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The effect of trust on the choice for crowdshipping services

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ABSTRACT

The fast growth of e-commerce in urban areas has led to a surge in last-mile transportation demand and an associated increase of external effects: congestion, noise and visual pollution. This paper analyses a new urban freight transport service that has a potential to reduce this footprint: crowdshipping. Crowdshipping is a service where a package is delivered via a traveller who is already making a personal trip for other purposes. The decision of whether or not to use crowdshipping is known to be subject to various service, time and price conditions, including trust in a correct delivery. The effect of trust has not been investigated explicitly, however. We conduct a stated choice experiment and estimate a hybrid choice model with trust as a situation-specific latent variable. The research design allows us to explore how the relevant attributes influence service adoption via trust. We find a significant influence of established choice attributes on service adoption, except for the delivery company's reputation and the possibility of damage. In addition, all attributes except delivery time have a significant influence on trust. We conclude that trust has a partially mediating effect on the adoption of the service except delivery time, and a fully mediating effect on adoption via reputation and damage.

1. Introduction

Increasing urbanisation brings several changes to the cities, together with consumer-to-consumer (C2C) and business-to-consumer (B2C) e-commerce. First of all, demand for last-mile delivery has grown rapidly as consumers are getting used to shop online. Also, customers are seeking more customised on-demand deliveries, leading to an increase in parcel shipments in urban areas by couriers. According to Yrjölä et al. (2017), C2C e-commerce is evolving into a new retailing sector, causing competitive pressure on retailers. Concerning B2C deliveries, most retailers provide a home delivery option to their customers with specific time windows so that the service can be customised. This creates additional fragmentation of flows, adding to negative externalities in urban areas, such as congestion and pollution (Ranieri et al., 2018). As an innovative solution to tackle these issues, shared mobility services such as crowdshipping are proposed for on-demand delivery requests.

The general idea behind crowdshipping is that the item is transported by a commuter who is already making their trip for other purposes, thus, not adding extra travelled kilometres to the operation (Le et al., 2019; Tapia et al., 2023). The service provides

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potentially faster and cheaper parcel deliveries for users since the system uses existing infrastructure and passenger flows to deliver the parcel (Devari et al., 2017; Arslan et al., 2019). In this way, traditional carriers could use fewer vehicles and make fewer vehicle kilometres in total, reducing the negative impact of last-mile shipments on the environment. In some cases, it can occur that new routes are generated, and existing trips are not reduced. Then, the service can lead to increase in travel costs, travel times and fuel consumption (Gatta et al., 2018; Buldeo Rai et al., 2018). Also, since the supply side of the market is not regulated, there are concerns about unreliability of the service due to damage and theft (Le et al., 2019). Jaller et al. (2020) provide an extensive review of the state-of-practice and discuss preconditions for a large-scale breakthrough of the service. While the number of service providers is steadily growing, the main current niches include long-distance haulage in remote areas (e.g. Nimber in Norway) and the provision of additional flexible capacity for mainstream logistics service providers (see also: Economist, 2018). Although conceptually crowdshipping fills a gap in the logistics services market for small parcels (Le Pira et al., 2021), it is not yet widely established, and there is no crowdshipping operation in the Netherlands. Research studying adoption behaviour is therefore of societal interest in order to investigate the possible impacts of crowdshipping.

Behavioural studies focusing on user adoption incorporate various factors that affect choice for the service. These include price, time, reliability, privacy, safety, and liability (Rougès & Montreuil, 2014; Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019a; Punel et al., 2018b). An emerging topic in the literature on crowdshipping has been the concept of trust in the capabilities of the service provider. Several studies focusing on the behavioural acceptance of crowdshipping state that trust is an important factor enabling service adoption (Rougès & Montreuil, 2014; Punel et al., 2018b, 2018a). In a more recent study, Upadhyay et al. (2021) assess the mediating structure of trust on sharing economy platforms. The research also addresses the mediating role of attitudinal variables towards the crowdshipping platform from the perspective of social, economic and reward point of view. The authors highlight the positive relation between intention to participate in sharing platforms and trust in occasional carrier (traveller). Even though this study identifies trust as a critical factor in the general context of sharing economy applications, it is still not clear how the level of trust can be measured and to what extent trust has a mediating role in the service adoption. Our research aims to address this void in the literature.

Given this background, the main objective of this research is to investigate the user's acceptance of crowdshipping services focusing on the role of trust. Firstly, a literature review is conducted to define trust in crowdshipping and the attributes that might impact the level of trust. Crowdshipping service platforms are not yet widespread, and records of these platforms store insufficient data to address the issue of trust. Therefore, we have constructed a stated preference experiment (SPE) for data collection. To test the effect of trust on crowdshipping service choice, six attributes are defined and validated through a crowdshipping service provider. A hybrid choice model is deployed to estimate the attribute weights. While the design of the SPE enables us to explore the effect of trust on crowdshipping per choice situations, the estimated HCM allows us to disentangle the direct, indirect (through trust) and total effects of the main attributes on the service adoption. This is the first time that trust is included in a hybrid choice model as a mediating latent variable in the crowdshipping domain. Hence, this study adds to an empirical understanding of crowdshipping service choice in the context of last-mile deliveries.

In the following section, a literature review on crowdshipping and trust is presented. Next, the applied methodologies are described, followed by the research results and their discussion. Lastly, research conclusions are presented.

2. Literature review

This section aims to find possible conceptual connections between consumer trust and the adoption of crowdshipping as well as the attributes highlighted in the literature that can be applied to measure trust.

Crowdshipping is an emerging service that requires the cooperation of technology firms, retailers, consumers, and travellers (Punel & Stathopoulos, 2017). This new delivery service emerged as an alternative to urban freight distribution by commercial carriers, by utilising existing personal travellers to perform goods transportation. The service is defined as a platform that links customers to a crowd of travellers that are willing to pick up and deliver packages. Research on crowdshipping acceptance is relatively recent. In their review study, Le et al. (2019) analyse real-world data to conceptualise the discussions and policy implications of crowdshipping service. The study uses three data sources including stated preference surveys and real-world data and shows that crowdshipping platform needs key functionalities such as ease of use, real-time assistance and hands-free capabilities. More recently, Le et al. (2021) and Wicaksono et al. (2021) documented the scarcity of studies in this context.

