Ride acceptance behaviour of ride-sourcing drivers

Ashkrof, Peyman; Homem de Almeida Correia, Gonçalo; Cats, Oded; van Arem, Bart

DOI
10.1016/j.trc.2022.103783

Publication date
2022

Document Version
Final published version

Published in
Transportation Research Part C: Emerging Technologies

Transportation Research Part C 142 (2022) 103783

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Ride acceptance behaviour of ride-sourcing drivers

Peyman Ashkrof *, Gonçalo Homem de Almeida Correia, Oded Cats, Bart van Arem

Department of Transport and Planning, Delft University of Technology, Netherlands

A R T I C L E I N F O

Keywords:
Ride-sourcing
Ride-hailing
Transport network companies
Ride acceptance behaviour
Ride-sourcing drivers' behaviour
Shared mobility

A B S T R A C T

The performance of ride-sourcing services such as Uber and Lyft is determined by the collective choices of individual drivers who are not only chauffeurs but private fleet providers. In such a context, ride-sourcing drivers are free to decide whether to accept or decline ride requests assigned by the ride-hailing platform. Drivers' ride acceptance behaviour can significantly influence system performance in terms of riders' waiting time (associated with the level of service), drivers' occupation rate and idle time (related to drivers' income), and platform revenue and reputation. Hence, it is of great importance to identify the underlying determinants of the ride acceptance behaviour of drivers. To this end, we collected a unique dataset from ride-sourcing drivers working in the United States and the Netherlands through a cross-sectional stated preference experiment designed based upon disparate information conveyed to the respondents. Using a choice modelling approach, we estimated the effects of various existing and hypothetical attributes influencing the ride acceptance choice. Employment status, experience level with the platform, and working shift are found to be the key individual-specific determinants. Part-time and beginning drivers who work on midweek days (Monday-Thursday) have a higher tendency to accept ride offers. Results also reveal that pickup time, which is the travel time between the driver's location and the rider's waiting spot, has a negative impact on ride acceptance. Moreover, the findings suggest that a guaranteed tip (i.e., the minimum amount of tip that is indicated upfront by the prospective rider, a feature that is currently not available) and an additional income due to surge pricing are valued noticeably higher than trip fare. The provided insights can be used to develop customised matching and pricing strategies to improve system efficiency. Since the study has been conducted during the COVID-19 crisis, the potential implications of the pandemic on ride acceptance behaviour have been examined using an Integrated Choice and Latent Variable (ICLV) model. The results show that drivers with a higher sensitivity to the COVID-19 effects tend to have a lower acceptance rate.

1. Introduction

Recent technological innovations in the mobility sector have facilitated the emergence of new modes of transport with ride-sourcing. Offering door-to-door transport services, these two-sided ride-sourcing platforms match passengers requesting rides through a mobile app with semi-independent drivers who do not only serve as chauffeurs but also act as private fleet providers. Ride-sourcing drivers mention benefiting from a considerable degree of flexibility, freedom, and independence as the most indispensable

* Corresponding author at: Department of Transport and Planning, Delft University of Technology, Stevinweg 1, Delft, Netherlands.
E-mail addresses: P.ashkrof@tudelft.nl (P. Ashkrof), G.correia@tudelft.nl (G. Homem de Almeida Correia), O.cats@tudelft.nl (O. Cats), B.vanarem@tudelft.nl (B. van Arem).

https://doi.org/10.1016/j.trc.2022.103783
Received 25 May 2021; Received in revised form 8 April 2022; Accepted 29 June 2022
Available online 18 July 2022

determinants for them choosing to join the platform, in one of the most prevalent examples of the gig economy (Hall and Krueger, 2018; Ashkrof et al., 2020). Drivers can freely decide where and when to drive for the platform. These choice dimensions dynamically impact the supply–demand intensity and limit the control of the central platform over drivers. Moreover, once ride-sourcing drivers decide to drive and select their working shift and area, they receive ride requests and can choose whether to accept or decline them. Drivers' choice making has far-reaching consequences for the system performance. For instance, a delayed response due to the low acceptance rate of drivers increases the waiting time of a rider and thus yielding a lower level of service. No response to a ride request decreases rider satisfaction and may affect customer retention. In both cases, this can have a direct and indirect negative impact on drivers' earnings and the platform profit. Xu et al. (2018) report that approximately 40% of the ride-hailing requests of the Didi Chuxing platform (a ride-sourcing platform in China) were aborted and received no response from drivers on 23 January 2017 in Shanghai. According to the data published by Didi Chuxing in 2017, they report that the platform also faced a low acceptance rate in the other big cities in China, even during non-peak hours, which carried considerable implications for the system performance (e.g., higher waiting time for riders).

A successful match between demand and supply is the key objective in ride-sourcing operations to safeguard the mutual interests of the actors. The rider is transported from the specified pickup point to the desired location while drivers providing the service earn money, and the platform making the matching obtains a profit. Notwithstanding, while passengers aim to minimize the trip costs, waiting and travel time, drivers' objective is to maximize their earnings and minimize idle time. The platform itself strives mostly for profit maximization and satisfying its paying customers. Hence, the matching process is non-trivial due to the need to satisfy contradictory objectives and choices of the stakeholders. That is why various policies and matching strategies are adopted to keep the balance between agents' interests. In such a novel economy, special attention should be devoted to drivers as service suppliers who make the final decision on ride requests impacting the rider satisfaction as well as the platform reputation and revenue. Nonetheless, since the entry of the ride-sourcing business into the market, the relationship between platforms and drivers has been fragile. Judging by the worldwide strikes and lawsuits filed around the world, an increasing tension has recently been observed due to the dissatisfaction of drivers with their working conditions (Hamilton and Hernbroth, 2019). Such dissatisfaction may cause distrust (Rosenblat and Stark, 2015; Wentrup et al., 2019) that can influence drivers' choices, particularly ride acceptance behaviour. Therefore, a win–win efficient matching strategy considers the utilities and limitations of all the parties through the purposeful assignment of ride requests with the nearby drivers with the highest acceptance probability. To assess this probability, it is crucial to gain a better understanding of the supply-side behavioural dynamics under different circumstances.

