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Delivering in Urban Areas: A Probabilistic-Behavioral Approach for Forecasting the Use of Electric Micromobility

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Abstract: Urban delivering is facing some significant changes that are heading towards unsustainable scenarios. At the same time, local administrations as well as city planners are involved in promoting new solutions that can help to improve city sustainability and livability. In this context, electric micromobility could offer a valuable contribution. In fact, electric micromobility systems such as e-bikes and e-scooters, both at an individual level or as a shared service, could represent sustainable mobility options for city logistics, especially for specific classes of parcel delivery, users' characteristics and travelled distances. Considering both the growth of e-commerce and the spreading of new options for delivering parcels (e.g., crowdshipping), electric micromobility (e-bikes and e-scooters) could support the penetration and acceptability of such new options, limiting the impacts of delivery operations. After analysis of the current e-commerce background and a review of the current delivery options to satisfy delivery demand, crowdshipping stands out. Thus, the potential shift from private transport to e-micromobility for crowdshipping is investigated, assuming that potential crowdshippers may, mainly, be commuters. The methodology is based on using probabilistic-behavioral models developed within random utility theory, which allow the potential shift towards e-micromobility for commuting to be forecasted. The models were calibrated in Rome, where more than 200 interviews with commuters were available.

Keywords: electric micromobility; e-scooters; e-bikes; floating car data; random utility models; city logistics; crowdshipping

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1. Introduction

Shifting toward sustainable development has been a focus since the 1980s [1,2]. In 2015, the United Nation Member States defined the Sustainable Development Goals (SDGs), [3], where the 11th SDG focused on urban contexts (*making cities and human settlements inclusive, safe, resilient and sustainable*). Following these trends, the European Commission (EC) promoted guidelines to develop and implement sustainable urban mobility plans—SUMP [4], also considering the evidence that plans can become rapidly obsolete and lack resilience with regard to future developments [5]. It should be noted that, in the context of SUMP and below, the functioning area refers to the geographical area that is covered by the plan, and it is determined based on the travel-to-work patterns of people travelling to and from the city from the suburbs. The geographical area of the plan reflects the pattern of journeys routinely made by people, as opposed to administrative boundaries [3].

City planners are promoting and funding sustainable solutions in different economic sectors, including transportation [6]. Regarding delivery of goods in urban areas, changes in the social structure—also motivated by the current health emergency (COVID-19)—significantly contribute to unsustainable behaviours, as shown by the extensive literature [7–10]. Indeed, the COVID-19 pandemic has transformed how people eat, work, travel, shop, and pursue entertainment, reshaping not only passenger transportation but also the freight system. Particularly, the increase in on-line shopping is a notable effect: retail sales via e-commerce in the United States (U.S.) increased by 31.8% from the first quarter to the second quarter in 2020, while total retail sales decreased by 3.9% during the same period [11]. Europe is the continent with the highest internet penetration, equal to 85% with an increase by 5% compared to 2018. In 2019, 70.6% of the population shopped online. Online retail sales amounted to EUR 309 billion, with a 10% growth compared to the previous year. Although e-commerce still represents a small part of overall purchases (7.3% penetration rate), it is now responsible for 65% of overall retail growth (on-line + off-line). In fact, online purchases have grown by 15%, while overall consumption is generally stable (+1.5%). Furthermore, in 2019, the incidence of B2C e-commerce in total retail sales increased from 6.5% to 7.3%, with a significant difference between products (6%) and services (11%). The difference in the incidence of e-commerce in the various product sectors remains important: it ranges from 36% in tourism and transport to 1% in food and grocery. In the middle, however, there are other relevant sectors such as furniture and home living, clothing, publishing, informatics and electronics with penetrations of between 7% and 27%.

This new trend will certainly have an impact on freight traffic in urban and metropolitan areas because purchases will have to be shipped to homes (or to similar locations) and the related travel will not always be optimized, resulting in an increase in the impact on sustainability and on the liveability of the city. In addition, there is an increase in costs for transport and logistics operators (for example, couriers) as a result of repeated deliveries. In fact, home deliveries usually require the recipient of the shipment and the transport operator to agree on the day and time to avoid "*delivery failure*". On the operator side, agreeing to carry out multiple deliveries can be an advantage in terms of revenues, but it is highly difficult to reconcile the different needs of recipients in terms of schedules.

