GREEN CITIES
GREEN LOGISTICS FOR GREENER CITIES

7th International Conference Green Cities 2026 – Green Logistics for Greener Cities, 15-17 April 2026, Szczecin, Poland

Behavioral Models for Crowdshipping in Sustainable Urban Logistics

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Abstract

The rapid expansion of e-commerce and the environmental pressure on last-mile delivery systems have stimulated research into innovative logistics. Among them, crowdshipping (i.e., the participation of private users in parcel deliveries along their daily routes) offers a promising pathway toward sustainable and participatory urban logistics. However, despite its potential to reduce costs and emissions for parcel delivery, large-scale implementation remains uncertain, mainly due to limited knowledge of the behavioral factors shaping user's acceptance and participation. This study addresses this gap by developing a behavioral modelling framework for crowdshipping participation. A survey was developed involving a heterogeneous sample of urban users to capture socio-demographic characteristics and preferences related to economic compensation, effort, and travel time deviations. The analysis explores how users perceive trade-offs between monetary incentives, effort, and travel time requirements when considering participation as crowdshippers. Results show a preference for low effort deliveries and small parcels, highlighting the suitability of crowdshipping for micro-logistics contexts. Although environmental sustainability is generally appreciated, it is rarely decisive compared to remuneration and reliability. These behavioral insights are translated into discrete choice models based on random utility theory, explicitly accounting for socio-demographic heterogeneity and differentiated sensitivity to monetary compensation across user groups. A key contribution of the study lies in the explicit distinction between systematic and non-systematic mobility contexts, with separate discrete choice models estimated for each type of travels, allowing differences in behavioral sensitivities and socio-demographic effects to be clearly identified.

Keywords: city logistics; crowdshipping; user's choice; stated preferences; urban logistics; crowdshipper, discrete choice model.

1 Introduction

The rapid growth of e-commerce has significantly increased pressure on urban freight systems, particularly in the last-mile segment, where congestion, emissions, and service inefficiencies are significant. Cities are therefore required to reconcile increasing delivery demand with sustainability and livability objectives, fostering interest in innovative logistics solutions that combine efficiency, environmental performance, and user requirements. Within this context, crowdshipping, defined as the participation of private individuals in parcel deliveries along their daily routes, has emerged as a promising approach (Comi & Hriekova, 2024a, 2024b). By leveraging existing mobility flows, crowdshipping can potentially reduce vehicle-kilometers travelled, operational costs, and environmental impacts, while promoting more participatory delivery systems.

However, despite these advantages, its large-scale deployment remains limited and highly context dependent.

A key reason for this limited diffusion lies in the behavioral nature of crowdshipping adoption. Participation is not driven solely by technological feasibility or operational efficiency, but it depends on the willingness of the users to accept delivery tasks, shaped by perceptions of compensation, effort, time requirements and personal constraints. Understanding and modelling these behavioral mechanisms is therefore essential to assess the real potential of crowdshipping services.

Although previous studies have explored users' attitudes and preferences, the literature still lacks predictive behavioral models capable of translating such insights into operationally usable decision frameworks. In particular, few contributions explicitly model the binary decision to participate or not, and even fewer distinguish between different mobility contexts, such as systematic and non-systematic trips.

This paper addresses these gaps by developing discrete choice models for crowdshipping adoption based on stated preference data. The main contribution lies in the explicit differentiation between systematic and non-systematic mobility contexts and in the explicit modelling of socio-demographic heterogeneity in both baseline

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participation propensity and monetary incentive sensitivity. The proposed framework provides a predictive tool for ex-ante evaluation of crowdshipping policies and platform design in sustainable urban logistics.

The remaining paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the methodological framework and the stated preference (SP) survey design. Section 4 discusses the empirical application and the estimated models. Section 5 concludes the paper and outlines future research directions.

2 Literature Review

Crowdshipping has been increasingly investigated as a complementary solution to improving the sustainability of last-mile delivery systems. By exploiting existing mobility patterns. It can reduce the need for dedicated delivery vehicles and associated environmental impacts, particularly in dense urban areas (Comi & Hriekova, 2024a; Gatta et al., 2018; Hriekova et al., 2025). Systematic literature reviews confirm the growing relevance of crowd-based logistics while highlighting the importance of behavioral factors alongside operational performance (Punel et al., 2018; Sina Mohri et al., 2023).