A limited number of studies have addressed trust of users in crowdshipping. According to Rougès & Montreuil (2014), building trust is a key performance indicator. A recent study regarding trust in occasional carrier explores the mediating role of trust in the context of shared economy applications for emerging economies (Upadhyay et al., 2021). Surprisingly, however, there is no study on measuring trust in crowdshipping context from the users' perspective. Trust has a clear relation to various service attributes. These include delivery time (Punel & Stathopoulos, 2017); the ability to define pickup time (Punel & Stathopoulos, 2017); delivery cost (Rougès & Montreuil, 2014) as well as driver performance, courier expertise, and experience. These latter features might also affect the trustworthiness of the crowdshipping service (Punel & Stathopoulos, 2017). Moreover, reliability is an indispensable part of a successful crowdshipping operation (Rougès & Montreuil, 2014; Punel et al., 2018a; Le et al., 2019). There is also a strong relationship between reliability and level of trust (Chancey et al., 2016). When the service is perceived as reliable, the user's trust will be higher for that specific service. Literature shows that availability of tracking and tracing affects the choice of crowdshipping service (Le & Ukkusuri, 2019a; Gatta et al., 2018); together with insurance for loss or damage, this might also increase users trust in the service (Rougès & Montreuil, 2014). Jøsang et al. (2007) state that there is a direct correlation between reputation and trustworthiness. Reputation is directly linked to trustworthiness, and it enables the user to envision the service quality as it provides other users' reviews and comments. This feature can be evaluated based on customer reviews and app ratings. Interestingly, in some studies, the

reputation of a crowdshipping company was found more influential than the cost of the delivery and the delivery time (Le et al., 2019). In parcel delivery, users can be exposed to risky service or poor service quality, with missed delivery or damage as unwanted outcomes. As a company's reputation provides information about the service, this knowledge can also be used to reduce unwanted service outcomes (Shao et al., 2019).

Finally, the literature shows that there is a relation between sociodemographic characteristics and crowdshipping service adoption. According to Punel et al. (2018b), young men and full-time employed individuals are more likely to adopt crowdshipping. Additionally, the building of trust would differ between different sociodemographic segments. Therefore, sociodemographic characteristics could be considered another important parameter for service adoption, in relation to trust.

Trust has been researched by different disciplines of social sciences such as psychology, political science, and economics. Each discipline explains the role of trust in social processes from a different perspective. Various trust categories can be found in the literature such as characteristic trust, rational trust, and institutional trust (Laeequddin et al., 2010; McEvily & Tortoriello, 2011). A plethora of studies assess the antecedents of trust, and the literature converges defining this behavioural factor as a complex psychological phenomenon (Laeequddin et al., 2010; McEvily & Tortoriello, 2011). Trust is necessary for organisational success but requires an effort that cannot be created in a short time (Lin et al., 2020). Building customer's trust in the organisation provides an effective operation and continuity of the business; as a result, the development of trust is expected to increase the willingness to use the service. Although there are different definitions of trust, the literature extensively cites two of them. First, trust can be seen as one person's willingness to act on another person's action or decision (McAllister, 1995). Based on this definition, trust is credence and positive expectation of the individual towards a person, situation or service. In crowdshipping, expectations that delivery will be carried out in a safe manner can improve trust levels. Secondly, trust is defined as one party's willingness to be vulnerable to another party's action (Mayer et al., 1995). Thus, one party's willingness to be involved in crowdshipping service plays a pivotal role in the trust-building process.

Trust has also been studied in different areas of technology adoption. In the area of financial technology, recent studies find that trust positively impacts the intention to use internet, mobile banking, robo-chat and mobile payment services (Dawood et al., 2021). Different approaches have been used to measure the effect of trust including multivariate regression (Lien et al., 2020) and structural equation modelling (Mainardes et al., 2022; Roh et al., 2022). Trust is treated as either an independent variable (Lien et al., 2020) or a dependent latent variable with a mediating effect (Roh et al., 2022; Mainardes et al., 2022). Trust has also been an important topic in the area of artificial intelligence (AI) and healthcare technology. Several studies envision trust as a critical determinant of human–machine interaction (Gille et al., 2020). Research on how to measure trust in healthcare is limited (LoCurto & Berg, 2016). Alrubaiee & Alkaa'ida (2011) explore the mediating effect of patient satisfaction on perceived healthcare quality and patient trust by using a service quality model (SERVQUAL). Another study investigates the mediation effects of trust in healthcare providers (Hong & Oh, 2020). In the above studies, trust is generally measured with a Likert scale based on person-level indicators provided in the experiment.

In the context of passenger transportation, establishing trust in services is challenging as technology evolves quickly and transportation methods vary widely. Novel services such as ride-sharing and ride-sourcing often include trust in the consideration of service adoption (Coulter & Coulter, 2002; Akhmedova et al., 2021). Promoting customer trust has been extensively explored. The mediating effect of trust has been studied with the help of structural equation modelling (Shao & Yin, 2019; Shao et al., 2020). While trust is measured related to service platforms (Shao & Yin, 2019), government support and reputation of a ride sharing company have also been considered recently (Shao et al., 2020). In addition, the ride sourcing literature considers various features to measure trust including travel time, cost, safety and privacy. The measurement of trust in ride sourcing is based on perceptions of vehicle or driver related risks (Nguyen-Phuoc et al., 2021), app related risks (Nguyen-Phuoc et al., 2021) and other perceived concerns (Asgari & Jin, 2020). In our study, similar to the previous research, trust is treated as a dependent mediating variable. However, in this study, the level of trust is measured through situation-specific attributes that affect trust rather than person-level statements indicating trust (Roh et al., 2022; Mainardes et al., 2022; Shao & Yin, 2019; Shao et al., 2020).

Based on the above review, the study is positioned as a first endeavour to model the mediating role of trust for the adoption of crowdshipping services, using a choice modelling approach with trust as a situation-specific latent variable. Our contributions include the conceptualisation of the model and its estimation within a SPE setting, as well as empirical findings that underline the important role of trust in this market, including its antecedents in the form of relevant service attributes. The research thereby supports the design of policies by private and public actors to strengthen trust in crowdshipping services.

3. Methodology

This section explains the conceptual framework derived from the literature review as well as the data collection and analysis method.

3.1. Conceptual model

Based on the research objective, the conceptual framework aims to represent not only the direct effect of the attributes on service choice but also their indirect effect on choice, via the concept of trust. The conceptual model of this approach is given in Fig. 1. While rectangular boxes are used to show the observed variables, the round boxes are used to represent the latent variables.