From the consumer's point of view, online purchases are associated with a series of advantages such as a greater choice of products, the possibility of obtaining products not sold locally, and a better price comparison, etc. From a logistic point of view, however, delivery solutions are very demanding. Efficient and reliable logistics is a key factor in the economic success of online stores, and shipping costs are a major concern for online customers. Above all, the "*not-at-home problem*", which derives from the delivery of goods requiring the presence of the customer, must be addressed. This leads to complex planning problems in the last link of the supply chain, namely, the last mile to the consumer.

With regard to the type of purchase, another crucial question is whether the recipient should be present at the time of delivery, either to sign the receipt or due to lack of storage facilities. Delivery to workplaces or collection points such as local shops, gas stations, restaurants, etc., may be another solution to the problem of the consumer not being at home.

Considering that last-mile deliveries alone account for about 30% of freight transport costs, the only viable solution today seems to be the restructuring of urban logistics structures. However, the price and the lack of urban spaces to be dedicated to industrial activities (transport and logistics) push us to find new models of urban distribution to meet customer demands.

Logistics operators are faced with an important challenge: to propose new organizational models suitable, at all times, to the commercial, urban and sustainable policies that are implemented in the respective territories. For example, among the various solutions proposed for the delivery of online purchases, there is the crowdshipping. Crowdshipping is the use of the community (city users: pedestrians, sportsmen, commuters, motorists, transporters, etc.) who normally use transport services by offering the opportunity to make profit (both personally—remuneration for the activity carried out—and collectively—a package delivered can lead to one less vehicle on urban roads) through a trip that will generally be carried out anyway, such as a commute. Therefore, the main objective of this research is derived: i.e., to point out the opportunity offered by electric micromobility and commuters to become crowdshippers. Thus, pushed by the need to have tools for forecasting potential crowdshippers and electric micromobility to be used in the SUMP (and subsequent plans), the research proposes a partial share approach, in which probabilistic-behavioural models are used to forecast electric micromobility trips by commuters that are available to become crowdshippers, taking into consideration their attitude and preferences. The synergy between passenger and freight mobility is, hence, also pointed out [5].

In this context, starting from an analysis of existing studies on alternative modes of e-delivering [12–15], the paper focuses on small-sized freight (parcels) to be sustainably delivered within historical and high-density areas of a city, for which crowdshipping can be used. The paper, thus, investigates the potential shift of users (mainly commuters) to become crowdshippers and to use sustainable transport solutions such as e-bikes and e-scooters (below referred to as e-micromobility).

The paper is structured as follows. Section 2 reviews crowdshipping as well as micromobility, specifically e-micromobility, as a valuable option for commuters during daily trips. Section 3 presents the methodology proposed for investigating delivering through e-micromobility, while Section 4 reports the analysis and models developed for forecasting the potential shift towards e-micromobility. Finally, conclusions and the road ahead are drawn in Section 5.

2. Background

A crucial challenge to sustainable urban freight distribution is represented by the growth of e-commerce and door-to-door services that are leading to significant changes in the delivery process [16].

According to Comi and Savchenko [7], three main research streams have been developed to limit the impacts of parcel deliveries (especially of e-deliveries): pick-up systems, crowdshipping and two (multi-)echelon delivery systems. While pick-up systems [17] and two (multi-)echelon delivery systems [18] were already introduced some years ago, and in some countries (e.g., pick-up points/delivery lockers in Germany; [19]) are quite familiar, crowdshipping is quite new and opens new research challenges both in terms of crowdshippers' involvement and sender/receiver points of view.

In particular, pushed by the opportunity to reduce the number of vehicles driving in urban areas and to perform parcel deliveries with trips that will be undertaken anyway (e.g., commuting trips), crowdshipping has emerged. Crowdshipping is an innovative delivery model that could, at least in principle, stimulate a better use of currently unexploited transport capacity, thus reducing transport costs and emissions [16]. In crowdshipping, individuals travelling to a certain area can perform parcel deliveries on their way. This integration of personal and freight transport is based on a matching process between demand (for deliveries) and supply (of transportation) through on-line platforms. Below, crowdshipping is first introduced as a new urban parcel-delivery pattern, then the studies on characteristics and willingness to become crowdshippers, including the first result on the acceptability of its use, are reviewed. Finally, the benefits in terms of environment impacts are examined.

