

Document Version

Final published version

Licence

CC BY-NC-ND

Citation (APA)

Hriekova, O., Tavasszy, L., & Comi, A. (2026). Clustering end consumers' decisions in receiving e-purchases. *Transportation Research Procedia*, 95, 1088-1095. <https://doi.org/10.1016/j.trpro.2026.02.137>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

In case the licence states "Dutch Copyright Act (Article 25fa)", this publication was made available Green Open Access via the TU Delft Institutional Repository pursuant to Dutch Copyright Act (Article 25fa, the Taverne amendment). This provision does not affect copyright ownership.
Unless copyright is transferred by contract or statute, it remains with the copyright holder.

Sharing and reuse

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Euro Working Group on Transportation Annual Meeting 2025 - EWGT2025

Clustering end consumers' decisions in receiving e-purchases

Olesia Hriekova^{a*}, Lóránt Tavasszy^b, Antonio Comi^a

^aDepartment of Enterprise Engineering, University of Rome Tor Vergata, via del Politecnico, 1, 00133, Rome, Italy

^bSection Transport and Logistics, Faculty of Technology, Policy and Management, Delft University of Technology, 2628 BX, Delft, The Netherlands

Abstract

Nowadays, e-commerce is gaining popularity worldwide. End consumers are shifting from in-store shopping to online due to the numerous advantages. The e-deliveries are associated with smaller and more frequent deliveries, failed and geographically sprawled ones. It causes the increase of the number of vehicles as well as of the kilometres travelled, and then the raise of the negative impacts, e.g., pollutant emissions, congestions. Therefore, new delivery channels have been developed to optimise the delivery system and new procedures are necessary for their assessment. A key role in these assessment procedures is played by the analysis of how each of the new delivery omni-channels are really chosen by end consumers. Then, this study points out end consumers' choices through a structured survey. The data collected are then analysed through a clustering approach. The aim is to find out the decision processes by comparing various delivery channels based on service attributes (e.g., delivery time and price, the place where the item is received), respondents' characteristics and choices made. The results show that such an analysis could be a powerful tool for forecasting end consumers' decisions, which should be taken into consideration when designing new city logistics scenarios.

© 2026 The Authors. Published by ELSEVIER B.V.

This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0>)

Peer-review under responsibility of the scientific committee of the Euro Working Group on Transportation Annual Meeting 2025 - EWGT2025.

Keywords: last mile; end consumer; e-delivery channel; e-delivery; stated preference survey; SP survey; city logistics; cluster analysis.

1. Introduction

E-commerce deliveries in urban areas have been steadily growing and are facing urban transport planners with new challenges related to flow prediction and scenario assessment (Alverhed et al., 2024; Gao and Zhu, 2022). Most of the current literature on transport flow prediction focuses on e-purchase deliveries from the perspective of transport operators, neglecting the effect of end consumers' point of view (Anand et al., 2015; Comi and Delle Site, 2023). Most city-level transport demand models incorporating e-commerce purchases include only a limited number of delivery channels for end consumers (Gatta et al., 2021; Hriekova et al., 2025).

Current research examines how end consumers decide on receiving e-purchases (Cebeci et al., 2023; Samani et al., 2025), emphasising the impact of the growing variety of delivery channels (alternatives) available to them in the

new omnichannel context (Joshi et al., 2024). According to the literature, the new alternatives include crowdshipping, delivery to parked car (into trunk), autonomous delivery robots, autonomous parcel lockers and staffed pickup points (Boysen et al., 2021). These delivery channels are transforming the landscape of last mile delivery and present new opportunities to improve urban transport systems. Therefore, understanding how end consumers make decisions is a prerequisite for developing predictive urban freight transport models (Alverhed et al., 2024; Aurambout et al., 2019).