Empirical studies show that the effectiveness of crowdshipping strongly depends on user participation rates and local conditions. As a result, recent research has progressively shifted from purely operational assessments toward the analysis of individual decision-making processes (Comi & Hriekova, 2024b; Marcucci et al., 2017). Within this behavioral perspective, monetary compensation is consistently identified as a key enabler of participation (Huang et al., 2020), while effort-related attributes, such as parcel weight and handling inconvenience, act as significant deterrents (Fessler et al., 2022).

Time-related factors, including additional travel time or detours, further contribute to the perceived cost of participation, although their relevance varies between contexts. Beyond observable attributes, trust, safety, and liability concerns have also been shown to influence acceptance, particularly in peer-to-peer delivery settings (Cebeci et al., 2023). These aspects are often modelled as latent variables or explored qualitatively rather than being directly incorporated into predictive frameworks.

Behavioral heterogeneity linked to socio-demographic characteristics and mobility habits has also been documented, suggesting that crowdshipping adoption is unlikely to be homogeneous across the population (Fessler et al., 2024). However, such heterogeneity is frequently analyzed descriptively, and its integration into calibrated choice models remains limited.

Despite the central role of monetary incentives, most existing studies implicitly assume homogeneous compensation sensitivity across users. However, economic theory and empirical evidence suggest that income constraints, employment status, and stage of life can significantly affect the marginal utility of monetary rewards. Ignoring such heterogeneity can lead to biased estimates and oversimplified policy implications. This gap is particularly relevant in crowdshipping, where participation is voluntary and closely linked to individual economic conditions.

From a methodological standpoint, crowdshipping has been studied using optimization models, simulations, (Ermagun et al., 2020; Ulmer & Savelsbergh, 2020) and agent-based approaches, which provide valuable insights into system-level performance but often rely on simplified assumptions regarding user participation (Mohri et al., 2025). Discrete choice models offer a theoretically grounded framework to represent individual decision-making under uncertainty, yet their application to crowdshipping adoption, particularly for modelling the binary participation decision, remains relatively scarce.

Moreover, the distinction between systematic and non-systematic mobility contexts has received limited attention, despite its behavioral relevance. Routine trips are typically characterized by habitual patterns and lower cognitive effort, while non-systematic trips involve higher uncertainty and different decision logics. Ignoring this distinction may conceal important behavioral differences. This study contributes to the literature by explicitly incorporating mobility regularity into discrete choice adoption models, translating stated behavioral responses into predictive decision frameworks.

3 The used methodology of analysis

This study adopts a structured methodological framework integrating stated preference (SP) survey techniques with discrete choice modelling to analyze users' willingness to participate in crowdshipping. The approach combines behavioral data collection with predictive modelling, allowing for both descriptive and explanatory insights. Special attention is paid to capturing behavioral heterogeneity in participation decisions, particularly with respect to sensitivity to monetary compensation and mobility context. Figure 1 summarizes the adopted methodological framework, which is articulated into six sequential steps. Step 0 concerns the identification of the choice alternatives and the relevant attributes influencing the participation decision. Step 1 focuses on the definition of attribute levels used to construct realistic crowdshipping scenarios. Step 2 refers to the design of the SP survey, while Step 3 consists of its administration. Step 4 involves the collection and descriptive analysis of the survey results. Finally, Step 5 is devoted to the development of the forecasting model based on discrete choice theory.

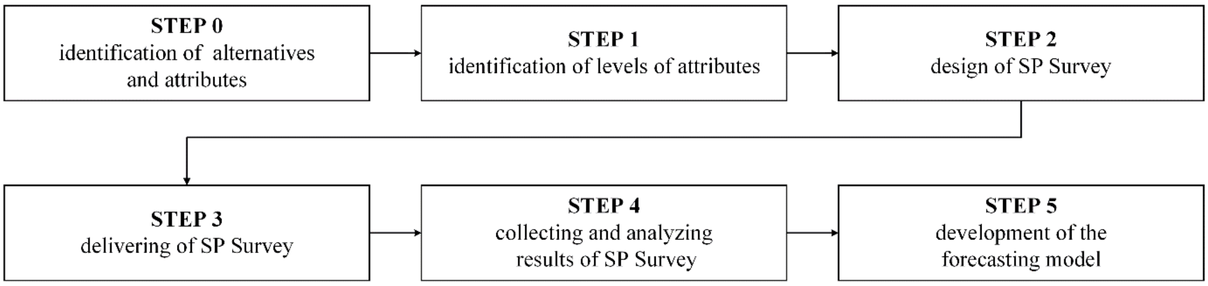

Fig. 1. The proposed methodology

The survey was designed to elicit users' stated preferences regarding participation in crowdshipping activities under controlled and hypothetical conditions. A SP approach was adopted to simulate realistic "what-if" decision scenarios in which respondents evaluated the acceptability of crowdshipping tasks embedded in their everyday urban trips.