Crowdshipping can be implemented in different ways. As in most existing services, "crowdshippers" can pick up a parcel and deliver it to the final customers by using privately owned means of transportation (similarly to ride-hailing services, but for freight). Alternatively, they can rely on existing public transport services. Due to several factors, including mode, length of detours and parking behaviour, social crowdshipping effects continue to be ambiguous. In fact, crowdshipping is a freight transport system outsourcing deliveries to a fleet of non-professional freight forwarders. The first difference between a courier and a casual courier is that there is no need for an additional trip. The selected courier may be the closest to the delivery route, the one who offers the cheapest shipping rate or who has the best reputation [20]. A second difference is that casual couriers are not required to have specific training. In addition, drivers decide where, when, and how much to work. In addition, casual couriers (crowdshippers) are typically recruited through internet platforms such as Taskrabbit [21] or Amazon Mechanical Turk [22,23]. This allows for large and heterogeneous groups of people to be engaged for a short period at a low cost [24].

To study the *behaviour characteristics* of potential couriers, a dedicated survey was designed by Miller et al. [25]. Specifically, the results show that the sociodemographic characteristics of non-professional couriers (age, income) as well as the value of the fare significantly influence the decision to participate in the temporary delivery market. Crowdshipping is prevalent among young people, men, and full-time employees, while low- and high-income earners are less inclined to change status from pure commuters to traveller–shippers [26]. Marcucci et al. [27] showed that 87% of students at Roma Tre University (Italy) are willing to become crowdshippers, but that percentage is influenced by the size of the drop boxes and the remuneration. Devari et al. [28] revealed that individuals would be willing to transport parcels for their friends. Furthermore, they would be willing to accept a detour as far as 15 min and a non-rewarded delivery. Similarly, Miller et al. [25] found that urban areas are preferred for crowdshipping developers and users are more likely to use the system for medium-distance deliveries. Moreover, Galkin et al. [29] identified that individuals with a strong sense of community and environmental concern are, respectively, 86.4% and 83.9% more likely to use crowdshipping. However, the users who may have concerns about trust, privacy and safety are 68.3% and 64.9% less likely to use crowdshipping, respectively.

Specifically, to *become a crowdshipper*, Le and Ukkusuri [30] studied individuals' willingness to work as crowdshippers using a binary logit model to estimate participants' discrete choices, through 549 survey responses that were used to develop the study. Results show that 78% of respondents were willing to work. Punel et al. [31] used a binary logit model to distinguish preferences between crowdshipping users and non-users by surveying 800 people in different states in the United States of America. They concluded that young men with full-time jobs are more willing to become crowdshippers.

The propensity to accept crowdshipping, as well as to be a crowdshipper, can be merged with the new trend of city logistics policies. For example, innovation in vehicles (i.e., adopting drones, cargo bikes, e-scooters, and autonomous robots for last-mile delivery) can enable crowdshipping. Bike couriers can transport mail, letters, packages, and other low-volume or low-weight goods [32]. More than 25% of all goods and 50% of all light goods in European cities can be transported by bicycle [33]. Moreover, more than 70% of shoppers want a fast delivery [34] and bicycles have the advantage of being faster and more reliable within congested urban areas than cars.

Several studies investigated the impacts of adopting micromobility (mainly bikes) instead of traditional transport options for freight transport. Dupljanin et al. [35] simulated bicycle and car-based freight transport in Copenhagen. The results show that bicycle-based fleets make for a faster, more environmentally sustainable, and potentially cheaper alternative to traditional car-based fleets. A study on cargo-bike ownership reports how these can substitute car trips by 41% (European Mobility Atlas, 2021); similar results have been estimated by the Cyclelogistics Project, where 51% of motorized trips can be substituted by e-bikes. Paloheimo et al. [36] simulated the distribution of book rentals in Finland to and from the city library through citizens. This is a first attempt of crowdsourced delivery, showing that most of the drivers used a bicycle to perform the task. Indeed, the choice of bikes usually leads to several benefits: there are no parking costs and it is easily accessible since no driver's license or extensive training are required [34]. In addition, Binetti et al. [37] studied a possible initiative of delivering goods through bikes, in this case, involving the users of a free-floating bike-sharing system. Comi and Savchenko [7] assessed urban delivery means within the inner area of Kyiv (Ukraine), also taking into account the adoption of bicycles in combination with public transport.