Research devoted to the supply side has hitherto been primarily focused on operational dimensions such as pricing strategies (Nourinejad and Ramezani, 2019; Xue et al., 2021), relocation guidance (Zha et al., 2018), matching strategies (Chen et al., 2021; Ke et al., 2021), and estimated travel time (Wang et al., 2018). In most cases, it is assumed that the fleet is operated by either fully automated vehicles which are not currently and may not be soon in operation (SAE International, 2018) or perfectly compliant rational drivers, whereas the evidence suggests that drivers' multidimensional and autonomous decisions can significantly influence the system performance.

A growing body of literature in both journalistic and academic formats has attempted to qualitatively and quantitatively investigate the labour properties of digital on-demand mobility services. Analysing a sample of around 18,400 taxi drivers working in the United States, Wang and Smart (2020) argued that the hourly income of taxi drivers has declined since the introduction of Uber. Leng et al. (2016) concluded that monetary promotion increases drivers' acceptance rate and reduces their idle time using the 40-day trip data of 9000 ride-sourcing services collected in Beijing. Zuniga-Garcia et al. (2020) proposed a framework to measure ride-sourcing driver productivity (i.e., drivers' hourly earnings across two consecutive trips ahead) based on the spatial and temporal variation. They found out that the principal element in ride-sourcing driver productivity is trip distance. Based on the findings, short trips result in lower productivity even in high-demand areas. Through a nine-month qualitative study into the Uber driver working experiences, Rosenblat and Stark (2015) reported that Uber manages the labour force and gains a soft control over drivers using algorithmic labour logistics such as pricing and information dissemination strategies, which constantly interact with drivers and shape their behaviour.

Ride-sourcing platforms collect and utilize historical and real-time information of the demand and supply sides to match ride requests with available drivers. This information is processed and selectively shared with the platform drivers to keep the balance between match quality (the attractiveness of a match – for both riders and drivers) and match rate (the number of matches within a specific time interval) which can conflict (Romanyuk, 2016). Aiming for a high match rate compels drivers to accept less attractive requests which leads to low match quality. On the other hand, a low match rate increases the waiting time for passengers and thereby lowering their satisfaction and loyalty. Moreover, it reduces the occupation rate of drivers, which is affecting negatively drivers' income and may contribute to traffic congestion (Beojone and Geroliminis, 2021), as well as decreases the platform revenue and its control over the workforce. Therefore, maintaining this balance improves system efficiency and the two-sided user experience.

To find such balance, an in-depth understanding of the behaviour of individual agents is needed. Despite the extensive literature on various aspects of the demand side, the supply-side behaviour remains so far largely unknown. Conducting a focus group study with ride-sourcing drivers working in the Netherlands, Ashkrof et al. (2020) proposed a conceptual framework that characterises the relationship between tactical (working shift selection) and operational decisions (ride acceptance and relocations strategies) of drivers and the potentially related factors. They reported the distinctive behaviour between part-time and full-time drivers, as well as beginning and experienced drivers. In a closely related paper, Xu et al. (2018), found that ride requests with economic incentives such as surge pricing are more likely to be accepted by drivers. To the best of our knowledge, our research is the first study that attempts to comprehensively investigate the quantitative effects of various determinants on drivers' ride acceptance behaviour through undertaking a cross-sectional stated preference (SP) survey. The experimental design includes a wide range of attributes from the existing features that are currently known to drivers such as pickup time, surge pricing, rider rating, idle time and so forth to several hypothetical ones including traffic congestion, trip fare, and guaranteed tip. The findings can provide new insights for algorithm developers, platform providers, policymakers, and researchers working in this field. The focus of this original empirical study is on the unique data collected from Uber and Lyft drivers working in the US where the ride-sourcing platforms have emerged and thrived. Moreover, the target group is extended also to drivers working for Uber and ViaVan (a European shared on-demand transit service) in the Netherlands to tentatively examine the transferability of the results to the European context. Since the survey has been conducted during the pandemic crisis, we also examine the effects of related views and attitudes on drivers' ride acceptance choices.

The remainder of this paper is organised as follows: Section 2 explains the methodologies applied for the data collection and the data analysis processes. Section 3 focuses on the study results including the descriptive analysis, the exploratory factor analysis, and the choice modelling estimation. Lastly, the findings are discussed and the paper is concluded in Section 4.

2. Methodology

Due to the binary decision of accepting or declining a request, the choice modelling approach is applied to analyse the data at the disaggregated level and estimate the effects of the identified attributes. This method is based on the probabilistic choice theory that assumes that the decision-making process has a probabilistic nature (McFadden, 1974; Hensher et al., 2005; Bierlaire and Lurkin, 2020). Although humans are presumed to be deterministic utility maximizers, the full specifications of the utilities are unknown to the analyst. This causes stochasticity that is addressed by the so-called Random Utility Maximisation (RUM) approach capturing the unexplained variation using random variables. The utility function of alternative j is mathematically formulated as follows:

$$U_j = V_j + \varepsilon_j \quad (1)$$

Where V_j and ε_j, which are typically assumed to be two independent and additive contributors of the utility function, represent the systematic (deterministic) part and the error term (random parameter), respectively. The error component captures the unobserved effects and randomness in choices. This component is constructed based on distributional assumptions on the joint distribution of the error term vector . It is typically assumed that the random variables are independently and identically distributed (IID) under an EV1 (Extreme Value Type 1) distribution.

In this study, ride rejection is considered as the reference alternative. Thus, all the attributes are incorporated into the systematic utility of the ride acceptance alternative, denoted by V_a which is assumed to be a linear association of the observed variables presented in Eq. (2):

$$V_a = \sum_{k=1}^{K} \beta_k . x_k + \sum_{m=1}^{M} \beta_m . x_m \quad (2)$$

The first term includes the variables x_k that are included in the SP choice sets such as drivers' spatiotemporal status, passenger characteristics, and ride attributes. The second component is associated with the individual-specific attributes x_m such as socio-demographic characteristics of the drivers. β_k and β_m represent the marginal impacts of the choice set attributes and individual-specific factors, respectively.