The questionnaire combined choice experiments with background questions aimed at characterizing respondents' socio-demographic profiles, mobility habits, and general attitudes toward crowdshipping. This structure allowed the sample to be properly described and provided the information necessary to investigate how individual characteristics and travel contexts interact with task attributes in shaping participation decisions. Binary accept–reject choices were used to ensure cognitive simplicity and to obtain reliable behavioral responses, in line with standard practice in stated preference studies.

The survey was administered online to a heterogeneous sample of urban users. Responses were screened for consistency and completeness, and descriptive statistics were first analyzed to explore respondents' socio-demographic profiles and preliminary choice patterns. This step provided initial insights into users' sensitivity to economic and operational attributes and informed the subsequent modelling phase. The resulting dataset was structured for discrete choice estimation, with each scenario representing an individual observation of stated choice behavior.

The final phase of the methodological framework consists of the development of a forecasting model grounded in random utility theory. Binary logit models were estimated using Nlogit5© software. The model specification explicitly accounts for behavioral heterogeneity by allowing the marginal utility of monetary compensation to vary across socio-economic groups and mobility contexts. The specification of the model, the calibration of the parameters, and the validation were carried out iteratively to ensure statistical robustness and behavioral consistency. Parameter significance was assessed using t-Student values, enabling the identification of the most influential attributes in determining users' willingness to participate in crowdshipping (Cascetta, 2009).

4 Application to a real case study

This section illustrates the application of the proposed framework using data collected through a SP survey carried out in Italy. The objective is to demonstrate how the methodological steps described in Section 3 can be operationalized to develop behavioral models supporting the evaluation of crowdshipping initiatives. In line with the research objectives, separate binary logit models are estimated for systematic (routine) and non-systematic (occasional) trips, allowing both preference heterogeneity and context-dependent decision mechanisms to be explicitly analyzed. In addition, heterogeneity in sensitivity to monetary compensation is pointed out through interactions with socio-economic characteristics, addressing a key gap identified in the literature.

4.1 Identification of alternatives and attributes

The individual decision is whether to accept or reject a crowdshipping. Accordingly, the choice set consists of two mutually exclusive alternatives:

- YES, willingness to act as a crowdshipper;
- NO, refusal to participate as crowdshipper.

Once the decision problem and the choice alternatives were defined, the attributes describing the crowdshipping task were identified. This step was based exclusively on an extensive review of the literature on crowdshipping, crowd logistics, and travel behavior, as discussed in Section 2:

- monetary compensation (*COMP*), representing the general economic incentive offered to perform the delivery;
- parcel weight (*WEIGHT*), capturing the physical effort and handling inconvenience associated with the task;
- additional travel time (*ΔTIME*), expressed as a percentage increase with respect to the original duration of the trip, representing the relative temporal effort required.

4.2 Identification of levels of attributes

After identifying the relevant attributes, specific levels were assigned to each factor to generate realistic crowdshipping scenarios. Attribute levels were selected based on urban delivery practices and aimed to cover a plausible range of operational conditions.

- monetary compensation (*€2, €5, €8*) reflecting typical remuneration for short-distance, informal delivery tasks, with a specific component designed to test differentiated responses among students;
- the weight of the parcel is represented through three ordered categories, corresponding to small and lightweight packages commonly associated with e-commerce deliveries (*1kg, 2kg, 3kg*);
- the additional travel time is defined as a percentage increase of the usually travel time (*10%, 20%, 30%*) capturing different levels of deviation from the individual's planned trip.

This design allows the analysis not only of general individual choices but also of how socio-demographic heterogeneity affects the perception and impact of specific attributes, enabling more realistic modeling of crowdshipping participation decisions.