Explanatory variables include delivery time, delivery cost, tracking-tracing options, insurance coverage, possibility of damage and reputation, along with some sociodemographic background variables. These have a direct effect on utility (arrow *c'* in the figure). The direct effect of these attributes on trust and the direct effect of trust on utility are shown by arrows *a* and *b* respectively. Based on this

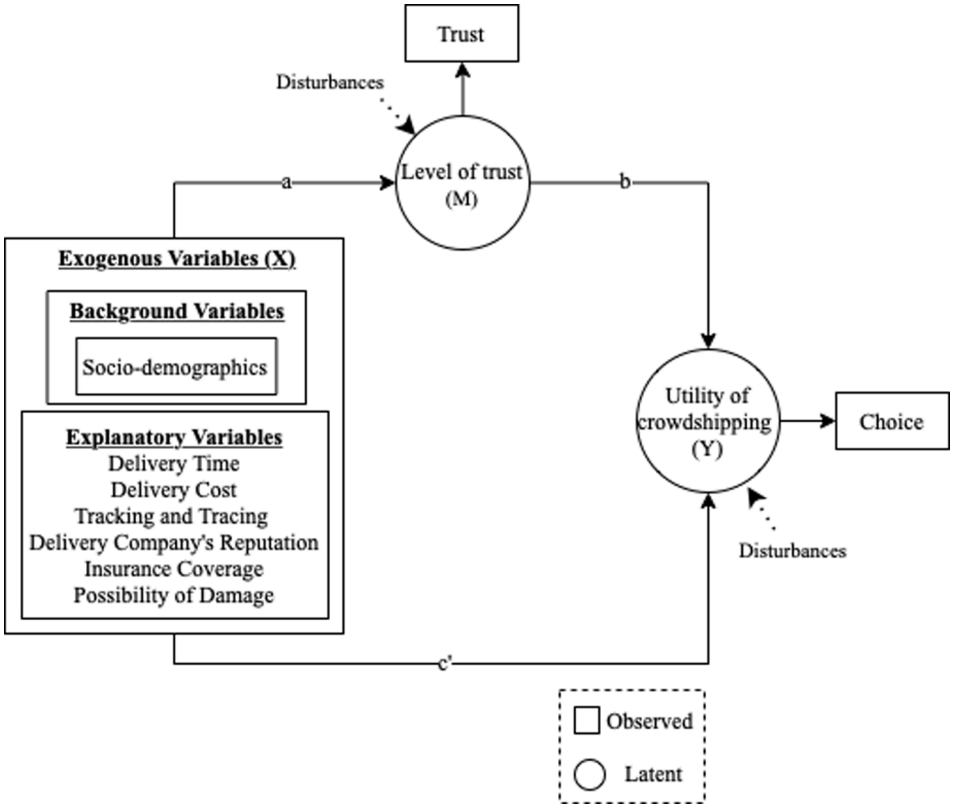

Fig. 1. Conceptual model.

conceptualisation, respondents are provided with several hypothetical scenarios concerning crowdshipping. By relating observed choices to observed attributes and the latent variable, their influence can be inferred statistically. As can be seen from the conceptualisation, mediating variable trust (M) and utility of crowdshipping (Y) are estimated with the help of observed variables in the experiment. If one is able to measure trust directly, its influence can be distinguished from that of the utility variable.

In this study, the level of trust is observed from a direct rating by respondents, specifically for each choice situation. This is based on their level of trust for the crowdshipping service on the provided attributes. Hence, it is assumed that respondents are able to assess the impact of different attributes generating a choice set and to provide an overall trust level for a given choice task. Moreover, the level of trust is assumed to impact the utility of crowdshipping, that is, high level of trust is expected to increase the probability of opting for crowdshipping comparing to traditional delivery.

3.2. Stated preference experiment

In this research, a stated preference (SP) survey is used since no crowdshipping service has been applied in the Netherlands yet, so there is no revealed preference (RP) data available. This experiment technique enables the authors to capture the decision to use the crowdshipping service, including all alternatives and their trust rating.

3.2.1. Data collection and survey design

In the SP experiment, individuals are asked to make choices based on a set of hypothetical situations. The attributes related to trust and the service itself were selected from the literature and validated through discussions with a crowdshipping service provider. The attributes identified in the literature and incorporated in the survey include delivery time (Devari et al., 2017), delivery cost (Wicaksono et al., 2021), tracing and tracking options (Rougès & Montreuil, 2014; Le & Ukkusuri, 2019c), insurance coverage (Rougès & Montreuil, 2014), possibility of damage (Le & Ukkusuri, 2019a), and delivery company's reputation (Le & Ukkusuri, 2019a; Jøsang et al., 2007).

Table 1 below shows the attributes which are used in the SP experiment for crowdshipping alternative.

Two levels are defined for delivery time: same day or next day delivery. There are two reasons of this choice. Firstly, the main goal of the research is to understand how the relevant attributes affect trust and if trust has a mediatory role in the service adoption, therefore, delivery time is not needed to be represented with hours specifically. Secondly, in practice, the parcel deliveries are also framed this way. Hence, only generic information (either same day or next day) is provided to assess the importance of delivery speed for the respondents. The cost of the service is assumed to be 5–7-10 and 12 €. Although crowdshipping service cost is usually calculated

Table 1
Attributes and their operationalisation for crowdshipping.

Attribute	Attribute levels	Values	Coding
Delivery time	2	Next day delivery	0
		Same delivery	1
Delivery cost	4	5€	5
		7€	7
		10€	10
		12€	12
Tracking tracing options	2	Only main steps can be seen in the app/website	0
		Real-time driver tracking by the app/website	1
Delivery company's reputation	2		0
			1
Insurance coverage	2	Up to 500€	0
		Up to 1000€	1
Possibility of damage	2	1 in 20 damaged delivery (5 %)	0
		1 in 30 damaged delivery (3 %)	1

Table 2
Summary of the attributes and attribute levels for traditional delivery.