Between the strengths of adopting micromobility and e-micromobility for last-mile deliveries, there is the reduction in *environmental impacts*. Browne et al. [38] studied an indepth case study on Gnewt Cargo in London, and showed that the total distance travelled and related CO_2 emissions per delivered parcel decreased by 14% and 55%, respectively. Nocerino et al. [39] showed that e-bikes and e-scooters for moving goods save between 1.7 and 21.0 kg of CO_2 per day, respectively. Gatta et al. [26] showed how crowdshipping in Rome produces a saving of 239 kg of particulate matter per year. This information can be used by crowdshipping companies to create management strategies, such as incentives, to recruit more occasional couriers. Buttgen et al. [40] simulated the use of cargo bikes in the city of Innsbruck and observed that 96% of emissions could be saved.

Inspired by how micromobility can represent a viable alternative to conventional transport solutions for delivering parcels in urban areas, and shown by the brief literature review presented above, the need to develop methods and models for assessing the opportunities and benefits for urban deliveries by electric micromobility emerged. Therefore, a methodology is proposed below for assessing the potential to forecast the involvement of commuters as crowdshippers using e-micromobility (e-bikes and e-scooters).

3. The Proposed Methodology

The innovation of this work consists of the investigation of the potential shift of users (mainly commuters) to become crowdshippers and to use e-bikes and e-scooters. Then, a random utility model (RUM) was developed through interviews carried out in Rome (Italy). Revealed preferences (RP) and stated preference (SP) surveys were used aiming to investigate the factors impacting the potential shifting from cars to owned electric micromobility for commuting trips.

Given a study area U and a given number of commuters N, the potential crowdshippers, N^{crowd} can be forecasted by a partial share approach as follows:

$$\begin{aligned} N^{crowd} &= \sum_{z \in U} N_z^{com}[crowd, m] = \sum_{z \in U} N_z^{com} \cdot p[crowd, m | z, \boldsymbol{tr}, \boldsymbol{sc}] \\ &= \textstyle\sum_{z \in U, m} N_z^{com} \cdot p[crowd | z, \boldsymbol{tr}, \boldsymbol{sc}] \cdot p[m | z, \boldsymbol{tr}, \boldsymbol{sc}] \end{aligned} \tag{1}$$

where

- N_z^{com} is the number of commuters living in traffic zone z within the study area U;
- $N_z^{com}[crowd, m]$ is the number of commuters living in traffic zone z, who would like to become crowdshippers and to travel by e-micromobility m;
- $p[crowd, m|z, \boldsymbol{tr}, \boldsymbol{sc}]$ is the percentage of commuters living in zone z, with socio-economic characteristics $\boldsymbol{sc}$ (e.g., age, employment status) travelling with trip characteristics $\boldsymbol{tr}$ (i.e., vectors reporting the characteristics of travel such as origin and destination, travel costs), that can potentially become crowdshippers and travel by micromobility means (m);
- $p[crowd|z, \boldsymbol{tr}, \boldsymbol{sc}]$ is the percentage of commuters living in zone z, with socio-economic characteristics $\boldsymbol{sc}$ (e.g., age, employment status) travelling with trip characteristics $\boldsymbol{tr}$ (i.e., vectors reporting the characteristics of travel such as origin and destination, travel costs), that potentially can become crowdshippers, which can be calculated with a *crowdshipper model*;
- $p[m|z, \boldsymbol{tr}, \boldsymbol{sc}]$ is the percentage of commuters living in zone z, with socio-economic characteristics $\boldsymbol{sc}$ (e.g., age, employment status) travelling with trip characteristics $\boldsymbol{tr}$ (i.e., vectors reporting the characteristics of travel such as origin and destination, travel costs), that use e-micromobility (i.e., e-bike and e-scooter), which can be calculated with a *crowdshipper-mode choice model*.

It should be noted that, in general, the probability that a commuter becomes a *crowdshipper* and travel by micromobility means m ($p[crowd, m]$) should be treated as a joint choice. However, according to some outcomes on crowdshipping analysis [16], we assumed that the decisions about becoming a *crowdshipper* and to use micromobility vehicles are taken at two times independently. Thus, we have a two-step model:

$$p[crowd, m|z, \boldsymbol{tr}, \boldsymbol{sc}] = p[crowd|z, \boldsymbol{tr}, \boldsymbol{sc}] \cdot p[m|z, \boldsymbol{tr}, \boldsymbol{sc}]$$

While some studies investigate the propensity to become crowdshippers, as reported in the references quoted earlier, few studies (to the authors' knowledge) focused on the probability of using an e-bike or e-scooter for crowdshipping, showing that further investigation is needed. Therefore, below, *crowdshipper mode-choice models* for using e-bikes and e-scooters are presented.