Given that the attitudes of individuals cannot be directly observed, a set of measurable variables is defined to identify the attitudinal factors associated with the COVID-19 pandemic and include them in the utility function. The latent components are initially identified by conducting an Exploratory Factor Analysis (EFA). Next, the so-called Integrated Choice and Latent Variable (ICLV) model is used to integrate the fitted latent and explanatory variables (Ben-Akiva et al., 2002). The ICLV model consists of two modules including a choice model and a latent variable model. The latent variables are identified using the measurement equations in the latent variable model. In the choice model, utility is also a latent component that is obtained from respondents' choices. Moreover, the structural equations represent the cause and effect relationships and link the observed/latent variables to the latent variables. The structural and measurement models are formulated as follows:

Structural Model.

$$X_l^* = \Upsilon_{0l} + \sum_{r=1}^{R} \Upsilon_{lr} x_r + \eta_l, \eta \; N(0, \Sigma_\eta) \quad (3)$$

$$U = \sum_{r=1}^{R} \beta_r x_r + \sum_{l=1}^{L} \beta_l x_l^* + \varepsilon, \varepsilon \; N(0, 1) \quad (4)$$

Measurement Model.

$$I_i = \alpha_{0i} + \sum_{l=1}^{L} \alpha_{il} x_l^* + \upsilon_i, \upsilon \; N(0, \Sigma_\upsilon) \quad (5)$$

$$y = \begin{cases} 0 \; if \; U \leq 0 \\ 1 \; if \; U > 0 \end{cases} \quad (6)$$

Where index l refers to a latent variable, r to an explanatory variable, i to an indicator; x and x^* to a vector of explanatory and latent variables, respectively; γ, β, α to parameters to be estimated; $\eta, \varepsilon, \upsilon$ to respective error terms with mean 0 and variance Σ (1 for ε); and y

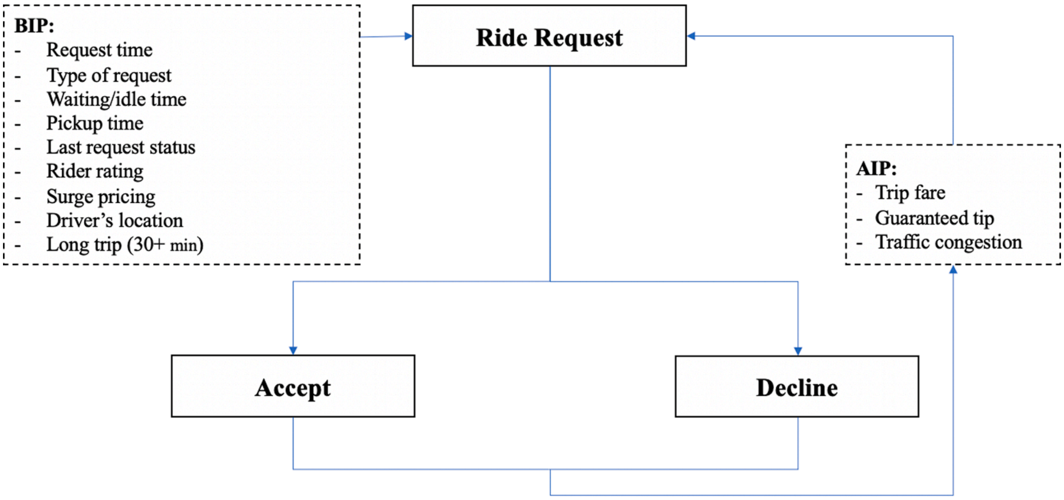

Fig. 1. Information provision setup in the SP choice experiment.

to a vector of choice indicator. It should be noted that the measurement equations are originally associated with continuous indicators and can also be applied to discrete measures using additional parameters accounting for the discrete levels. A simultaneous maximum likelihood estimation was employed to consistently and efficiently integrate discrete choice and latent models. The ICLV modelling framework is presented in Section 4.3.

The software package PandasBiogeme (Bierlaire, 2020) was employed to estimate the choice models using the Maximum Likelihood Estimation (MLE) approach. The objective of MLE is to find parameter estimates by maximising the likelihood function which includes the choice probabilities related to the alternatives chosen in the data.

3. Survey design and data collection

3.1. Choice experiment design

Central operators apply various information-sharing policies which yield a partial disclosure of information about ride requests and the characteristics of passengers and drivers. Such policies are adopted by ride-hailing platforms which leverage the inherent asymmetry in access to information, providing drivers with limited information when making work-related decisions. Specifically, ride acceptance behaviour is affected by such policies that restrain the thorough assessment of the ride quality (Ashkrof et al., 2020). In both the US and the Netherlands, the information provided to drivers is remarkably limited. Most notably, trip fare and final destination are not shown to drivers before ride acceptance. This so-called blind passenger acceptance is meant to avoid destination-based discrimination (Smart et al., 2015) but at the same time, it can decrease the income for drivers (Rosenblat and Stark, 2015). Despite such ambiguity, drivers can still evaluate the attractiveness of incoming requests based on the available information to maximize the utility of ride acceptance (Ashkrof et al., 2020).

In this study, two scenarios are defined based on the platform information-sharing policy: Baseline Information Provision (BIP) and Additional Information Provision (AIP). In both scenarios, drivers are requested to decide whether to accept or decline ride requests based on a finite set of information provisioned. The BIP scenario mimics the current system operations where a driver needs to decide on the ride request based upon their current spatiotemporal status, ride attributes, and passenger characteristics. Then, in the AIP scenario, some additional - currently unavailable - information such as monetary features about the same request, is added to the previously shown information giving drivers a second chance to make a choice. This enables investigating which and to what extent factors impact the decision of drivers in the existing system setting, as well as examining drivers' response to the information that is not currently available for them. Moreover, some studies including Morshed et al. (2021) argue that the COVID-19 pandemic has influenced the demand side which can potentially affect how drivers make choices such as accepting more/fewer rides, changing working shift or relocation strategies. That is why the attitudes of drivers towards the pandemic are also investigated in this research. To this end, a cross-sectional SP survey has been designed to collect the required data for further analysis.