Several studies have examined end consumers' choices concerning specific delivery channels analysed individually: crowdshipping (Cebeci et al., 2023), staffed pickup points (Buldeo Rai et al., 2019) or autonomous parcel lockers (Tsai and Tiwasing, 2021). Studies on choice between different alternatives are quite limited. For example, Nguyen et al. (2019) investigated alternatives provided by online retailers such as self-collection service and traditional mail with the main focus on delivery service attributes. Meanwhile, Merkert et al. (2022) compared traditional mail, autonomous delivery robots (drone) and autonomous parcel lockers in Australia. However, this study characterised alternatives using four attributes and does not consider other innovative delivery channels, such as crowdshipping or delivery to parked car (into trunk). Furthermore, Wang et al. (2024) examined traditional mail, autonomous parcel lockers and staffed pickup points in Singapore. The analysis of end consumers' decisions regarding purchase reception has been developed from the perspective of the willingness to travel for collecting items, the effort required for social interactions with staff, and the product value. However, the data were collected during the COVID-19 pandemic and end consumers' preferences might have been influenced by external factors. Based on the literature, there is a quite clear gap in the study of innovative delivery channels compared to well-established ones, as well as a limited research investigating users' choice of delivery channels among all the available alternatives characterised by a significant set of attributes. For instance, the identified attributes are destination location, delivery time and price, possibility to choose time window, data protection level, tracking and tracing service, potential damage of the e-purchase, flexibility in rescheduling or redirecting deliveries, payment timeframe, level of sustainability (Baia et al., 2025; Belcore et al., 2024; Buldeo Rai et al., 2019; Merkert et al., 2022; Nguyen et al., 2019; Wang et al., 2024). Therefore, there is a need of further research in such field.

In addition, it is important to note that end consumer preferences are often analysed in the literature by grouping respondents according to socio-economic characteristics such as gender, age, income level, level of education, etc. This segmentation enabled researchers to identify similarities in end consumer choices within specific groups due to level of familiarity with technologies, purchasing power and shopping habits. For example, Johnson and Ramirez (2020) group respondents by generation (millennials) and interpret their preferences based on the generational differences, i.e., youngers are more familiar with technologies, while elders have difficulties in using autonomous/digital devices/platforms. Therefore, an appropriate grouping could be relevant for analysing end consumers' choice for receiving e-purchases. In this context, the paper analyses the choices made by end consumers taking into consideration their socio-economic characteristics. In particular, the analysis is performed through clustering which is an unsupervised machine learning technique that helps researchers to discover hidden patterns and structures in data without prior knowledge of what those structures might be. Clustering algorithms group together users with similar traits, based on their likelihood to purchase/to use technologies. With these groups or clusters defined, the analysis of how they prefer to receive their e-purchase could become more effective, helping to refine policies to push end consumers towards more sustainable alternatives.

The paper is organised as follows. Section 2 presents the survey design, data collection, while Section 3 presents the methodology implemented and descriptive analysis of results obtained. Finally, conclusions and road ahead are given in Section 4.

2. Survey design and data collection

A stated preference (SP) survey has been developed to investigate end consumers' choice in receiving e-purchases (Maltese et al., 2021; Marcucci et al., 2021; Oyama et al., 2024; Wang et al., 2024). The survey was launched in the second half of last year and it is still ongoing, with 359 responses collected to date. The SP survey considers the following six delivery channels: traditional mail, crowdshipping, delivery to parked car (into trunk), autonomous delivery robots, staffed pickup points and autonomous parcel lockers. These alternative delivery channels were characterised through service attributes, including destination location, delivery time and price, time window, data

protection level, traceability, potential for damage, flexibility, payment timeframe, and sustainability. The design process of SP involved generating a fractional factorial design based on the defined attributes and levels for the different delivery channels. The 36 hypothetical scenarios were designed using Ngene 1.4 © software, which facilitates the creation of choice experiments. This allowed for the inclusion of a wide range of combinations of the service attributes while keeping the total number of scenarios manageable. To ensure efficient data collection, the 36 scenarios were split into 4 blocks, with each respondent randomly assigned to one block. This ensured that each respondent would evaluate a subset of the total scenarios, but the design remained balanced and statistically efficient. The use of blocks helps to ensure that all relevant combinations of the attributes are represented across the full sample, without overwhelming individual respondents.