Attribute	**Levels**
Delivery time	Next day delivery
Delivery cost	10€
Tracking tracing options	Only main steps can be seen in the app/website
Delivery company's reputation	
Insurance coverage	Up to 750€
Possibility of damage	1 in 25 damaged delivery (4 %)

based on the distance travelled, as travel distance is not included in the experiment, respondents are directly provided with pre-specified cost values. The tracking and tracing options indicate whether the alternative has real-time tracking. Due to the novelty of the platform, it is assumed that this feature might impact the reliability of the service and users' level of trust. Insurance coverage is represented with an upper bound value in the choice situations. These values are used to describe the limit of the insurance since this is also the way insurance coverage is represented in real-life. The possibility of damage is expressed in the probability of the item getting damaged or lost. To show the delivery company's reputation, the number of stars is provided using a typical app-based rating system. The stars reflect the credibility of the delivery company, expressing the level of trustworthiness. Earlier, reputations have been measured as low, medium, or high based on driver's app ratings (Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019c). However, this is the first time that stars-based rating scheme is considered in a user's service choice. Extreme ratings such as one or five stars might lead to bias in attributes; hence, two and four stars are applied in the experimental design.

While the attribute levels of crowdshipping vary, the traditional delivery option values are fixed. The reason for this choice is that the traditional delivery option is considered the base alternative permitting respondents to compare it with the crowdshipping option. Table 2 represents the selected intermediate attribute levels for traditional delivery.

In practice, delivery time for local-to-local (L2L) parcels is generally the next day since these delivery requests are executed via small number of depots in the city. Tracking and tracing facility for traditional delivery company is generally provided as main steps throughout the delivery operation. Similarly, in our experiment, traditional delivery is assumed to have only next day delivery option and only main steps can be seen as a tracking and tracing feature. With these selections, it is possible to represent the realism in the case of traditional delivery. Moreover, delivery cost in Dutch transport market ranges from 8€ to 15€ among main carriers for L2L parcels. In our experiment, 10€ is attributed for traditional delivery option to be comparable with the crowdshipping alternative. Lastly, the attribute levels of traditional delivery for insurance coverage, possibility of damage and reputation of the company are defined as average values comparing to crowdshipping option. This is done in order to avoid bias in the experiment.

To combine the defined attribute levels into a choice situation, an orthogonal fractional factorial design with one 4-level (delivery cost) and five 2-level attributes (the rest) are chosen, which result in 16 unique profiles. The experiment was designed in two different blocks. These blocks were randomly assigned to the respondents. In this part of the survey, individuals filled in 8 choice situations with two sub-questions each (shown in Fig. 2). Ngene software was used to generate the choice tasks (Ngene, 2018).

As the crowdshipping service in the Netherlands can be seen as a relatively new concept, there is no service present that one can relate to. For this reason, in the choice experiment, people were asked to make the selection between two different unlabelled alternatives, namely crowdshipping delivery and traditional delivery options. In the beginning of the online survey, respondents encountered the information below, highlighting the context for respondents to make them consider the same assumptions while selecting their preferences. To this end, respondents were asked to consider the last item that they had bought and the value of that item while choosing their preferences. In addition, the statements given in the box below were provided in the choice experiment so

that every respondent could imagine a similar context.

Imagine the last item that you bought online; the shop (website) provides two alternatives to deliver your package to your intended location with the following features.
In this specific case;
It is assumed that you don't need the product urgently,
It is assumed that you have to be at your predefined location to collect the package,
Imagine that you can only reach out to the commercial transportation company for your claims in case of damaged or wrong delivery.

In the beginning of the SPE, respondents were notified with explanations of the attributes. In Table 3 below, we show the attributes and their explanation.

After defining the general context and assumptions of the experiment, respondents were asked to answer two questions. In the first part, they were asked whether they prefer the crowdshipping delivery option or not. Secondly, in line with the conceptual model, they were asked to rank their level of trust towards crowdshipping, even if they did not select the crowdshipping option in the first question. Fig. 2 shows an example of these two questions.

From the delivery options below, select the one that fits your preference the most.

Along with the SPE, the survey consists of a description of the respondent's sociodemographic characteristics. The questionnaire was developed in the online web platform: Qualtrics. The data collection process took place in the last week of April 2021 and was kept online for three weeks. Respondents who lived in the Netherlands and were above 18 years of age were asked to fill in the survey. In the end, 248 responses were collected, of which 215 were fully completed with 1720 choice observations.

3.2.2. Sample characteristics

In the survey, five sociodemographic variables are used: gender, age, occupation, education and income level. Since the main focus of the research is to explore the effect of trust on the crowdshipping service choice, it is also important to investigate the heterogeneity in preferences which is estimated through these variables. Hence, the levels of these variables were selected in a way to realise this aim. Based on the sample data, the frequency distribution of sociodemographic characteristics is shown in Table 4.

As can be seen, the sample consists of approximately the equal number of men and women. Regarding the age group, a considerable number of respondents (85 %) belong to the 18–33 age segment, and more than half of the respondents are students who are doing master's or bachelors. People older than 33 years of age account for almost 15 % of the data set. As the most dominant responses belong to students, the monthly income represented with less than 1000€ in a month appears to be 47.2 % of the total respondents. According to the sample characteristics, the sample consists of slightly more men than women, which accounts for almost 55 % of the sample. Moreover, there is a large share of young population with a low-income level. Therefore, multiple groupings are done to test the sociodemographic characteristics in order to have a sufficient number of respondents in each category, which is needed to test heterogeneity in discrete choice models. To this aim, the age group is classified as 18–25 years of age and older than 25 years of age. In addition, occupation is combined as students and working and others. Next, education is represented as highly educated respondents (master/PhD) and others. Lastly, income level is combined as less than 500€ of income and more than 500€ of income.

Due to the fact that the survey circulation was initiated among student groups and their social networks, in the end almost 65 % of the sample consisted of students. In addition, part of the data collection took place in the train station in Delft, the Netherlands in order to have more heterogeneity in sociodemographic characteristics. Even though the sample had a large proportion of students and low-income level respondents, we had sufficient number of people from the non-student population to test if there are differences in preference between the groups (Ben-Akiva & Lerman, 1985). As reported below, this is confirmed by the estimations which indicated significant levels of heterogeneity in some of the population groups. In addition, young individuals are more keen to use crowdshipping, as also highlighted in previous studies (Punel & Stathopoulos, 2017; Wicaksono et al., 2021). In any case, it is important to highlight that generalising the findings of the study should be done with care.

3.3. An Adapted hybrid choice model

To estimate the direct, indirect, and total effects of the main attributes on the crowdshipping service choice, a hybrid choice model (HCM) is applied. This method provides a modelling framework where the aim is to bridge the gap between discrete choice models and behavioural theories by explaining unobserved parts of the decision-making process, such as attitudes, perceptions, and preferences (Abou-Zeid & Ben-Akiva, 2014). The novelty of these types of models is the availability of combining discrete choice models with models including latent variables, namely trust in the current study. Finally, a three-variable system is needed in order to ensure that

Table 3
Context of the experiment.