3.1. Survey and Data Description

The survey was conducted during November 2020–January 2021 with about 300 inhabitants of the city of Rome. The questionnaire was shared online, via social-media networks, instant-messaging apps and e-mails. Regarding the impact of COVID-19 on the survey, it has to be underlined that the pandemic boosted the development of e-micromobility options in Italian cities due to the spreading of e-micromobility operators in the market and the promotion of incentives for buying micromobility vehicles [41].

The questionnaire consists of 4 main sections:

- *personal-data* section (first section), to collect data on age, gender and employment condition. This section allows to filter respondents that do not perform commuting trips, such as retired or unemployed people. The remaining categories used in the calibration process are students, workers and working students;
- *socio-demographic-data* section (second section), to collect data on the user and their household, such as level of education, place of residence, number of household members and drivers' license ownership;
- *systematic-trips*-data section (third section), to investigate trip destination (workplaces or schools/universities) locations, ownership and availability of private vehicles (car, moped/motorbike, bike, scooter), transport mode mainly used to carry out the specific commuting trip, travel times, parking availability, and public transport subscription ownership;
- *hypothetical e-micromobility usage* configurations evaluated through stated preferences scenarios (fourth section): potential e-bike or e-scooter ownership (evaluating preferred road safety levels, travel times and willingness to purchase the vehicle) and potential e-bike- or e-scooter-sharing-service usage (considering preferred service costs, vehicle accessibility and road safety levels).

Table 1 reports the comparison between the age classes in the sample and in the population of Rome and shows that young users (18–24 and 25–34) are more represented in the sample than in the census data, whereas older users (55–65 and >65) are less represented. However, having a higher number of young respondents is expected to have in the sample more potential micromobility users, given that young individuals from 18 to 34 years old are most likely the potential users of micromobility services [42,43]. Differences between sample and related population are usually considered in the expansion phase by weighting the results of each sample group according to the population values.

Table 1. Age-classes comparation between sample and Rome population.

Age	Sample (%)	Rome Population (%)
<18	4%	5%
18–24	18%	8%
25–34	29%	13%
35–44	13%	18%
45–54	25%	23%
55–64	9%	19%
>65	2%	14%
Total	**100%**	**100%**

Regarding the employment conditions, workers are 46% of respondents, students are 27% and working students are 8% of the sample. In the following sections, only the users belonging to these categories continued to compile the questionnaire, giving answers about their household, their systematic trips and their opinions about micromobility. The remaining users were questioned about the frequency (always, often, rarely and never) of availability of different private vehicles in their household (second section): 64% of respondents always have a car available to use and 11% of respondents always have either a moped or motorcycle available to use; 34% of users always have a bike available and a further 41% have a bike often/rarely. For scooters, the percentage of users who have a private e-scooter available to use is much lower (6%) and the percentage of users who never have an e-scooter available is 64%.

Then, systematic trips were investigated in the third section: regarding the mode of transport, workers prevalently use the car (76%); 43% of students choose the car to reach their school/university whereas 48% use public transport (either subway, train, or bus). Only 3% of workers and 2% of students picked bikes or scooters as their transport mode of choice. Commuting trips have small or medium lengths: 72% of respondents take less than 30 min to reach their destination using either private cars (or motorcycles) or public transport, mainly taking between 16 and 30 min; parking is available at 92% of their destinations, the majority being available for free. Lastly, 27% of respondents (47% of students) declared having either a monthly or annual public transport subscription.

In the final section, micromobility was proposed as a potential mode of transport for commuting trips: users answered hypothetical scenarios about the safety level of the infrastructures where they would be willing to use an e-bike or an e-scooter, the maximum amount of time which they would spend on electric micromobility, and their willingness to purchase an electric micro-vehicle.