Fig. 1 illustrates the information provision setup in the SP choice experiment. Drivers receive a ride request associated with certain characteristics and they then indicate their choice to accept or decline it. This is the BIP scenario that simulates what drivers presently experience and provides the following set of relevant information:

- Request time: The time when a ride request (ping) pops up.
- Type of request: Private or shared rides.
- Waiting/idle time: The duration between the last drop-off and the incoming ride.
- Pickup time: Travel time between driver's current location and rider's waiting location.

Table 1
Attributes, attribute levels and labels.

	Attributes	Attribute levels/labels
BIP	Request time	Pivoted around the working shift
	Type of request	Uber X, Uber Pool
	Waiting/idle time (min)	0, 5, 15
	Pickup time (min)	5, 10, 15, 20
	Last request status	Declined, Accepted
	Rider rating (stars)	3, 4, 5
	Surge price ($/€)	0, 1.5, 3
	Driver's location	City centre, Suburb
	Long trip (30+ min)	Yes, No
AIP	Estimated trip fare ($/€)	8, 16, 24
	Guaranteed tip ($/€)	0, 1.5, 3
	Delay due to traffic congestion (min)	0, 15, 30

Table 2
Segmentation of the request time based on the working shift of drivers.

	Morning (5–11)		Midday (11–15)		Afternoon (15–19)		Evening (19–23)		Night (23–5)	
	8 h	**4 h**	**8 h**	**4 h**	**8 h**	**4 h**	**8 h**	**4 h**	**8 h**	**4 h**
Request time	8	8	13	13	17	17	21	21	2	2
	12	10	17	15	21	19	1	23	6	4
	16	12	21	17	1	21	5	1	10	6

- Last request status: Whether the previous ride request has been declined or not.
- Rider rating: The average rating of the rider given by drivers.
- Surge pricing: A bonus for drivers offered by the platform when demand (locally) exceeds supply.
- Driver's location: The type of built environment where the driver is located.
- Long trip (30+ min): Whether the ride takes more than 30 min.

Once drivers make a decision, they are given more information, which is currently unavailable, about the same ride while the baseline information is still shown. The additional information in the AIP scenario includes:

- Trip fare: The gross amount of trip fare.
- Guaranteed tip: We hypothesize that passengers can indicate how much they are willing to tip when requesting a ride and this info can be shared with drivers when a ping pops up. As soon as the ride request is matched, the specified amount of tip is enforced in case the trip is successful.
- Traffic congestion: The estimated delay between the pickup point and the destination caused by traffic congestion.

In order to generate the experimental design of the SP survey, we identify the alternatives, attributes, and attribute levels and thereafter the type of design, model specifications, and experiment size are determined. This process is replicated with the updated input to ensure all the elements are in line with the research objectives. In the context of the choice dimension taken into account, Accept and Decline is the binary decision of drivers on ride requests which are considered as the alternatives and the information shown in each scenario are the attributes. Table 1 shows the attributes, attribute levels and labels derived by the current system operations, literature, interview with drivers, and posts on drivers' forums and then adjusted through a soft launch of the survey.

Except for request time, the levels and labels of all the variables are specified in the table. UberX and Uber Pool refer to the private and shared-ride services, respectively. Waiting/idle time ranging from 0 to 20 min in this survey indicates the duration of the driver's idle status since the last drop-off. The previous request that has been declined is assumed to play a role in ride acceptance. The average rating of the riders is always shown to the drivers. Travel time between the location of driver and rider varies between 5 and 20 min in this experiment. The location of the driver is presumed to be either in the city centre or suburb. Surge pricing is a value that is added to the trip fare when applicable. If a trip is estimated to be taking longer than 30 min, drivers are notified in advance. Estimated trip fare, guaranteed tip, and the delay due to traffic congestion that are not currently available in the app are shown in the AIP scenario.

Request time is assumed to be pivoted around the reported working shift of the respondents. This is because ride-sourcing drivers can freely select their working shift and area thanks to the flexible labour model. Given that demand and supply intensity significantly varies at different times of the day as well as days of the week, drivers may have various experiences depending on the selected working