4.3 Design of SP Survey

Building on the attributes identified from the literature and refined through exploratory analysis, a SP survey was designed to elicit users' willingness to engage in crowdshipping under realistic hypothetical scenarios.

The questionnaire was structured to maximize clarity and internal consistency, ensuring that respondents could understand and evaluate each scenario accurately. Quality checks were implemented to filter incomplete or inconsistent responses. The questionnaire is composed of two main sections. The first section collects general information on respondents, including socio-demographic characteristics and mobility habits. This part is aimed at characterizing the sample and at gathering information on individuals' travel patterns, trip regularity, and attitudes toward crowdshipping, which are subsequently used in the analysis and modeling of stated choices. The second section consists of the SP experiment. In this section, respondents are presented with a series of hypothetical crowdshipping scenarios and are asked to decide whether to accept or refuse a delivery task integrated into an ongoing trip. Each scenario is characterized by a specific combination of task-related attributes, defined according to the experimental design. A key element of the survey design is the explicit distinction between two mobility contexts:

- systematic trips, representing routine and habitual travel patterns (e.g., commuting);
- non-systematic trips, representing occasional or non-routine mobility contexts.

This distinction reflects the hypothesis that behavioral responses to crowdshipping opportunities depend not only on task attributes but also on the regularity and predictability of the underlying mobility pattern.

To ensure robustness and avoid respondent fatigue, a fractional factorial experimental design was adopted. This approach allows the selection of a reduced but statistically efficient subset of scenarios from the full factorial combination of attributes and levels. Each respondent evaluated fourteen scenarios, defined in Table 1, divided into two blocks of seven scenarios corresponding to systematic and non-systematic trips, respectively.

Table 1. Proposed choice scenarios

Scenario	**Trip type**	***COMP [€]***	***WEIGHT [kg]***	***ΔTIME [%]***
Scenario 1	Systematic	8	2	+30
Scenario 2	Systematic	8	3	+20
Scenario 3	Systematic	5	1	+30
Scenario 4	Systematic	5	2	+10
Scenario 5	Systematic	3	1	+10
Scenario 6	Systematic	5	3	+10
Scenario 7	Systematic	3	2	+10
Scenario 8	Non-systematic	8	2	+30
Scenario 9	Non-systematic	8	3	+20
Scenario 10	Non-systematic	5	1	+30
Scenario 11	Non-systematic	5	2	+10
Scenario 12	Non-systematic	3	1	+10
Scenario 13	Non-systematic	5	3	+10
Scenario 14	Non-systematic	3	2	+10

4.4 Delivering of SP Survey

The SP survey was administered online to a sample of urban users in Italy. The target population included individuals with heterogeneous socio-demographic characteristics and mobility habits, ensuring sufficient variability for behavioral modelling.

The final dataset consists of 268 respondents, each exposed to fourteen choice scenarios, yielding a total of 3,752 stated choice observations, evenly distributed between systematic and non-systematic mobility contexts. Quality checks were implemented to identify and exclude incomplete or inconsistent responses, ensuring the reliability of the dataset used for subsequent analysis. After data cleaning, 189 observations were excluded in the non-systematic sample and 238 in the systematic sample, yielding two balanced datasets for context-specific model estimation.

4.5 Collecting and analyzing results of SP Survey

Before model estimation, a descriptive analysis of the SP data was developed to explore participation patterns in scenarios and mobility contexts. The analysis reveals a moderate overall willingness to participate in crowdshipping, with acceptance rates strongly influenced by economic compensation and perceived effort. The rates of participation are generally higher for systematic trips, suggesting that routine mobility patterns facilitate the integration of delivery tasks. Conversely, heavier parcels and higher relative increases in travel time (expressed as a percentage of the usual trip duration) reduce participation, particularly in non-systematic contexts, where delivery tasks are perceived as more disruptive. Using relative travel time (expressed as a percentage increase) instead of absolute minutes allows us to measure how sensitive respondents are to additional travel time in a way that is comparable across people with short or long usual trips.