Regarding safety concerns, bike lanes fully separated from car traffic would be used from 44% of respondents with an e-bike and 39% with an e-scooter; 21% of users would ride an e-bike on bike lanes of any type, even those not physically separated from traffic, whereas 16% of users would use an e-scooter on these lanes. A total of 23% of users declared a willingness to use an e-bike even if bike lanes were not available, but only on roads with low levels of traffic, while, for e-scooter, this percentage is 10%; furthermore, 4% answered they were willing to use an e-bike on roads with any traffic condition, 3% of users with an e-scooter. Lastly, 8% of users stated they were not willing to use an e-bike in any condition; this percentage rises to 32% of respondents for e-scooters.

Willingness to purchase an e-scooter was confirmed by 41% of respondents, but only 11% of respondents claimed to be willing to purchase an e-bike (because they are more expensive). In addition, the maximum time users would spend on an electric micromobility vehicle were investigated: 17% and 20% of the respondents stated they were willing to ride, respectively, an electric bike and an electric scooter for more than 20 min; for travel times greater than 30 min, the percentages are, respectively, 48% and 26%.

3.2. Model Development

Through the above-described survey, a crowdshipper mode-choice model according to random utility theory [44,45] was estimated and validated. It allows to infer the potential usage of owned electric bikes and owned electric scooters.

The calibrated models include travel patterns and several socio-economic characteristics of interviewed users and their attitudes towards the usage of micromobility, investigated through several scenarios. Some attributes were not in the database: i.e., travel time was simulated through the distance between stated origin and destination points and the average speed, assumed as 20 km/h for e-bikes and as 10 km/h for e-scooters, according to the literature [45].

Stated behaviours regarding safety (*LSaf*) concerns were computed on a Likert scale (*0–4*):

- *0* = micromobility use in any condition;
- *1* = micromobility use only on roads with low traffic;
- *2* = micromobility use on bike lanes not physically separated by traffic;
- *3* = micromobility use on protected bike lanes;

- *4* = no use of a micromobility in any infrastructural conditions. In this case, the vehicle was considered to be an unavailable choice for users due to its very low perceived safety.

Users' socio-economic characteristics were elaborated for their use in the mathematical models:

- *gender*, as a binary attribute (*1* if female, *0* otherwise);
- *age*, as an ordinal variable with *6* classes (*14–25*; *26–35*; *36–45*; *46–55*; *56–65*; *>65*);
- *age_bis*, as a binary attribute (*1* if age $\leq$ *34* years, *0* otherwise);
- *level of education*, as an ordinal attribute (from *0* if user has no education, to *5* if user has a postgraduate degree).

In the ownership-based models, the ownership of the vehicle and the user's propnsity to eventually purchase the vehicle determines the availability of the potential choice: if the user does not already own an electric micro-vehicle and does not want to buy one, then the ownership-based alternative is not available to the user.

The users' potential choice was then defined with a "scenarios" approach: owned micro-vehicle could be chosen if the simulated travel time was less than the maximum travel time accepted by the users and the perceived infrastructural safety of the proposed scenario is higher than what the user was willing to accept (i.e., if the user declared to be willing to use a micro-vehicle only on bike lanes, even those not physically separated from car traffic, but the proposed scenario indicates the absence of bike lanes and the presence of high volume of car traffic, then the micromobility alternative was not considered to be a viable option).

After the database processing for preparation for calibration, several models were tested. The type of models chosen between the family of RUMs was the logit one [44]. Logit models have the simplest formulation, with the basic hypothesis that the rationality of the user means they choose the alternative with the maximum perceived utility. The utility U for each alternative j belonging to the set of alternatives J for the user i is composed by a systematic element V and a stochastic error ε:

$$U_i^j = V_i^j + \varepsilon_i^j \quad \forall\, j \in J \tag{2}$$

Logit model assumes that the random elements ε^j are distributed independently and identically as a Gumbel distribution with a parameter ϑ. This hypothesis allows the computation of the probability of choice, p_i^j, as follows:

$$p_i^j = \frac{e^{V_i^j}/\vartheta}{\sum_{j' \in J} e^{V_i^{j'}}/\vartheta} \quad \forall\, j' \neq j,\ j' \in J \tag{3}$$