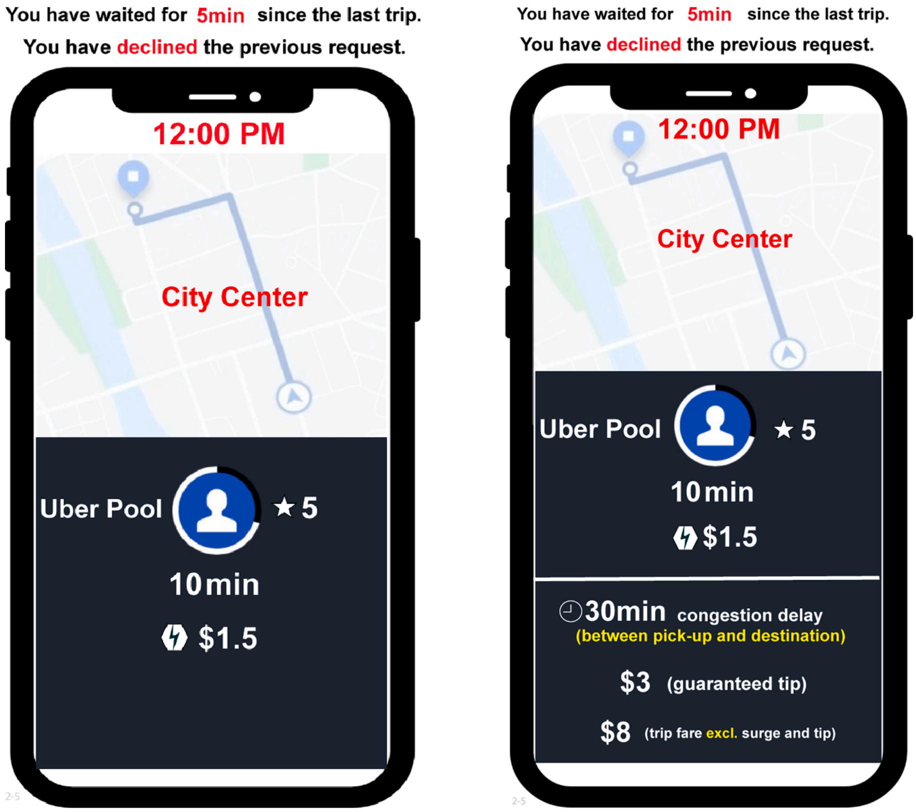

Fig. 2. Experiment interface in the BIP (left) and AIP (right) scenarios.

shift. The pivot design ensures that drivers can relate to the temporal characteristics of the experiment by closely resembling the experienced context to improve the response reliability. This also helps to compare the behaviour of individual drivers on different days of the week and various time slots such as peak or off-peak hours and the beginning or end of the shift.

To set up an individual-specific experiment, the segmentation procedure is applied. In this procedure, a set of designs is constructed to segment the population based upon multiple identified reference points (Rose et al., 2008). In this study, time of day is clustered into five categories: morning (5–11), midday (11–15), afternoon (15–19), evening (19–23), night (23–5) and also drivers are assumed to start their shift in one of these categories and work for either 4 hours a day (half a shift) or 8 hours a day (full shift). Therefore, the working shift in a day is divided into 10 groups as shown in Table 2. Each column indicates a separate working shift that corresponds to a group of drivers. Accordingly, a library of designs is generated for the request time that has three levels in each working shift. These levels represent the beginning, the middle, and the end of the shift, respectively. Ultimately, each respondent is systematically assigned to one of these pre-defined designs based on their reported working pattern. For example, a driver who starts his/her shift at 16:00 and works for 4 hours in a day is assigned to the Afternoon 4 h column, hence, the request time levels for this driver will be 17:00, 19:00, and 21:00.

Even though a full factorial design takes into account all the possible combinations of the attribute levels resulting in a more reliable estimation of the parameters, it does so at the cost of imposing a significant cognitive burden on respondents due to generating numerous choice sets. Therefore, a fractional factorial design is used to construct the design matrix. This method may lead to a bias given the loss of some information. Hence, an appropriate strategy should be adopted to minimize such error. To this end, the efficient design method is used to generate an efficient combination of the attribute levels by minimizing the possible standard errors of the parameter estimates. To this end, the efficient design method is used to generate an efficient combination of the attribute levels by minimizing the possible standard errors of the parameter estimates. These standard errors are estimated by calculating the roots of the diagonal of the asymptotic variance–covariance (AVC) matrix. Next, the so-called D-error which is the determinant of the AVC matrix is used to set up the most efficient design with the adequately low $D-error$ (Bliemer and Rose, 2010). Since no prior information about the parameters was available, $D_z-error$ (priors equal to zero) was initially used to construct the choice sets. A pilot of 50 responses was conducted to obtain the priors. Then, $D_p-error$ was applied to minimize the standard error of the estimated parameters and reconstruct the experiment design accordingly. However, due to the small sample size, the estimated priors were statistically insignificant which might result in a less efficient design (Walker et al., 2018). The following equations present the mathematical formulation of the $D-errors$:

$$D_z - error = \det(\Omega_1(X,0))^{\frac{1}{K}} \tag{7}$$

Table 3
Working and sociodemographic characteristics of the respondents.

Item	Categories	Sample Composition (%)		Code in the model
		US	**NL**	
Platform	Uber	46.4	77.6	NA
	Lyft (US) / ViaVan (NL)	12.8	1.7	
	Both	40.8	20.7	
Experience	Less than 12 months [Beginners]	5.4	10.1	Dummy Variable 1 = Beginners 0 = Other
	13–24 months	28.8	23.5	
	25–36 months	27.4	34.2	
	More than 36 months	38.4	32.2	
The most common working day	Monday	28.8	19.0	Dummy Variable 1 = Weekend/Friday 0 = Other
	Tuesday	12.2	8.6	
	Wednesday	9.0	3.4	
	Thursday	6.8	8.6	
	Friday	21.9	24.1	
	Saturday	16.5	34.5	
	Sunday	4.9	1.7	
Working Shift Start Time	Morning	73.1	67.2	NA
	Midday	14.6	17.2	
	Afternoon	7.5	8.6	
	Evening	3.6	6.8	
	Night	1.2	0.0	
Satisfaction level	Rating the system operations with 4.5/5 out of 5 stars [Fully satisfied]	49.8	17.2	Dummy Variable 1 = Fully satisfied 0 = Other
	Other	50.2	82.8	
Gender	Male	73.8	72.4	Dummy Variable 1 = Male 0 = Female
	Female	26.2	27.6	
Age	18–30	16.8	60.3	Continuous Variable
	31–40	66.5	20.7	
	Older than 50	16.7	19.0	
Employment status	Part-time	60.9	62.1	Dummy Variable 1 = Part-time 0 = Full-time
	Full-time	39.1	37.9	
Education level	Having a college degree or higher [Educated]	66.7	22.3	Dummy Variable 1 = Educated 0 = Other
	Other	33.3	77.7	

$$D_p - error = \det(\Omega_1(X,\beta))^{\frac{1}{K}} \tag{8}$$

Where Ω is the AVC matric, X refers to the choice set design, K denotes the number of parameters, and β is the best estimate of parameters derived from the soft launch.