Features	Explanation
Delivery time	This feature refers to **same day** or **next day** delivery options.
Delivery cost	This feature represents the **cost** of the service.
Tracking and tracing options	This feature represents whether the alternative has a tracking and tracing feature or not (**real-time/only main steps).**
Delivery company's reputation	This feature refers to **credibility** of the delivery company and the rating of the company's app.
Insurance coverage	This feature shows the **insurance limits** for the alternative.
Possibility of damage	This feature represents the possibility that the item can get **damaged or lost**.

Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**7€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation		
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
- *Yes*
- *No*

Based on the given scenario, how much would you trust crowdshipping?
- *Strongly distrustful*
- *Distrustful*
- *Neutral*
- *Trustful*
- *Strongly trustful*

Fig. 2. An example choice situation.

there is a mediating structure in the modelling framework. As a consequence, HCMs requires two essential estimations: (1) the measurement model and (2) the structural model. The measurement model represents the link between estimated parameters to their observable indicators and several indicators are included to measure the latent variable. The structural model represents the link between observable and latent variables to the utility (Ben-Akiva et al., 2002; Walker & Ben-Akiva, 2002).

In HCMs, a psychological construct is usually measured on the level of a person with multiple indicators. However, in this study, unlike in a traditional HCM, the regressors are the service attributes. We build on the approach of Molin & Kroesen (2022) to include the construct of trust in choice situations. In their paper, the authors assess the safety perceptions of and support for policy measures by applying two approaches: (1) a mediation choice model and (2) a latent class choice model. In their mediation choice model, the authors use six attributes to measure the safety perception in a SPE. We proceed along the same line focusing on the concept of trust. Prior studies applied similar techniques, combining choice models with latent mediators. Burke et al. (2020) test the effect of multiple product features on consumer choices and the perceived benefits in terms of healthiness and cost. Borriello et al. (2021) propose a hybrid choice model by taking into account electricity mix choices among renewable and non-renewable energy alternative choice

Table 4
Frequency distribution of sociodemographic characteristics of the sample (N = 215).

Sociodemographic Characteristic	Category	Frequency (N)	Relative (%)
Gender	Male	116	54.2 %
	Female	93	43.5 %
	Non-binary/ Third gender	4	1.9 %
	Prefer not to say	1	0.5 %
Age	18–25	100	46.7 %
	26–33	83	38.8 %
	34+	31	14.5 %
Occupation	Working full time	61	28.5 %
	Working part time	9	4.2 %
	Student	135	63.1 %
	I have no work at the moment	8	3.7 %
	Volunteer work	1	0.5 %
Education level	High school	10	4.7 %
	Bachelor	52	24.3 %
	Master	129	60.3 %
	PhD	23	10.7 %
Income level	Less than 500€	56	26.2 %
	501–1000€	45	21.0 %
	1001–1500€	20	9.3 %
	1501–2000€	15	7.0 %
	2001–2500€	10	4.7 %
	2501–3000€	11	5.1 %
	3001–3500€	8	3.7 %
	More than 3500€	16	7.5 %
	I prefer not to answer this	33	15.4 %
Total		214	100 %
Missing value*		1	0.5 %

*A set of sociodemographic characteristics has not been filled by a respondent.

situations. Another recent study explores the attractiveness of incentives on the choice for difficult-to-staff and remote schools (Burke & Buchanan, 2022). A benefit of these types of models is that they allow us to explore the direct and indirect effects of a latent construct. Finally, the latent variable varies across product attributes instead of person level characteristics, as also mentioned by Burke et al. (2020).

In this study, unlike traditional conceptualisations of trust as a person-level characteristic, the latent variable is conceptualised as a situation-specific variable. In addition, it is assumed that trust varies depending on the attributes of the crowdshipping alternative. In line with this conceptualisation, we measured the level of trust for each choice situation instead of using a multiple-item scale at the person level. In the model design, two causal paths are used in order to estimate the dependent variable, as shown in Fig. 3, where path c' shows the direct effect of the exogenous variable (independent variable, X) on the dependent variable (Y) and path a indicates the role of the mediating latent variable (M), namely trust. Finally, from the mediating variable, there is another path b showing the direct effect of the mediating latent variable on the dependent variable (Y).

Thanks to this analysis, mediation can be explored in independent, dependent, and mediating variable settings (Hayes & Preacher, 2014; MacKinnon et al., 2007). This analysis is preferred to quantify direct and indirect pathways where an independent variable transmits its effect on a dependent variable through a mediating variable (MacKinnon, 2012). The generic equations below are used for the mediation choice model (MacKinnon et al., 2007).

$$Y = i_1 + cX + \epsilon_1$$

$$Y = i_2 + c^{'}X + bM + \epsilon_2$$

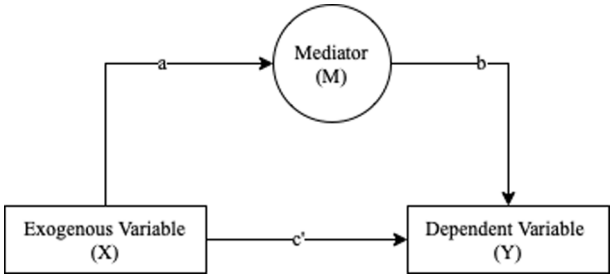

Fig. 3. Structure of the mediation model (Source: Adapted from Hayes & Preacher, 2014; MacKinnon et al., 2007).

$M = i_3 + aX + \epsilon_3$Where:
X = The independent variable.
Y = The dependent variable.
M = The mediator.
a = The coefficient showing the direct effect of the independent variable on the mediator.
b = The coefficient linking the direct effect of the mediator variable to the dependent variable.
c = The coefficient representing the total effect of the independent variable on the dependent variable.
c′ = The coefficient linking the direct effect of the independent variable on the dependent variable.
i_1, i_2, i_3 = Intercepts.
$\epsilon_1, \epsilon_2, \epsilon_3$ = Residual terms.

In the hybrid model, it is tested if the level of trust acts as a mediator between the choice situations and the utility of the crowdshipping. Moreover, background variables, namely, sociodemographic characteristics, are estimated as independent variables to test their effect on the utility of crowdshipping as well as the level of trust, as represented in the conceptual model (Fig. 1).