The systematic utility component V_i can be expressed as a linear combination of attributes X_k through their relative coefficients β_k and an additional coefficient ASC (alternative specific constant), which represents all the factors not expressed through the parameters:

$$V_i^j = \left(\sum_k \beta_k * X_{i,k}^j\right) + ASC^j \tag{4}$$

Thus, the probability L of observing the whole sample is a function (the likelihood function) of the unknown parameters, or, more conveniently, its natural logarithm (the log-likelihood function). It consists of the sum of natural logarithm of the probability of the chosen alternative (j') of each user i:

$$\ln L(\beta,\ \vartheta) = \sum_i \ln p^{j'}(i)\left(V_i^{j'}\left(X_{i,k}^{j'},\ \beta\right),\ \vartheta\right) \tag{5}$$

The goodness of all the calibrated models were then evaluated through formal tests such as rho-square and adjusted rho-square (ρ^2 and $\overline{\rho^2}$), the statistical consistency of their coefficients through *t*-test values and the accuracy of the model, given by the percentage of model-based choices equal to the users' interview-based choices (*%-of-right*).

4. Models for E-Micromobility Use

According to the SP survey results and the model specification, earlier described, below the models set up is presented. Two binomial logit models were developed, one for e-bike (model 1) and one for e-scooter (model 2), both of them with the alternatives to adopt, or not, the considered means. In both binomial logit models, the systematic utility part V of not adopting e-means (e-bike or e-scooter, i.e., to continue to travel as usual) is fixed equal to zero (i.e., reference alternative). The below random-choice models are the output of a loop procedure where the specification, calibration, and validation were repeated until a good model (a model whose parameters passed validation, i.e., the model's capability to reproduce the observed choices) was obtained.

4.1. Model 1: Adopt an Owned E-Bike/Not Adopt

Regarding owning an e-bike, a binomial logit model was calibrated with two alternatives: *adopt e-bike* and *not adopt* (assumed as reference alternative). The calibration was performed by the maximum likelihood (ML) method (Equation (5)) and the model capability to reproduce the choice made by the sample was measured by the ρ^2 statistic. The systematic function of the "*adopt e-bike*" alternative was expressed as follows (the *t*-test value in brackets):

$$V_{adopt\,e-bike} = \underset{(-9.10)}{-0.053} \cdot tt_{e-bike} + \underset{(9.75)}{1.196} \cdot LSaf - \underset{(-4.82)}{1.106} \cdot age\_bis - \underset{(-3.11)}{0.861} \tag{6}$$

where

- $tt_{e\text{-}bike}$ is the travel time to perform the commuting trip by e-bike;
- *LSaf* is the perceived level of infrastructural safety (ordered variable; see Section 3.2);
- *age_bis* is the binary attributes of age (see Section 3.2).

The capability to reproduce the revealed observations was measured by the ρ^2 and $\overline{\rho}^2$ statistics. All parameters are correct in sign and are statistically significant as shown by *t*-test values (in brackets in Equation (6)). Table 2 summarizes the main model statistics and the total number of scenarios that the 200 respondents were asked to answer. As revealed by the SP surveys, we can see that the probability of owning an e-bike rises if infrastructural safety level increases. This probability also increases for elders (i.e., *age_bis* equal to zero) while decreasing with travel time. The model allows us to evaluate the impacts of the implementation of infrastructural safety actions, the socio-characteristics of users, as well as the characteristics of commuting trips (i.e., trip duration).

Table 2. Adoption of owning e-bike: model statistics.

Model Statistics	Value
N. of observation	956
Likelihood ratio test	514.412
Rho-square (ρ^2)	0.501
Adjusted rho-square ($\overline{\rho}^2$)	0.494
Sample reconstitution (*%-of-right*)	85.13%

4.2. Model 2: Adopt an Owned E-Scooterbike/Not Adopt

The expression of the systematic utility part V related to the calibrated model is expressed by Equation (7). As in model 1 (Equation (6), features and factors influencing the choice probability are: travel time, infrastructural safety level and age:

$$V_{adopt\,e-scooter} = \underset{(-6.91)}{-0.070} \cdot tt_{e-scooter} + \underset{(5.54)}{1.245} \cdot LSaf - \underset{(-5.96)}{1.250} \cdot age + \underset{(2.60)}{1.826} \tag{7}$$

where

- $tt_{e\text{-}scooter}$ is the travel time to perform the commuting trip by e-scooter;
- $LSaf$ is the perceived level of infrastructural safety (ordered variable; see Section 3.2);
- age is the ordinal variable on age (see Section 3.2).