The 15-minute questionnaire was carried out across several European countries to investigate end consumers' preferences for different delivery channels. The questionnaire was made available in both English and Italian to ensure wider accessibility. The survey was distributed via email and face-to-face interviews. Respondents were asked to provide information about their socioeconomic characteristics, online shopping habits, and to choose the delivery channel in a hypothetical scenario in which they purchase an item online for 25 euros, with specific dimensions (e.g., small e-parcel). The first section of the questionnaire helped analyse the socioeconomic characteristics (e.g., gender, age, level of education, household composition, ownership of a driving licence, car and motorcycle ownership), habits of respondents (e.g., the modes of transport used for commuting and leisure journeys) and e-purchasing behaviour.

The sample has the following characteristics. The gender distribution is relatively balanced, with 53% identifying as female and 47% as male. In addition, the majority of respondents live in Italy. Regarding age, most respondents (58%) belong to the 18-24 age group (*young* respondents). Meanwhile, recent trends indicating the high engagement of youngers in digital services and e-commerce platforms. Respondents aged 35 years and over make up around 27% of the total sample, providing valuable insight into preferences across different age groups and various status of occupation. A significant share of the sample is either students (36%) or full-time employees (40%), with the majority holding a bachelor's degree, indicating a relatively high level of education. This educational background may influence both awareness and adoption of innovative delivery channels. Furthermore, a notable proportion of respondents (65%) have children and report incomes within the middle-income range (1000 euros to 5000 euros per month), which reflects to sufficient purchasing power. The deeper analysis of the monthly income of young respondents allows the authors to conclude that those with a higher monthly income are more open to innovations such as crowdshipping, delivery to parked car (into trunk) and autonomous delivery robots (Table 1). It is worth noting that respondents with low incomes choose traditional mail, while those with middle incomes almost equally choose traditional mail and staffed pickup points. In addition, nearly half of the respondents report making online purchases less than once a week but at least once a month. Thus, purchasing power and behaviour characteristics allow a valid assessment of delivery channel choice in a realistic context. It is worth to note that the respondents are generally familiar with digital technologies. This is particularly important when considering innovative delivery channels that rely on end consumers interaction with applications. Overall, the sample composition reflects a wide range of socio-economic characteristics, allowing for a detailed analysis of delivery channel preferences among different groups. Also, it worth to notice that 63% of the respondents have a driver licence allows them to drive a car and 77% has a car always available for both commuting and leisure journeys.

In addition, the questionnaire allows the authors to investigate five product categories: clothing and footwear, electronic devices, beauty and health products, books, and furniture. Respondents indicated their purchase frequency within these categories as "always", "sometimes" or "rarely/never." The most frequently purchased items online were electronic devices, books, and clothing or footwear, while furniture and beauty or health products were the least popular. Large furniture items are usually delivered via traditional mail due to their large size and high cost, while beauty and health products often require professional consultation, leading end consumers to purchase them in-store. For respondents choosing staffed pickup points or autonomous parcel lockers, the preferred holding period for their e-purchases ranged between one and six days, with a considerable proportion favouring a delivery timeframe of one to two days. Only a small percentage accepted more than a week to receive their e-items.

In the choice experiment part, traditional mail was the most chosen alternative, followed by autonomous parcel lockers and staffed pickup points. Interest in emerging alternatives was also observed, including crowdshipping, delivery to parked car (into trunk), and autonomous delivery robots. Male preferred crowdshipping among the innovative delivery channels, while female favoured autonomous delivery robots.

Among the identified alternatives, autonomous parcel lockers were the most familiar one. The innovative option of delivery to parked car (into trunk) was less recognised, with some respondents unfamiliar with how it operates in practice. The survey also explored end consumer dissatisfaction with delivery experience. The most common complaint, cited by a significant proportion of respondents, was delivery delays. While traditional mail remains the preferred alternative, respondents showed openness to new delivery channels, particularly crowdshipping. Another significant issue was difficulty in tracking e-purchases, affecting a notable number of respondents, many of whom preferred autonomous parcel lockers or were open to autonomous delivery robots. Damage of the e-purchase during delivery process was another concern, with many respondents preferring the autonomous delivery robot in the choice experiment part. Only a small proportion of respondents reported being fully satisfied with their current delivery channels, showing little interest in innovative alternatives.