Our exogenous variables consist of six main attributes: delivery time, delivery cost, tracking and tracing options, insurance coverage, the possibility of damage, and the delivery company's reputation. The level of trust, which is the mediating latent variable, is assumed to be a dependent ordered level measurement and directly measured with a 5-point Likert scale in the choice experiment. This part of the model is investigated through an ordered logit regression model. In this way, it is possible to analyse how relevant attributes in the choice sets would impact the level of trust. To estimate this relation, the following equation is used.

$$Trust_j^* = C^{Trust} + \sum \beta_i^{Trust} X_{ij} + \varepsilon_{Trust} \tag{1}$$

$$Trust = \begin{cases} 0 if Trust_j^* \le \mu_{1,} \\ 1 if \mu_1 < Trust_j^* \le \mu_{2,} \\ 2 if \mu_2 < Trust_j^* \le \mu_{3,} \\ 3 if \mu_3 < Trust_j^* \le \mu_{4,} \\ 4 if \mu_4 < Trust_j^* \le \mu_5 \end{cases}$$

where
$Trust_j^*$ = Level of trust for a crowdshipping choice situation j.
C^{Trust} = Regression constant.
β_i^{Trust} = Regression coefficient for attribute i on level of trust.
X_{ij} = Dummy coded attribute i (shown in Table 1) for crowdshipping choice situation j.
ε_{Trust} = Error term for trust Gumbel (i.i.d. EV type I).

Concerning the utility of crowdshipping (Y), the respondents are asked to make a choice if they would opt for the crowdshipping service or not. Thereby, the choice of the service is treated as a dichotomous dependent variable. This part of the model is measured with a binary logistic regression model. The function below is applied to estimate this part of the model.

$$Adopt_j^* = logit = ln\left(\frac{P_{Yes}}{P_{No}}\right) = C^{Trust} + \beta_{Trust}^{Adopt} * Trust_j + \sum \beta_i^{Trust} * X_{ij} + \varepsilon_{Trust} \tag{2}$$

where
$Adopt_j^*$ = Choice of the crowdshipping service for choice situation j.
P_{Yes} = Probability of opting for crowdshipping service.
P_{No} = Probability of rejecting crowdshipping service.
C^{Trust} = Regression constant.
β_{Trust}^{Adopt} = Regression coefficient for level of trust on the adoption of the crowdshipping.
$Trust_j$ = Level of trust for a crowdshipping choice situation j.
β_i^{Trust} = Regression coefficient for attribute i on level of trust.
X_{ij} = Dummy coded attributes i (shown in Table 1) for crowdshipping choice situation j
ε_{Trust} = Error term for trust Gumbel (i.i.d. EV type I).

The impact of sociodemographic characteristics is studied in order to improve the model and to test if the heterogeneity in preferences exists. Sociodemographic variables are introduced as interaction effects in the utility equation both for the trust and the choice of the service. This enables the authors to capture the effect of each sociodemographic characteristic which might vary in the attributes. To do this, interaction terms are defined similar to the approach in Tapia et al. (2021) and computed as follows:

$$\beta^*(1 + \beta_{interaction} * \delta) \tag{3}$$

In the equation, while β is the coefficient of the variable at hand, $\beta_{interaction}$ and δ are the interaction coefficient and the dummy variable for the interaction respectively.

The HCM was estimated using R studio-Apollo (Hess & Palma, 2019), which allows to model latent variable models and discrete

choice models.

4. Results

This section first presents the estimation outcomes. Next, we interpret the coefficients found and compare these results to existing literature, where appropriate.

4.1. Estimation outcomes

The model results in a final loglikelihood (LL) value of −2694.76 and AIC and BIC values are 5433.51 and 5553.42 respectively. In terms of goodness-of-fit, adjusted McFadden's rho-squared (ρ^2) is estimated 0.31. Normally, a value of 0.2–0.4 for ρ^2 represents a good fit (McFadden, 1978). Moreover, the bootstrap estimation has been conducted to draw inferences about the population by resampling. The results of the test did not lead to different coefficient values compared to the model estimations, which shows the accuracy of the sample estimates.

Based on the conceptual model represented in Fig. 1, the HCM is estimated, and results are shown in this section. Table 5 shows the direct effect of exogenous variables on crowdshipping service choice, as well as their effect on trust.

The result of the direct effect of trust on crowdshipping service adoption is statistically significant and the coefficient, with a value of 1.023, is fairly strong. Combined with the satisfactory model fit, this provides strong evidence for the role of trust in crowdshipping.

Regarding the calculation of indirect effects, the form of coefficient values can be estimated by multiplying the trust coefficient (1.023) and the direct effect of the corresponding variable on trust. However, the Sobel test, so-called Delta method gives an accurate calculation of the standard errors for such derived measures (MacKinnon, 2012; Cheung, 2009). Hence, we applied the Sobel test to derive standard errors of the indirect effect of the exogenous variables on the crowdshipping service adoption through trust, as shown in Table 6. Finally, the total effect is the sum of the direct and indirect effects.

In this part, only the indirect effects of the main crowdshipping attributes on the service choice are given. The reason for this is that sociodemographic characteristics are only found to be significant on the choice of crowdshipping. Concerning the effect of trust, no significant indirect effect on the background variables is found. Finally, the results show that only delivery time is not mediated by the level of trust, and trust has a mediating role for the rest of the attributes. We compare the detailed findings to the existing literature in the Discussion section that follows.

Table 5
Estimation results (direct and total effects).

		Direct effect on the service adoption		Direct effect on trust		Total effect on the service adoption	
	Reference level	Est.	p-value	Est.	p-value	Est.	p-value
Main attributes							
Delivery time (Same day delivery)	Next day delivery	0.266	0.028*	0.141	0.100	0.410	0.005*
Delivery cost	—	−0.338	0.000*	−0.095	0.000*	−0.435	0.000*
Tracking and tracing options (Real-time driver tracking)	Only main steps can be seen	−1.183	0.000*	0.408	0.000*	−0.766	0.000*
Delivery company's reputation (Four stars)	Two stars	0.199	0.207	1.548	0.000*	1.782	0.000*
Insurance coverage (Up to 1000€)	Up to 500€	0.251	0.030*	0.288	0.000*	0.545	0.000*
Possibility of damage (1 in 30 damaged delivery (3 %))	1 in 20 damaged delivery (5 %)	0.113	0.189	0.378	0.000*	0.499	0.000*
Socio-demographics							
Education level (Master/PhD)	Others	−0.651	0.003*				
Interaction effects							
Tracking-Occupation	Student	−1.013	0.011*				
Tracking-Education	Others	−1.082	0.000*				
Intercepts		−3.235	0.000*	1.365	0.000*		
Cut 1		−4.839	0.000*				
Cut 2		−1.686	0.000*				
Cut 3		1.022	0.000*				
Cut 4		3.966	0.000*				
Level of trust		1.023	0.000*				
Model fit							
LL (0)		−3960.45					
LL (final)		−2694.76					
Adj. McFadden's rho-squared (ρ^2)		0.31					
AIC		5433.51					
BIC		5553.42					
Number of individuals		215					
Number of choice sets		1720					

*Significance level on 95 % confidence interval (p less than 0.05). The coefficient values stand for unstandardised estimates.