Moreover, two scenarios need to be designed based on the identified framework. The BIP choice design comprises the existing attributes that are currently shown to drivers. In the AIP experimental design, both existing and hypothetical attributes are included in a way that the levels of the attributes shown in the BIP scenario remain unchanged enabling respondents to reassess the same ride request with more information. To implement this strategy, the model averaging method that allows multiple experiments to be evaluated at the same time is used. In this technique, the estimated AVC matrices are merged into one matrix that can be optimized for an efficiency measure such as $D-error$ (Rose and Bliemer, 2009). Therefore, both BIP and AIP models were designed simultaneously which led to a single design optimized for both models. Furthermore, a level constrained design is used to avoid unrealistic/unfeasible combinations of the attribute levels (e.g., a long ride with a fare of $8). Eventually, 24 choice sets in 4 blocks were constructed using the NGENE software package (ChoiceMetrics, 2018).

3.2. Questionnaire structure

An online questionnaire instrument is used to transform the design matrix into meaningful choice sets that are randomly shown to respondents. Fig. 2 displays a screenshot of the experiment interface which is carefully designed and checked through feedback from the pilot study to clearly simulate the ride request arrival process in both BIP (left) and AIP (right) scenarios.

Table 4
The indicators measuring the attitudes of drivers towards the COVID-19 pandemic.

No.	Statements	US	NL
		Mode	Mode
1	I believe that the COVID-19 pandemic has negatively impacted my job as a driver.	5	5
2	I accept more rides than before the pandemic.	4	4
3	To comply with social distancing measures, I don't like to have more than one passenger in my car.	4	3
4	I don't care about the COVID-19.	1	1
5	I have completely changed my working shift due to the pandemic.	4	3
6	If I end up in a busy area, I don't wait there because of the risk of getting infected.	4	3
7	I'm afraid of getting infected by my passengers.	4	4
8	I don't drive to surge or high demand areas because those areas are more crowded and the risk of virus transmission is higher.	4	3
9	There is no change in what I had been doing as a driver before the pandemic.	4	2
10	I take preventive measures such as wearing a face mask, disinfecting my car, etc. to protect myself and my passengers.	5	5
11	I receive many more rides than before the pandemic.	4	2

Furthermore, a set of screening questions is embedded at the beginning of the survey to ensure respondents are eligible to take part in this survey. The criteria are being older than 18 years old, Uber/Lyft drivers in the US or Uber/ViaVan drivers in the Netherlands (For the sake of consistency, Lyft and ViaVan drivers require to have some experience with driving for Uber), and also working at least once a week. After meeting the requirements, respondents are asked about their working pattern as input for getting assigned to the relevant design. The next part of the questionnaire is the choice experiment followed by some questions about their working pattern, employment status, experience, attitudes towards the COVID-19 pandemic and their socio-economic characteristics.

3.3. Data collection

As a highly specific target population, recruiting ride-sourcing drivers was a laborious task. A panel provider was employed to reach out to Uber and Lyft drivers in the US as well as Uber and ViaVan drivers working in the Netherlands. The data collection process took about three months from November 2020 to February 2021. Respondents were offered $50 (€50 in the Netherlands) to take part in this study. In total, 4367 respondents in the US and 1045 ones in the Netherlands were contacted. The respondents who failed one of the screening questions were screened out. Eventually, a sample of 752 and 68 drivers was drawn in the US and the Netherlands, respectively. After conducting a thorough data quality analysis, 576 responses in the US and 58 cases in the Netherlands were approved and the other observations were excluded from further analysis due to either short response time or lack of sufficient attention. Despite all the efforts, a larger Dutch sample within the designated time frame was not attained due to the relatively smaller number of active ride-sourcing drivers in the Netherlands. Therefore, the focus of this study is on the US sample and the Dutch data is mainly used for a brief tentative comparative analysis.

4. Results

4.1. Descriptive analysis

The working and sociodemographic characteristics of the respondents are reported in Table 3. Almost half of the drivers in the US exclusively drive for Uber while only 13% drive solely for Lyft. Multihoming strategy (i.e., working for several platforms simultaneously) is used by 41% of the respondents in the US. Uber is more dominant in the Dutch context where 77%, 2%, and 21% drive for Uber, ViaVan and both, respectively. In both countries, the majority of drivers have working experience of 13–36 months as ride-sourcing drivers. Regarding the working days, Monday in the US and Saturday in the Netherlands are the most popular days to work in our sample. About 70% of the respondents start their shift in the morning and work for either 8 or 4 hours. The drivers in the US sample are more satisfied than the Dutch counterparts with around half of them rating the system operations with 4.5/5 out of 5 stars.

Male drivers compose more than 70% of the sample. The average age of the drivers is 36 and 31 years old in the US and the Netherlands, respectively. Around 60% of the sample consists of the drivers who have other work-related sources of income, from here on labelled as part-time drivers. The data also demonstrates that the part-time drivers on average work fewer hours per week than full-time ones do. In our sample, the US drivers are more educated given that more than 65% of the drivers in the US have a college degree or higher, hereafter "educated", as opposed to the Dutch sample with roughly 20% educated drivers.

The experience, views and attitudes of drivers towards the COVID-19 pandemic are measured by a set of statements presented in Table 4. A 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to capture the opinions of the respondents. The mode (the most chosen response) for each indicator is calculated to measure the central tendency of the sample in each country. Most of the drivers stated that they were concerned about the pandemic and getting infected by passengers and that they also took preventive measures to protect themselves and their clients. Furthermore, they believed that their job had been negatively

Table 5
The results of the BIP models.