Table 1 – Young end consumers’ preferences according to monthly income

Delivery channel	Less than 1000 euros	1000-2000 euros	2000-3000 euros	3000-5000 euros	More than 5000 euros	Average
Traditional mail	36%	45%	30%	34%	31%	35%
Crowdshipping	6%	7%	7%	11%	18%	9%
Delivery to parked car (into trunk)	3%	4%	5%	8%	6%	6%
Autonomous delivery robot	8%	7%	8%	10%	11%	9%
Staffed pick up point	17%	22%	29%	18%	21%	23%
Autonomous parcel locker	31%	15%	21%	20%	14%	19%
Total	100%	100%	100%	100%	100%	100%

3. Descriptive analysis

Based on the described characteristics of data collected, the next step is to point out the similarities and dissimilarities in the choices collected through a cluster analysis. Then, below first the methodology is described, subsequently the clusters are identified and discussed.

3.1. Methodology

Descriptive analysis was used to identify data groupings (clusters) based on similarities derived from patterns among independent variables (e.g., six delivery channels: traditional mail, crowdshipping, delivery to parked car (into trunk), autonomous delivery robots, staffed pickup points, autonomous parcel lockers; ten associated service attributes: destination location, delivery time and price, possibility to choose time window, data protection level, tracking and tracing service, potential damage of the e-purchase, flexibility in rescheduling or redirecting deliveries, payment timeframe, level of sustainability; socio-economic, demographic characteristics: gender, age, level of education, household composition, possession of a driving licence, car and motorcycle ownership, and the modes of transport typically used for both commuting and leisure journeys, employment status, income level, and the extent of technology usage; and e-purchase behaviour of end consumers: frequency of e-purchases across different product categories (i.e., clothing and footwear, electronic devices, beauty and healthcare products, books, and furniture), respondents’ willingness to receive deliveries out-of-home locations, the need to store items at out-of-home points, and potential sources of dissatisfaction related to the delivery process). This approach enables the identification of patterns and underlying structures. In this study, *R* software © was used for data mining and cluster development. Specifically, the clustering was performed using the *k-means* algorithm, a well-established non-hierarchical clustering method that widely adopted across disciplines due to its computational efficiency and simplicity. *K-means* clustering is particularly effective in partitioning data into *k* mutually exclusive groups. The algorithm ensures that data points within one cluster are as similar as possible, while maximising inter-cluster dissimilarity (Comi et al., 2022). Although *k-means* clustering is traditionally suited for continuous variables. In this study, it was applied after converting categorical variables into numerical format through one-hot encoding. In more details, it will be discussed below. The decision to apply *k-means* clustering was motivated by its efficiency, scalability, and interpretability, particularly

when dealing with large-scale datasets.

The term k denotes the predetermined number of clusters and serves as a critical input to the algorithm, allowing researchers to control the segmentation process. The term *means* refers to the fact that each cluster is characterised by the centroid of all records within that group for each variable under consideration. These centroids are iteratively updated during the clustering process until convergence is reached. The algorithm begins by randomly assigning k initial centroids, followed by an iterative refinement process in which each data point is allocated to the nearest centroid based on a distance metric. Subsequently, centroids are recalculated based on the new groupings, and this process is repeated until the cluster assignments stabilise. This iterative refinement is heuristic in nature which converges rapidly to a local optimum, making it highly suitable for large datasets. Moreover, the algorithm is well-suited for applications where the number of clusters can be reasonably estimated or determined using techniques such as the *elbow* method, which assists in identifying the optimal value of k by evaluating the trade-off between model complexity and explanatory power. In this context, *k-means* clustering method enabled the segmentation of the sample into different groups, allowing a deeper understanding of end consumers' preferences based on socio-economic, demographic and behavioural variables.

3.2. Results and discussion

The methodology comprised several key stages: data preparation, transformation of categorical variables, normalisation, determination of the optimal number of clusters, execution of clustering, and visualisation of the resulting clusters.