4.2. Discussion

Table 5 and 6 present different outcomes for each attribute and sociodemographic variables. These can be compared to earlier findings in the literature, and they provide new interpretations of the role of trust in crowdshipping. We discuss these below.

The results show that *same day delivery* has a positive impact (0.266) on the crowdshipping service adoption, confirming the findings of earlier studies (Le & Ukkusuri, 2019a; Dayarian & Savelsbergh, 2020). However, the direct effect of the same attribute on trust is not statistically significant (0.100). This means that trust has no mediating effect on this attribute. These results are in line with the expectations due to the fact that providing shorter delivery times for on-demand delivery requests is essential in the delivery service choice. However, when taking trust into account, delivery time is not a factor affecting the perceived level of trust.

The direct effect of *delivery cost* on the crowdshipping service choice is statistically significant with the value of −0.338. This means that as the cost increases the possibility of opting for crowdshipping service decreases; hence, the negative relation of the cost can be seen as an expected outcome and is in line with the previous studies (Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019b). An interesting point is the direct effect of delivery cost on trust. The value of delivery cost is negatively correlated, meaning that when the cost of the delivery increases, the perceived level of trust decreases. This outcome can be linked to different perspectives of trust, in this case rational trust. According to Laeequddin et. al. (2010), a reduced expectation of reward can affect trust negatively. Another reason for the negative correlation could be that people think they are being overcharged and the service provider is not well-organised to provide low delivery costs. The direct effect of the cost on crowdshipping service choice and trust show that trust has a partially mediating effect on the delivery cost.

Surprisingly, the *tracking and tracing* feature of the crowdshipping service negatively correlates with service choice. This result conflicts with the literature where real-time tracking was so far reported to have a positive impact on service choice (Le & Ukkusuri, 2019b; Gatta et al., 2018). A plausible reason may be the detailed distinction in our model between 2 levels of availability of tracking and tracing. Possibly due to privacy concerns, a basic level of transparency could suffice, and higher levels are appreciated less. Concerning the direct effect of the same feature on trust, real-time tracking and tracing is statistically significant and has the value of 0.408. This result is in line with expectations since the mere existence of this service could install trust in the service. In the end, there is a partially mediating role of trust through the adoption of the service.

The delivery company's *reputation and possibility of damage* are not significant for the adoption of crowdshipping directly, but these attributes have a significant direct impact on trust. This means that when the crowdshipping service provider has a good reputation and provides a lower number of damaged deliveries, the user's trust would be positively impacted by the corresponding values (1.548 and 0.378, respectively). All in all, trust has a fully mediating effect on the service choice for the delivery company's reputation and the possibility of damage. Although in a narrow sense, the absence of a direct effect of these variables conflicts with previous research (Le & Ukkusuri, 2019b), it is consistent with the novel finding of a fully mediating role of trust in service adoption for these variables.

Next, the direct effect of *insurance coverage* on the service adoption is statistically significant. The reason could be that this feature positively affects service quality, hence, the choice of the service. Concerning the effect of trust, there is a positive correlation with the value of 0.288. This outcome is also interesting to investigate in detail since there is a partially mediating effect of trust. A likely explanation for this outcome might be that higher insurance coverage of the delivery enables individuals to trust the system and indirectly affects the choice of the crowdshipping service. Finally, the result shows that trust has a partially mediating effect on the service choice.

Overall, the significant direct effect of same day delivery, delivery cost, reputation, insurance coverage and possibility of damage is consistent with earlier studies which applied a reduced version of our model (Wicaksono et al., 2021; Le & Ukkusuri, 2019b; Le et al., 2019; Le & Ukkusuri, 2019a). However, this research provides evidence that, in addition, trust has a partially or fully mediating effect for these attributes, except delivery time, which constitutes a new finding to the crowdshipping literature.

In the experiment, five *sociodemographic characteristics* were asked: age, gender, education level, occupation and income level. To be able to test the heterogeneity in the choices, it is also necessary to test the effect of sociodemographic characteristics on the crowdshipping service adoption and trust. In Table 5, only the statistically significant results are represented. The results show that the direct effects of sociodemographic characteristics on trust are not statistically significant. Unlike the result of the study from Punel et al. (2018a), where the effect of the level of education was found to be not significant, the model findings show that the direct effect of education level on the service adoption is statistically significant, and decision to choose crowdshipping service is higher among the bachelor's and less educated people.

Table 6
Estimation results (indirect effects).

		Indirect effects on the service adoption	
	Reference level	Est.	p-value
Main attributes			
Delivery time (Same day delivery)	Next day delivery	0.144	0.102
Delivery cost	—	−0.097	0.000*
Tracking and tracing options (Real-time driver tracking)	Only main steps can be seen	0.417	0.000*
Delivery company's reputation (Four stars)	Two stars	1.582	0.000*
Insurance coverage (Up to 1000€)	Up to 500€	0.295	0.000*
Possibility of damage (1 in 30 damaged delivery (3 %))	1 in 20 damaged delivery (5 %)	0.386	0.000*

Moreover, *interaction effects* of main attributes and sociodemographic characteristics are also included in the model to investigate heterogeneity in preferences. Although there is no significant interaction effect associated to trust, the results show that there is an interaction effect between tracking and tracing and sociodemographic characteristics on the crowdshipping service choice. The findings show that students who are holding a bachelor's degree (at the most) are more inclined to choose crowdshipping even if there is no real-time tracking and tracing feature in the service. This result shows that even if there is no real-time tracking provided by the service, young people would opt for crowdshipping. The reason for this could be related to the privacy concerns of young individuals which is in line with the findings of the *tracking and tracing* feature of the crowdshipping.