Parameters	BIP					
	Primary	P-value	Full	P-value	Panel	P-value
ASC_Accept	1.810	0.000	0.417	0.028	0.831	0.000
Pickup time [min]	−0.050	0.000	–	–	–	–
Pickup time * Full-time drivers [min]	–	–	−0.027	0.011	−0.033	0.009
Pickup time * Part-time drivers [min]	–	–	−0.072	0.000	−0.093	0.000
Idle time [min]	−0.017	0.007	−0.018	0.005	−0.023	0.003
Working time [1 = Peak hours]	−0.560	0.000	−0.368	0.001	−0.497	0.004
Working day [1 = Weekend/Friday]	−0.443	0.000	−0.334	0.000	−0.664	0.000
Driver's location * Shift segment [1 = City centre and Beginning of the shift]	−0.303	0.003	−0.284	0.007	−0.384	0.002
UberX*Long ride*Rating*Declined ride	0.091	0.001	0.102	0.000	0.120	0.000
Surge pricing [USD]	0.101	0.002	0.110	0.001	0.139	0.001
Employment status [1 = Part-time drivers]	–	–	1.110	0.000	1.420	0.000
Experience [1 = Beginners]	–	–	0.353	0.001	0.473	0.041
Gender [1 = Male]	–	–	0.421	0.000	0.765	0.000
Satisfaction level [1 = Fully satisfied]	–	–	0.607	0.000	0.851	0.000
Education [1 = Educated]	–	–	0.080	0.332	0.176	0.272
Sigma_ASC_Accept	–	–	–	–	1.43	0.000
Initial Log-Likelihood	−2395.517		−2395.517		-2395.517	
Final Log-Likelihood	−2031.504		−1959.983		-1823.965	
Rho-square	0.152		0.182		0.240	
AIC	4079.008		3947.966		3677.930	
BIC	4128.191		4034.036		3743.272	

affected by the pandemic. In some cases, the majority of drivers in the US and the Netherlands had different points of view. Most of the drivers working in the Netherlands neither agreed nor disagreed with changes in working shift and not driving to the busy areas while the US counterparts indicated their agreement with these statements. A contrasting viewpoint is observed between two groups of drivers about the number of incoming requests since the pandemic. The majority of the US drivers stated that they receive more requests compared to before the pandemic whereas the Dutch sampled drivers disagreed with that. Moreover, most of the drivers in the Netherlands believed that the pandemic has changed the way that they work as ride-sourcing drivers while the drivers working in the US had the opposite perception.

4.2. Choice model estimation and results

In total, six different models for both BIP and AIP scenarios are estimated for the US data. In each scenario, three types of models are estimated: Primary, Full, and Panel models. The primary model includes only the alternative-specific variables that are provided in the choice experiment. Driver's sociodemographic characteristics and working pattern are added to the ride-related attributes in the full model. This categorisation gives insights into the effects of various sets of variables depending on the application of interest. For instance, the primary model can be applied when no information about the drivers' characteristics and attitudes is available. Given that each driver completed six choice tasks in each experiment, the panel models are estimated using 10,000 random draws to account for the correlation between choices made by the same individual (panel effects). The random component (Sigma_ASC_ACCEPT) is highly significant which shows a strong consistency in an individual's choice of whether to accept rides when performing repeated. The values of the estimated parameters are larger in the panel models due to the relaxation of the IID error. Furthermore, the distinction between the AIP and BIP experiments is associated with the additional information shared with the drivers. It should be noted that a bottom-up modelling approach was applied to estimate various models with main and interaction effects. We present and discuss the results of the final models with the highest model fit. In addition, the primary model estimation with main-effects-only in both scenarios is reported in Appendix 1.

Table 5 summarises the results of the BIP model estimation including the parameter estimates, their significance value, and the model fitness. ASC_Accept represents the alternative specific constant incorporated in the utility function of the ride acceptance alternative. The positive significant parameter suggests an unobserved tendency towards ride acceptance. This implies the overall effects of the factors that have not been included in the experiment are in favour of the ride acceptance alternative.

As expected, pickup time which refers to the drive time from the driver's current location to the pickup point has a negative effect on ride acceptance. This is due to the fact that the pickup time increases ride disutility since drivers are not paid while driving without a passenger. Moreover, given that no information about the trip fare and the ride destination is available in this scenario, it is not guaranteed that the incurred cost is compensated by the ride. In the full model, an interaction between the pickup time and the employment status of drivers is found significant. Part-time drivers who have other sources of income are noticeably more sensitive (almost three times) to the pickup time than full-time drivers who are entirely financially reliant on the job. This observed reluctance to take a risk may presumably stem from the more constrained working shift which makes them more conscious of time. Moreover, part-time drivers may pick up passengers on their way to/from work which can explain their time sensitivity.

Another temporal component is idle time which has a marginal negative effect on ride acceptance. Drivers' expectations may rise in relation to the time between the last drop-off and the incoming request. This is because waiting for a request leads to being idle which

Table 6
The results of the AIP models.

Parameters	AIP					
	Primary	P-value	Full	P-value	Panel	P-value
ASC_Accept	1.560	0.000	0.388	0.116	0.618	0.052
Pickup time [min]	−0.053	0.000	–	–	–	–
Pickup time * Full-time drivers [min]	–	–	−0.021	0.092	−0.027	0.047
Pickup time * Part-time drivers [min]	–	–	−0.076	0.000	−0.091	0.000
Idle time [min]	−0.005	0.522	−0.005	0.518	−0.008	0.374
Working time [1 = Peak hours]	−0.057	0.629	0.027	0.825	−0.155	0.304
Working day [1 = Weekend/Friday]	−0.507	0.000	−0.412	0.000	−0.532	0.000
Driver's location * Shift segment [1 = City centre and Beginning of the shift]	−0.135	0.252	−0.137	0.253	−0.230	0.086
UberX*Long ride*Rating*Declined ride	0.086	0.011	0.087	0.011	0.105	0.003
Surge pricing [USD]	0.075	0.048	0.076	0.049	0.086	0.040
Trip fare [USD]	0.039	0.000	0.041	0.000	0.049	0.000
Guaranteed tip [USD]	0.090	0.014	–	–	–	–
Guaranteed tip * Full-time drivers [USD]	–	–	0.208	0.000	0.242	0.000
Guaranteed tip * Part-time drivers [USD]	–	–	0.021	0.647	0.012	0.694
Traffic congestion [min]	−0.011	0.002	−0.011	0.002	−0.015	0.001
Employment status [1 = Part-time drivers]	–	–	0.981	0.000	1.170	0.000
Experience [1 = Beginners]	–	–	0.271	0.023	0.284	0.14
Gender [1 = Male]	–	–	0.113	0.259	0.133	0.400
Satisfaction level [1 = Fully satisfied]	–	–	0.190	0.029	0.218	0.126
Education [1 = Educated]	–	–	0.461	0.000	0.607	0.000
Sigma_ASC_Accept	–	–	–	–	1.140	0.000
Initial Log-Likelihood	−2395.517		−2395.517		−2395.517	
Final Log-Likelihood	−1752.026		−1722.981		−1654.379	
Rho-square	0.269		0.281		0.310	
AIC	3526.053		3481.963		3346.757	
BIC	3593.679		3592.624		3429.523	