The analysis began with the clustering of the delivery channels under investigation, along with their associated service attributes and the socio-economic, demographic characteristics, and e-purchase behaviour of end consumers. This grouping enabled the identification of potential correlations in end consumers' preferences, if any. The variables considered in the analysis are categorical, including all variables discussed above (delivery channels and service attributes, socio-economic characteristics and e-purchase behaviour of end consumers). Categorical variables represent qualitative levels that cannot be interpreted numerically without transformation. This transformation step is necessary due to the nature of the *k-means* clustering algorithm, which requires numerical input. In this context, one-hot encoding (also known as dummy coding) was applied to convert categorical variables into binary format using 0 and 1. More specifically, when an attribute had more than two levels, the software created a separate binary column for each level, assigning 1 if a row corresponded to that level, and 0 otherwise. For example, the delivery time attribute included levels such as 1-2 days, 3-5 days, and more than 6 days, which needed to be encoded since their labels or order do not correspond to meaningful numeric distances. In cases where an attribute had only two levels, the R software © treated them as binary by assigning values of 0 and 1. For instance, the traceability attribute comprised two levels: tracking at main stages (coded as 0), or in real time (coded as 1).

The data normalisation step was not applied to clustering due to the fact that all variables were binary, taking values of either 0 or 1. Since these binary and dummy-coded variables inherently share the same scale and range, they are directly comparable without further transformation. The *k-means* algorithm relies on Euclidean distances, which can be disproportionately influenced by variables with larger numerical ranges. However, in this case, as all features are uniformly scaled, the distances computed reflect genuine similarities without bias from differing magnitudes. Applying normalisation in this context would transform the binary variables into continuous values, thereby losing their original interpretability and potentially distorting the clustering results.

The next step aimed to determine the appropriate number of clusters. To this end, the *elbow* method was applied. This involved running *k-means* clustering repeatedly for different values of k . For each value of k (from 1 to 10), the algorithm calculated the total within-cluster sum of squares (WSS). It is a measure of how close the data points are to the centre of their assigned cluster. Lower WSS values indicate more compact clusters. As the number of clusters increases, WSS naturally decreases because data points are grouped into smaller, tighter clusters. However, after a certain point, the improvement becomes minimal. This point of diminishing returns is known as the *elbow*. It reflects the point where adding more clusters does not significantly improve the model. The WSS values for each k were plotted to create an *elbow* plot. Based on this method, the optimal number of clusters was identified as two, providing a balance between model simplicity and data differentiation. The resulting clusters comprise 1253 and 1978 records, respectively, indicating a relatively balanced segmentation of the dataset.

Cluster 1 is predominantly associated with preferences for traditional mail. Further analysis allows the authors to associate such cluster with older respondents from the sample. Also, it considered individuals who mostly occupied or partly at home such as freelancers. It is notable these respondents generally remain at home during the day and, consequently, exhibit limited consideration of delivery channels different than traditional mail. Their choices reflect a reliance on familiar and well-established delivery channels, and potentially a lower level digital engagement (i.e., awareness of innovative delivery channels). The clustering result supports the notion that familiarity, age group, and lifestyle compatibility are critical drivers of delivery channel selection within this group.

In contrast, Cluster 2 comprises respondents who favour a wide range of innovative delivery channels, including crowdshipping, delivery to parked car (into trunk), autonomous delivery robots, autonomous parcel lockers, and staffed pickup points. This cluster is associated with younger respondents, predominantly aged 18-24 years. Previous studies indicate that this group demonstrates greater familiarity with technological innovations and higher levels of openness toward new delivery channels. Their occupational status – often as students or office workers – makes them less inclined to opt for traditional mail, which explains their preference for more flexible, technology-driven delivery channels. This is consistent with delivery issues such as inconvenient time window or the inability to provide work address for delivery. Moreover, these respondents tend to possess a higher level of education (master's degree or above) and report middle or high income levels (exceeding 3000 euros per month).

In summary, the analysis reveals two distinct respondent clusters: one associated with traditional mail, and another that includes all other delivery channels. The second group consists of younger, well-educated individuals with high technology engagement. Notably, joint with what discussed in the earlier section, the respondents do not possess full knowledge of delivery channels different than traditional mail, identifying a gap that may limit the adoption of innovative alternatives. This insight has considerable implications for policy makers and transport operators, indicating the need for targeted communication strategies to increase awareness of new delivery channels.