Finally, the *intercept* is defined as the mean of the dependent variable if all the independent variables are set to zero. In the model, dummy coding is used, and the reference values are set to 0, which can also be seen in Table 1. To this arrangement, the intercept for the trust is 1.365 and it is in between the regression cut points 3 and 4, meaning that the level of trust towards crowdshipping adoption on the reference points is nearly trustful on the ordered rating scale. Additionally, the alternative specific constant for traditional delivery (ASC_{TR}) shows the choice probability of the crowdshipping alternative when all the independent variables are set to 0. As the value (-3.235) is statistically significant, it indicates that the preference towards crowdshipping is also systematically affected by unobserved attributes which are not considered in the scope of this research.

5. Conclusions

The adoption and application of an innovative service is significantly influenced by the trust that users have for a service. Hence, it is also of interest to identify factors that directly or indirectly affect the level of trust. In this study, various service attributes were explored in an HCM, answering the question to what extent the effects of these attributes are mediated by the perception that the delivery of the parcel is executed in a trustworthy manner. To do this, we conceptualised trust as a situation-specific latent variable and measured the level of trust for each choice situation in the experiment. The findings showed the importance of trust and to what extent it affects crowdshipping service adoption. By disentangling the direct and indirect effects of trust towards the service adoption, it became clear that trust has a partially and, for some features, fully mediating effect towards the crowdshipping service choice. The main contributions of this study are threefold. Firstly, this is the first time that trust is included in a choice model as a mediating latent variable in the crowdshipping domain. Although SP experiments are already applied to other studies, the concept of trust has not been included before. Secondly, there is no existing research using a direct measurement of trust in a crowdshipping context. Generally, studies measure trust with the help of trust-related person level indicators, whereas in in this paper, we observe trust in the survey and employ the features of crowdshipping service, to model their relation to trust and the adoption of the service. Thirdly, this study provides tangible evidence on the effect of trust and its associated features for the future development of such a service in The Netherlands.

The results of the estimations largely confirm earlier findings and enrich these with the specific role and influence of trust on the crowdshipping service choice. The main highlights are the following. Firstly, the model shows that trust has no mediating effect on the same-day delivery feature. This outcome is important to highlight since the direct effect of the same feature positively affects the service choice. Secondly, the delivery company's reputation and the possibility of damage are fully mediated by trust, meaning that these features directly affect trust towards service adoption. This outcome is interesting since a strong reputation and lower damage risk increase the level of trust towards the service adoption. As the rating given in the experiment provides different levels of reputation strength, this could create different levels of trust towards crowdshipping. Thirdly, for the remainder of the attributes, trust has a partially mediating affect. Fourthly, our model shows that there is no mediating effect of trust on sociodemographic characteristics on the service choice, However, the propensity to choose a crowdshipping service is stronger among people with a lower education; interestingly, the lack of real-time tracking and tracing is less of a barrier for students than for other segments.

One of the main limitations of the research is the large participation of students and low-income segment interviewees in the sample. Without future research, this might limit the application of the model findings for business recommendations and policy making; therefore, an extended sample is recommended in future studies. Even though sociodemographic profiles are not a reflection of Dutch socioeconomic profile for each segment of the population, we note that (1) we were able to test heterogeneity in preferences through different sets of segments with a sufficient number of respondents and (2) significant estimates were obtained for education level and significant interaction effects were found for occupation and education level on the tracking and tracing feature. Additionally, the SP approach is known for not necessarily providing reliable population levels elasticity values and forecast models – this requires revealed preference data (Kroes & Sheldon, 1988). Moreover, we need to have particular care regarding the post-rationalisation effect that might occur. Due to the design of the choice experiment, respondents' level of trust rating might be affected by their choices, which might potentially lead to bias on the trust scale. Finally, dominant alternatives in choice situations might emerge, especially in SP experiments with unlabelled alternatives (Bliemer et al., 2017). In this research, two of the choice situations have dominance over traditional delivery option. Due to the fact that the existence of dominant alternatives provides insights on the level of trust towards crowdshipping, these choice situations are not excluded from the experiment. However, a replication of this study might help to further explore whether the dominance of crowdshipping over traditional delivery (one in each block) biases parameter estimates in the model.

For future research, more service alternatives to crowdshipping could be added in a choice experiment. To be able to investigate the impact of policy making, various aspects of trust such as institutional trust can be included. As regulation of crowdshipping services is in a far less advanced state as in incumbent logistics services, several regulatory policy issues could be studied. For instance, the level of trust in service could be affected by various standards for services, prices or insurance. Next, the proposed experimental design needs to be seen as one of the possible ways to measure trust for crowdshipping users. Other ways to measure trust include structural equation

modelling (SEM) (see, for example, Shao & Yin, 2019; Shao et al., 2020; Upadhyay et al., 2021) or traditional HCM (see, for example Jin et al., 2020). Even though our research is unique in terms of measuring trust as a situation-specific variable, trust can also be treated as a person-level characteristics in a SEM or traditional HCM context. Hence, further research is needed exploring multiple item scale to measure trust. The current research takes only the user side of the service into account. To have a deeper understanding of the actors, the level of trust from the occasional carrier point of view needs to be studied since the carrier can also be asked to deliver dangerous/illegal or hazardous items. Therefore, considering the carrier's point of view would provide more detailed knowledge regarding the trust and the parties involved in crowdshipping. So far this supplier perspective on trust has not yet been considered in research.

From a practical point of view, various recommendations can be given to provide roadmaps for crowdshipping service providers. Firstly, our research showed that the reputation of the delivery company has the biggest impact on the level of trust towards the service choice. Even though flexible or outside service hours parcel delivery would be possible in crowdshipping, these advantages can only be effective if the company has a good reputation. Thereby, a crowdshipping service provider who is new in the market might have difficulty establishing a profitable demand without building a high service quality reputation. Secondly, distinguishing between market segments could be important as our findings also indicate significant heterogeneity in acceptance behaviour between user groups.

Declaration of Competing Interest

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

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Author statement.

The authors confirm contribution to the paper as follows: study conception and design: Cebeci, Tapia, Kroesen, Tavasszy; data collection: Cebeci; analysis and interpretation of results: Cebeci, Tapia, Kroesen, de Bok, Tavasszy; draft manuscript preparation: Cebeci, Tapia, Kroesen, de Bok, Tavasszy. All authors reviewed the results and approved the final version of the manuscript.

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