4.6 Development of the forecasting model

The discrete choice analysis of crowdshipping participation has been carried out using NLogit5©, following the standard three-step procedure:

- *specification*, the systematic utility of participation explicitly includes economic, physical, temporal, and individual attributes, reflecting the multidimensional nature of the crowdshipping participation decision; specifically, the utility function is defined as a function of monetary compensation, physical effort, time deviation, age cohorts, and occupational status, consistently with the behavioral literature on voluntary logistics and travel-related decisions;
- *calibration*, model parameters were estimated using maximum likelihood estimation based on the stated preference data collected through the survey; each stated choice scenario represents one observation of individual choice behavior, and the estimation exploits the variation in attribute levels across scenarios to identify behavioral trade-offs; the estimation process was iterative and alternative specifications were tested to identify the best-performing models in terms of statistical robustness and goodness of fit; the probability that an individual chooses to participate in crowdshipping, denoted as $p[y]$, is expressed as:

$$p[y] = \exp(V_y) / \left[1 + \exp(V_y)\right] \tag{1}$$

where V_y is the systematic utility associated with the participation alternative (*YES*), defined as a linear combination of the model attributes and the corresponding parameters β;

- *validation*, the consistency and statistical significance of the estimated parameters were assessed, together with the overall ability of the models to reproduce observed stated choices; parameter significance was evaluated using t-Student statistics, computed as the ratio between each estimated coefficient and its standard error; parameters with absolute t-values greater than 1.96 were considered statistically significant at the 95% confidence level; model performance was further evaluated using standard goodness-of-fit indicators, including the log-likelihood at convergence (LLf), likelihood ratio tests with respect to constant-only models, Rho2 and rho2 corrected (Rho^2Adj).

This process is iterative, repeating specification, calibration, and validation until a validated and robust model is obtained.

The systematic utility of the participation alternative YES (equ. 2) is specified as a linear-in-parameters function of the attributes:

$$U[YES] = \sum_k \beta_k \cdot X_k \tag{2}$$

where X_k is the k-1 attribute and β_k the parameter to be estimated.

It is important to note that, in addition to the attributes identified in the literature, reported in Section 4.1, the model incorporates specific attributes derived from the survey data. Analysis of individual responses revealed that certain attributes are relevant only for particular user groups. For instance, monetary compensation for students (*COMP_ST*) captures the specific sensitivity of this socio-economic segment. Socio-demographic variables, including gender (*SEX*), age group (*YOUNG, YOUNG ADULTS, ADULTS, OLDER*) and employment status (*STUD, FULL-TIME, PART-TIME, RETIRED, UNEMPLOY*), are also included to account for observed behavioral heterogeneity. The attributes used are explained in Table 2.

Table 2. Attributes of the logit model

SEX	the gender, equal to 1 for female, 0 otherwise
YOUNG	dummy variable equal to 1 if the respondent is between 18-25 years old, 0 otherwise
YOUNG ADULTS	dummy variable equal to 1 if the respondent is between 26-35 years old, 0 otherwise
ADULTS	dummy variable equal to 1 if the respondent is between 36-50 years old, 0 otherwise
OLDER	dummy variable equal to 1 if the respondent is between over 65 years old, 0 otherwise
STUD	dummy variable equal to 1 if the respondent is a student, 0 otherwise
FTIME	dummy variable equal to 1 if the respondent is a full-time worker, 0 otherwise
PTIME	dummy variable equal to 1 if the respondent is a part-time worker, 0 otherwise
RETIRED	dummy variable equal to 1 if the respondent is retired, 0 otherwise
UNEMPLOY	dummy variable equal to 1 if the respondent is an unemployed, 0 otherwise

For identification purposes, the utility of the non-participation alternative is captured through an alternative-specific constant, while all observed attributes are associated with the participation alternative. This comprehensive specification is intentionally theory-driven rather than parsimonious, as its primary purpose is to test the relevance and statistical contribution of all conceptually plausible determinants of participation. The full model thus serves as a behavioral benchmark, against which reduced specifications are subsequently derived. Table 3 reports the estimated coefficients and corresponding t-Student statistics for the full binary logit specifications, separately estimated for systematic and non-systematic mobility contexts.