As for model 1, the main model statistics are reported in Table 3 (while the t-test values are in brackets in Equation (7)) including the total number of scenarios that the 200 respondents were asked to answer. All parameters are also correct in sign and are statistically significant, as shown by t-test values. The probability of owning an e-scooter decreases for elders and with travel time. In fact, the negative coefficient β for *age* means that young users are more inclined to adopt e-scooters. Model 2 also allows us to evaluate impacts due to the implementation of infrastructural safety actions, the socio-characteristics of users, as well as the characteristics of commuting trips (i.e., trip duration).

Table 3. Adoption of owning e-scooter: model statistics.

Model Statistics	Value
N. of observation	956
Likelihood ratio test	510.087
Rho-square (ρ^2)	0.754
Adjusted rho-square ($\bar{\rho}^2$)	0.742
Sample reconstitution (*%-of-right*)	92.62%

Summarising the above results obtained for the binomial logit models, the travel time by e-bike and e-scooter were found to be statistically significant. Potential crowdshippers experience a negative weight of travel time and the estimated travel time parameters have increasing absolute values for e-bike and e-scooter. As expected, the e-scooter pays for its novelty, as users have low familiarity with it and owners of e-scooters prefer to use them for trips shorter than those with an e-bike. This trend against novelty is also confirmed by the weight of safety level. In fact, e-scooter users are generally more comfortable with a high level of road safety. In addition, the different perceptions of using an e-bike or e-scooter is also confirmed by the parameters of age: for e-bike, elders prefer to travel by e-bike, while owning an e-scooter is preferred by younger respondents. In fact, as shown by the studies reviewed in Section 2, younger people are more devoted to innovations. Further, another of the main findings is that each user can have similar utility specifications although they combine attributes differently (e.g., the estimated parameters for the same attribute can be statistically different among users).

5. Conclusions and the Road Ahead

The paper proposed a methodology to support innovation in city logistics by presenting the results of involving commuters in using e-bikes and e-scooters. Furthermore, commuters can be enrolled as crowdshippers for delivering parcels within urban areas along their commuting trips. In particular, the paper presents the first results of such research, which mainly consists of two stages: usage of e-micromobility as well as becoming crowdshippers. Since, in the literature, some preliminary results exist about becoming crowdshippers [20], we dealt with the former stage.

The analysis of survey results shows that the factors with the highest impact on the potential demand for e-micromobility is the infrastructural safety level: ensuring the existence of bike lanes (physically separated or not, i.e., temporary bike lanes) means the potential demand appreciably increases. Policies for e-micromobility attractiveness must, therefore, consider supply-related aspects, realizing the separation of the different traffic flows and connecting bike lanes in cities with fragmented bike networks.

The approach of the paper was to first point out the acceptance of becoming crowdshippers and then to characterise these commuters according to use of electric micromobility. In particular, as shown by the literature review, no studies have jointly analysed passenger and freight transport within the sphere of urban sustainability. Usually, crowdshipping is studied without considering that users can be pushed to changes in their daily travel behaviour when there is a further potential source of gain from daily activity. According to the literature, the proposed method falls within the class of partial share, well-known in travel demand forecasts. The base formulation allows worldwide technicians to have a tool for a preliminary assessment of the potential crowdshippers as well as to identify the number of parcels that can be delivered without truck trips. The easy-to-obtain attributes appear to have significant explanatory power regarding how commuters perceive alternative options in an urban road network.

According to these preliminary results, further developments of the study can be derived. First, the probabilistic-behavioural models were joined with the choice to be a crowdshipper, as reported in (1); then, the potential to be a crowdshipper also using shared e-micromobility services and considering additional features in the behavioural models (accessibility and cost of the shared services) were investigated. In addition, further investigation refers to the possible correlation among the observations coming from the same users. Then, further specification advancement was addressed to develop the mixed logit, as proposed by Train [45]. In addition, thanks to the recent widespread adoption of e-bikes and e-scooters, previous respondents could be asked to participate again in a survey for evaluating changes in their behaviours towards electric mobility. Finally, taking inspiration by Nigro et al. [46], the calibrated models can be paired up with floating car data (FCD) in order to micro-simulate the potential shifting from cars to e-micromobility for commuting trips and crowdshipping services. This potential shift will allow assessment of external-costs reduction, thus demonstrating the sustainability and the strengths of crowdshipping by e-micromobility for both logistic operators and for city users.

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