Subsequently, a more detailed analysis was carried out to understand the perceived correlations between delivery channels. This classification was based on a set of alternatives and ten service attributes (discussed above). Once again, the *elbow* method was used to determine the optimal number of clusters. Three clusters were then identified containing 1262, 1349 and 620 records respectively: cluster 1 associated with the choices of traditional mail; cluster 2 comprises delivery channels already in use, such as staffed pickup points and autonomous parcel lockers, which are characterised by self-collection whereby end consumers receive their e-purchases from predefined location; cluster 3 represents hypothetical/emerging alternatives, including autonomous delivery robots, crowdshipping and delivery to car (into trunk), all of which remain in pilot or prototype stages.

This classification suggests that end consumers categorise delivery channels taking into account perceived familiarity, convenience and the degree of innovation. Notably, the distinct clustering of innovative delivery channels into a separate cluster 3 suggests that, although a segment of end consumers demonstrates openness to innovation, these delivery channels are still perceived as experimental. Consequently, their rate of adoption may remain constrained until such alternatives achieve greater integration into the reality. Furthermore, the findings contribute to a valuable tool for forecasting end consumers' decisions in receiving e-purchases, which should be taken into due consideration when designing new sustainable city logistics scenarios.

4. Conclusions

E-commerce is booming all over the world with advantages, especially for the end consumers. However, this phenomenon causes issues such as smaller and more frequent deliveries, failure and sprawled deliveries. Consequently, this effects on increasing the number of vehicles used in delivery process in the cities. Urban freight transport leads to numerous issues such as congestions, pollutant emissions, etc. These issues have prompted researchers and stakeholders to develop solutions for last mile delivery aimed to improve both the sustainability and efficiency of delivery process. The recent innovations within last-mile logistics have led to the development of various delivery channels aimed to address the identified issues, offering end consumers a range of alternatives for receiving their e-purchases.

The end consumers' preferences depend on service attributes that characterised the alternatives such as destination location, delivery time and price, possibility to choose time window, data protection level, tracking and tracing service, potential damage of the e-purchase, flexibility in rescheduling or redirecting deliveries, payment timeframe, level of sustainability. To investigate end consumers' preferences, a stated preference experiment was carried out, involving a sample of 359 respondents. One of the key limitations of the research is the large participation of respondents live in Italy and a small number of respondents were from non-EU countries, further affecting the diversity of the sample. As such, future research would benefit from expanding the sample size and improving the geographic distribution to enhance the representativeness of the findings. Another limitation of the research concerns potential self-selection bias. As participation in the survey was voluntary, it is possible that respondents with a particular interest in e-shopping or technology were more inclined to complete the questionnaire. This may have led to an overrepresentation of digitally active individuals, potentially limiting the generalisability of the findings to the wider population.

For the classification of delivery channels, the *k-means* clustering technique was used. The initial results indicate that respondents perceive traditional mail as a distinct and separate alternative compared to others. Further analysis revealed that younger, highly educated individuals, who are more familiar with digital technologies, are more likely to choose innovative delivery channels over traditional one. These insights suggest that future investigations should incorporate additional socioeconomic characteristics, such as vehicle ownership and travel behaviour patterns, for example, when analysing preferences for delivery to parked car (into trunk). This is essential to assess the degree to which such alternatives represent hypothetical interest versus actual behavioural intent.

A deeper analysis of the chosen delivery channels and their associated service attributes provided further insight into how end consumers perceive and categorise these alternatives. Three clusters were identified such as (i) traditional mail, (ii) delivery channels already in use such as staffed pick-up points and parcel lockers and (iii) hypothetical delivery ones still in pilot or prototype stages such as autonomous delivery robots, crowdshipping and delivery to car trunk. These findings demonstrate that end consumers differentiate delivery channels based on a combination of operational characteristics, convenience, and the degree of innovation. This classification suggests underlying patterns in how end consumers evaluate and categorise alternatives.