Table 3. Comparison of estimated coefficients and t-Student values

	Sistematic trips		**Non – systematic trips**			**Sistematic trips**		**Non – systematic trips**	
parameter	value	t-student	value	t-student	parameter	value	t-student	value	:-student
β_{COMP}	0.356	4.80	0.416	5.53	β_{ADULTS}	0.522	2.22	0.060	).25
β_{COMP_ST}	0.251	4.23	0.216	3.63	β_{OLDER}	-0.670	-1.96	0.233	).71
β_{WEIGHT}	-0.295	-2.17	-0.236	-1.72	β_{STUD}	-1.888	-2.80	-1.306	-2.11
$\beta_{\Delta TIME}$	-0.018	-1.36	-0.019	-1.47	β_{FTIME}	-0.400	-0.70	0.280	).56
β_{SEX}	-0.368	-3.38	-0.133	-1.21	β_{PTIME}	-0.559	-0.91	-0.094	-0.17
β_{YOUNG}	0.831	4.03	0.750	3.62	$\beta_{RETIRED}$	-0.260	-0.40	-1.020	-1.68
$\beta_{YOUNGADULTS}$	0.362	1.76	0.335	1.63	$\beta_{UNEMPLOY}$	-1.819	-2.60	-1.158	-1.79
LLf	-1005.153		-1009.644		**Rho^2**	**0.113**		**0.128**	
					Rho^{2}Adj	**0.110**		**0.120**	

The models exhibit satisfactory goodness-of-fit, with McFadden's rho² values equal to *0.113* and *0.128*, respectively, and only marginally lower adjusted values (Rho^{2}Adj).

Across both mobility contexts, monetary compensation emerges as the most robust determinant of participation. Both the general compensation parameter (β_{COMP}) and the student-specific compensation parameter (β_{COMP_ST}) are positive and highly statistically significant. The larger coefficient in non-systematic trips indicates a stronger reliance on economic incentives when participation decisions are not embedded in habitual travel, while the significance of β_{COMP_ST} confirms heterogeneous sensitivity to monetary rewards, consistent with differentiated opportunity costs of time and income.

Parcel weight exhibits the expected negative sign in both models, confirming that physical effort discourages participation. The effect is statistically significant for systematic trips and marginally significant for non-systematic ones, indicating that physical effort represents a relevant behavioral cost across mobility contexts.

In contrast, additional travel time (*ΔTIME*) does not emerge as a statistically significant determinant. Although negative, its low t-Student values suggest that moderate detours are absorbed within habitual schedules in systematic trips and are less binding in non-systematic contexts, justifying its exclusion from the reduced specifications.

Socio-demographic effects are strongly context-dependent, reinforcing the need for separate models by mobility type. In systematic trips, gender emerges as a statistically significant factor, with a negative coefficient indicating a lower baseline propensity to participate among female respondents. This may reflect differences in perceived safety, risk attitudes, or compatibility with routine travel constraints. Age-related effects are also relevant in systematic contexts; younger individuals show a significantly higher willingness to participate, while older cohorts display a reduced propensity, consistent with life-cycle effects and physical capability considerations.

In non-systematic trips, these effects largely disappear, while occupational status becomes more relevant. Students, retired individuals, and unemployed respondents exhibit lower participation probabilities, with coefficients that are statistically significant or borderline significant. This pattern suggests that, in occasional mobility contexts, differences in availability, perceived benefits, and opportunity costs associated with employment conditions play a more important role than gender or age per se.

Starting from the full specifications, reduced models were obtained by removing statistical significance or did not contribute meaningfully to behavioral interpretation. This reduction was guided by both statistical criteria (low absolute t-Student values) and behavioral reasoning, ensuring that the exclusion of parameters did not compromise overall model fit or alter the signs and magnitudes of the remaining coefficients.

For systematic trips, the values of the estimated coefficients and the related t-student values are shown in Table 4:

Table 4. Estimated coefficients and t-Student values for systematic trips

Sistematic trips			Sistematic trips		
parameter	*value*	*t-student*	parameter	*value*	*t-student*
β_{COMP}	0.273	6.36	β_{ADULTS}	0.372	1.70
β_{COMP_ST}	0.252	4.24	β_{OLDER}	-0.717	-2.95
β_{WEIGHT}	-0.145	-1.82	β_{STUD}	-1.415	-4.04
β_{SEX}	-0.377	-3.50	$\beta_{UNEMPLOY}$	-1.416	-3.42
β_{YOUNG}	0.621	3.66			
LLf	-10007.820		**Rho^2**	**0.111**	
			Rho^{2}Adj	**0.105**	

For non - systematic trips, the values of the estimated coefficients and the related t-student values are shown in Table 5:

