO_2 emissions per parcel [kg/parcel] and average kilometres per parcel [km/parcel]: Standard deviation.

Time	CO_2 [kg/parcel]			Vehicle kilometres [km/parcel]		
	1: Current state	2: Crowd-shipping	3: Full innovation	1: Current state	2: Crowd shipping	3: Full innovation
t = 0	0.001	0.001	0.001	0.005	0.002	0.003
t = 20	0.000	0.000	0.000	0.002	0.001	0.094

Table A.5
Distance per parcel and tour Scenario 1: Current state.

Carrier	t = 0 [quarter]			t = 20 [quarter]		
	Interdistance [km/parcel]	Intradistance [km/parcel]	Tour distance [km/tour]	Interdistance [km/parcel]	Intradistance [km/parcel]	Tour distance [km/tour]
PostNL	0.39	0.18	100	0.27	0.22	88
GLS	1.62	0.15	304	1.03	0.18	213
DHL	0.53	0.19	125	0.33	0.22	98
UPS	0.97	0.18	202	0.63	0.21	149
DPD	0.87	0.18	188	0.57	0.22	140
FedEx	2.28	0.12	394	1.42	0.15	266

Data availability

The authors do not have permission to share data.

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