City logistics planners and policy makers can use these insights to support the design of sustainable last-mile infrastructure, balancing between well-established and emerging delivery channels. The novelty of the paper is that the end consumers' choices in receiving e-purchases is pointed out according to a large set of relevant and perceived service attributes as well as of users' socio-economic characteristics. Through the proposed clustering approach, the three more significant groups of delivery channels have been recognised, and the identified similarity of users could help city planners and policy makers in defining the more sustainable delivery system that meets their needs. Thus, it is possible to analyse the willingness to choose new alternatives by clusters, as to adapt it to real users' expectations taking into due to consideration the propensity to use a delivery channel including where end consumers prefer to receive e-purchases, which has been revealed as one of the main factors in simulating the delivery-channel choice. In addition, local authorities aimed at fostering smart, sustainable and liveable city could consider end consumer readiness and segmentation to ensure inclusive access to innovative delivery channels. These results could be used in future research to identify which groups of end consumers are more likely to choose one alternative over another and why. To develop a sustainable delivery system, it is essential to analyse which groups of end consumers are willing or unwilling to adopt innovative delivery channels. Such knowledge could help prepare end consumers for choosing certain delivery channels, potentially encouraging uptake of more sustainable alternatives or raising awareness of their benefits, in line with the principles of sustainable urban development. As a next step, these clusters may serve as a valuable foundation for the development forecasting models to be included in a scenario assessment framework (e.g. nested logit model), which would allow researchers a more detailed analysis of the correlation structure among alternatives and a further refinement of end-consumer preference modelling in the context of last-mile delivery.

Funding

PNRR - Missione 4, Componente 2, Investimento 1.1 - Prin 2022 - Decreto Direttoriale n. 104 del 02-02-2022, Project: PULSe: Pre-feasibility analysis for Urban Logistics Solutions based on Eco-friendly vehicles. CUP Master: F53D23005490006; CUP: E53D23010110006 - Identification Code: 20225YY2HL. Funded by the European Union - Next GenerationEU.

Acknowledgements

The authors thank the reviewers for their valuable suggestions that allowed paper to be better developed.