Table 5. Estimated coefficients and t-Student values for non-systematic trips

Non - sistematic trips			Non-sistematic trips		
parameter	*value*	*t-student*	parameter	*value*	*t-student*
β_{COMP}	0.324	7.44	β_{STUD}	-1.420	-4.02
β_{COMP_ST}	0.218	3.67	$\beta_{RETIRED}$	-1.173	-4.49
β_{WEIGHT}	-0.0708	-0.89	$\beta_{UNEMPLOY}$	-1.304	-3.22
β_{YOUNG}	0.520	3.18			
LLf	-1014.47772		**Rho^2**	**0.123**	
			Rho^{2}Adj	**0.119**	

The reduced models maintain goodness-of-fit levels comparable to the full specifications, confirming that parsimony is achieved without loss of explanatory power. A key outcome of the reduction process is the high degree of stability observed in the core parameters. The estimated coefficients for monetary compensation and parcel weight retain similar signs and magnitudes across full and reduced specifications, indicating that the exclusion of non-significant variables does not distort the underlying behavioral trade-offs. This stability supports the robustness of the reduced models, confirming that the retained variables capture the essential structure of crowdshipping participation decisions.

The originality of the framework lies not in the individual attributes, but in the explicit structuring of behavioral models around mobility regularity. By empirically demonstrating that the relevance of time, gender, age, and occupational status depends on whether trips are routine or occasional, the study advances current crowdshipping research beyond aggregated and context-neutral behavioral representations. Although based on SP data, the final reduced models are explicitly formulated for forecasting applications. Their parsimonious, context-dependent structure supports scenario analysis and demand forecasting, enabling more accurate participation estimates than context-neutral models. The comparison between systematic and non-systematic models also suggests that crowdshipping platforms should not rely on uniform incentive schemes. Applying parameters estimated on routine trips to occasional mobility would lead to biased participation forecasts, typically overestimating acceptance rates.

5 Conclusions

This study investigated the behavioral determinants of crowdshipping participation in urban logistics by combining SP data with discrete choice modelling. The results indicate that participation decisions are governed by a compensation–effort trade-off, with monetary incentives emerging as the dominant driver of acceptance and physical effort, proxied by parcel weight, acting as a systematic deterrent across model specifications.

A central contribution of the research lies in the explicit and structured differentiation between systematic and non-systematic mobility contexts. The findings demonstrate that behavioral sensitivities are not homogeneous across trip types. In non-systematic trips, participation decisions exhibit a stronger responsiveness to economic incentives, reflecting higher discretion and flexibility in occasional mobility. Conversely, in systematic trips, effort-related attributes such as parcel weight play a more statistically robust role, while routine travel patterns appear to partially absorb the burden associated with integrating delivery tasks into habitual movements. This distinction enables a more nuanced interpretation of participation mechanisms and highlights the importance of explicitly accounting for travel regularity when modelling crowdshipping adoption.

From a methodological standpoint, the study advances the existing literature by moving beyond descriptive analyses of user attitudes and providing calibrated, context-dependent behavioral models. The use of comprehensive full specifications as behavioral benchmarks, followed by empirically grounded reduced models, ensures both interpretability and parsimony. The inclusion of socio-demographic variables, and in particular a student-specific compensation component, reveals selective forms of behavioral heterogeneity linked to differentiated opportunity costs of time and income. In particular, additional travel time does not emerge as a statistically significant determinant in either mobility context, suggesting that within the tested range, time deviations are secondary to compensation and physical effort in shaping participation decisions.

From a practical perspective, the results offer relevant insights for policymakers and platform designers. Effective crowdshipping schemes should adopt context-sensitive design strategies, differentiating incentive structures and task characteristics according to mobility patterns. Higher compensation levels and reduced physical effort are especially important in non-systematic trips, whereas systematic travel contexts provide greater potential for integrating delivery tasks with limited behavioral resistance. Such targeted strategies can enhance participation rates and support the integration of crowdshipping into sustainable urban logistics systems.

Future research should aim to validate the proposed framework using revealed preference data, investigate longitudinal behavioral dynamics, and explore advanced modelling approaches capable of capturing unobserved heterogeneity and learning effects. These developments would further strengthen the empirical foundations of context-dependent crowdshipping adoption models and enhance their applicability in real-world policy and operational settings.

Acknowledgements

This study was co-funded by "Implementation of Sustainable Urban Development Goals in Transport Bachelor Degree - ISDEGO"- Project ID: 101179915. The authors thank Dr. Gaia Pizzuti and Dr. Massimo Junior Morgani for their support in data collection.

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