References

- Alverhed, E., Hellgren, S., Isaksson, H., Olsson, L., Palmqvist, H., Flodén, J., 2024. Autonomous last-mile delivery robots: a literature review. *Eur. Transp. Res. Rev.* 16, 4. <https://doi.org/10.1186/s12544-023-00629-7>
- Anand, N., van Duin, R., Quak, H., Tavasszy, L., 2015. Relevance of City Logistics Modelling Efforts: A Review. *Transport Reviews* 35, 701–719. <https://doi.org/10.1080/01441647.2015.1052112>
- Aurambout, J.-P., Gkoumas, K., Ciuffo, B., 2019. Last mile delivery by drones: an estimation of viable market potential and access to citizens across European cities. *Eur. Transp. Res. Rev.* 11, 30. <https://doi.org/10.1186/s12544-019-0368-2>
- Baia, B.D.S., Da Silva, A.M., Filenga, D., 2025. Relevant attributes for pick-up points in last-mile logistics. *RAM, Rev. Adm. Mackenzie* 26, eRAMR250005. <https://doi.org/10.1590/1678-6971/eramr250005>
- Belcore, O.M., Polimeni, A., Gangi, M.D., 2024. Potential Demand for E-grocery Delivery Services: The Effect of Delivery Attributes on Consumers Preferences. *Transportation Research Procedia* 79, 329–336. <https://doi.org/10.1016/j.trpro.2024.03.044>
- Boysen, N., Fedtke, S., Schwerdfeger, S., 2021. Last-mile delivery concepts: a survey from an operational research perspective. *OR Spectrum* 43, 1–58. <https://doi.org/10.1007/s00291-020-00607-8>
- Buldeo Rai, H., Verlinde, S., Macharis, C., 2019. The “next day, free delivery” myth unravelled: Possibilities for sustainable last mile transport in an omnichannel environment. *IJRDM* 47, 39–54. <https://doi.org/10.1108/IJRDM-06-2018-0104>
- Cebeci, M.S., Tapia, R.J., Kroesen, M., De Bok, M., Tavasszy, L., 2023. The effect of trust on the choice for crowdshipping services. *Transportation Research Part A: Policy and Practice* 170, 103622. <https://doi.org/10.1016/j.tra.2023.103622>
- Comi, A., Delle Site, P., 2023. Estimating and forecasting urban freight origin–destination flows, in: Marcucci, E., Gatta, V., Le Pira, M. (Eds.), *Handbook on City Logistics and Urban Freight*. Edward Elgar Publishing, pp. 78–97. <https://doi.org/10.4337/9781800370173.00012>
- Comi, A., Polimeni, A., Balsamo, C., 2022. Road Accident Analysis with Data Mining Approach: evidence from Rome. *Transportation Research Procedia* 62, 798–805. <https://doi.org/10.1016/j.trpro.2022.02.099>
- Gao, Y., Zhu, J., 2022. Characteristics, Impacts and Trends of Urban Transportation. *Encyclopedia* 2, 1168–1182. <https://doi.org/10.3390/encyclopedia2020078>
- Gatta, V., Marcucci, E., Maltese, I., Iannaccone, G., Fan, J., 2021. E-Groceries: A Channel Choice Analysis in Shanghai. *Sustainability* 13, 3625. <https://doi.org/10.3390/su13073625>
- Hriekova, O., Comi, A., Tavasszy, L., 2025. End-consumer preferences for e-purchase delivery location. *Transportation Research Procedia* 86, 191–198. <https://doi.org/10.1016/j.trpro.2025.04.025>
- Johnson, O., Ramirez, S.A., 2020. The influence of showrooming on Millennial generational cohorts online shopping behaviour. *IJRDM* 49, 81–103. <https://doi.org/10.1108/IJRDM-03-2020-0085>
- Joshi, A., Pani, A., Sahu, P.K., Majumdar, B.B., Tavasszy, L., 2024. Gender and generational differences in omnichannel shopping travel decisions: What drives consumer choices to pick up in-store or ship direct? *Research in Transportation Economics* 103, 101403. <https://doi.org/10.1016/j.retrec.2023.101403>
- Maltese, I., Le Pira, M., Marcucci, E., Gatta, V., Evangelinos, C., 2021. Grocery or @grocery: A stated preference investigation in Rome and Milan. *Research in Transportation Economics* 87, 101096. <https://doi.org/10.1016/j.retrec.2021.101096>
- Marcucci, E., Gatta, V., Le Pira, M., Chao, T., Li, S., 2021. Bricks or clicks? Consumer channel choice and its transport and environmental implications for the grocery market in Norway. *Cities* 110, 103046. <https://doi.org/10.1016/j.cities.2020.103046>
- Merkert, R., Bliemer, M.C.J., Fayyaz, M., 2022. Consumer preferences for innovative and traditional last-mile parcel delivery. *IJPDLM* 52, 261–284. <https://doi.org/10.1108/IJPDLM-01-2021-0013>
- Nguyen, D.H., De Leeuw, S., Dullaert, W., Foubert, B.P.J., 2019. What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing. *J of Business Logistics* 40, 299–321. <https://doi.org/10.1111/jbl.12210>
- Oyama, Y., Fukuda, D., Imura, N., Nishinari, K., 2024. Do people really want fast and precisely scheduled delivery? E-commerce customers’ valuations of home delivery timing. *Journal of Retailing and Consumer Services* 78, 103711. <https://doi.org/10.1016/j.jretconser.2024.103711>
- Samani, A.R., Talebian, A., Mishra, S., Golias, M., 2025. Evaluating consumer shopping, delivery demands, and last-mile preferences: An integrated MDCEV-HCM approach. *Transportation Research Part E: Logistics and Transportation Review* 197, 104067. <https://doi.org/10.1016/j.tre.2025.104067>
- Tsai, Y.-T., Tiwasing, P., 2021. Customers’ intention to adopt smart lockers in last-mile delivery service: A multi-theory perspective. *Journal of Retailing and Consumer Services* 61, 102514. <https://doi.org/10.1016/j.jretconser.2021.102514>
- Wang, X., Wong, Y.D., Shi, W., Yuen, K.F., 2024. An investigation on consumers’ preferences for parcel deliveries: applying consumer logistics in omni-channel shopping. *IJLM* 35, 557–576. <https://doi.org/10.1108/IJLM-07-2022-0288>