decreases the occupation rate and increases drivers' costs that need to be compensated. Consequently, this result suggests that drivers might prefer cherry-picking with increased elapsed waiting time.

The drivers mostly working during the evening peak hours (16:00–00:00), weekends and Fridays, when demand is relatively higher, are more prone to decline ride requests, everything else being equal. When the frequency of incoming requests rises, drivers become more selective given that a strategical wait may lead to receiving a more profitable ride. Similarly, there is a tendency towards ride rejection at the beginning of the shift and in the city centre. These effects may be due to the expectation of having more opportunities during the remainder of the shift.

The estimated parameter of UberX*Long ride*Rating*Declined ride suggests that there exists an interaction between request type (Uber X/Pool), long-distance trips (+30 min), rider rating, and the previously declined ride. The positive sign implies that the chance of ride acceptance is higher when a private ride (e.g. Uber X) taking more than 30 min is requested by a high-rated passenger while the previous request has been declined. The combination of these components indicates a favourable ride type, one that is perceived to be profitable (long ride), less complicated (private ride), trustworthy (high-rated rider), and pressure reliever (offered after a declined ride).

As expected, surge pricing - a spatial–temporal pricing strategy that aims at managing supply–demand intensity - increases the probability of ride acceptance. When a request is subject to surge pricing, drivers can earn more money which incentivises them to accept it. Surge pricing which is the only monetary variable in the BIP experiment can be used to calculate the value of pickup time by computing the ratio between Pickup time and Surge pricing. Based on the results of the primary model, the value of pickup time is 0.50 USD/min. This implies that a minute increase in the pickup time can be offset by an increase of 0.50 USD in the value of surge pricing. According to the full model, this value for the full-time drivers and part-time drivers is 0.25 USD/min and 0.65 USD/min, respectively.

Among the socioeconomic factors, employment status, satisfaction degree, gender, and experience level have the highest impact on the ride acceptance behaviour, in descending order. Part-time drivers are more likely than full-time drivers to accept ride requests. This may be because they consider this job as an extra income and also their available time is limited. The level of experience also plays an important role in accepting/declining ride requests. Beginners – drivers with one year or less experience – accept rides more often. As drivers learn about the system operational strategies over time, they are better positioned to make more informed decisions. Male drivers as well as highly satisfied drivers – drivers who rated the system operations with 4.5/5 stars - have a preference for accepting rides when limited information is provided. In such a blind decision-making scenario, they may have a higher tendency to trust the platform matching algorithm.

Table 6 presents the results of the AIP scenario in which more information is provided to drivers. The results show that some alternative-specific factors such as idle time and driver's location, as well as individual-specific attributes such as working time and gender are no longer significant. In contrast, several new alternative-specific factors including trip fare, guaranteed tip, and congestion level, as well as the individual-attribute education play an important role in explaining drivers' choices. Such changes possibly stem from the importance of monetary information related to all other attributes. As expected, trip fare and tip have a positive impact on ride acceptance whereas the level of congestion indicating the delay between the pickup point and the destination motivates drivers to

Table 7
Relative attribute importance based on the Primary model.

Attributes	Relative importance	
	BIP	**AIP**
Pickup Time	27.7%	28.0%
Idle time	9.4%	–
Working time	20.7%	–
Working day	16.4%	17.9%
Driver's location * Shift segment	11.2%	–
UberX*Long ride*Rating*Declined ride	3.4%	3.0%
Surge pricing	11.2%	7.9%
Trip Fare	–	22.0%
Guaranteed tip	–	9.5%
Traffic Congestion	–	11.6%

decline ride requests.

Although the education level was not found to be an influential factor in the restricted information-sharing policy, the results of the AIP models indicate that drivers that attained higher levels of education (i.e. have a college or a higher degree) are more likely to accept rides. Similar to the BIP experiment, beginning and fully satisfied drivers tend to accept more rides. Beginning drivers may lack sufficient knowledge of the system operations to evaluate the ride quality and fully satisfied drivers have a higher trust in the system performance. As observed in the BIP models, pickup time increases the disutility of accepting a ride. It should be noted that the pickup time is more negatively valued compared to the delay associated with traffic congestion. This is arguably because drivers are paid based on trip distance and travel time, so traffic congestion is possibly taken into account although not a desired experience. Driver's employment status still has significant interaction with pickup time. Part-time drivers are more sensitive to pickup time due to more constrained working hours. Additionally, the probability of accepting a ride by a part-time driver is substantially higher than for a full-time driver. As in the BIP scenario, the interaction between request type, long ride, rider rating, and the previous declined ride is still present and leads to higher ride acceptance.

Drivers' ride acceptance behaviour can be greatly affected if ride-sourcing platforms ask riders in advance about their minimum willingness to tip and then share this information with drivers when the request appears. Once the request is accepted by the driver, the specified amount of tip is automatically secured if the driver successfully picks up the rider. The results of the primary model suggest that drivers are roughly two times more sensitive to tip and surge price than to trip fare per monetary unit. In other words, one monetary unit of tip and surge is worth at least two monetary units of trip fare. This effect stems from tip and surge being considered as an add-on to drivers' income. Moreover, no platform service fee is deducted from the tip while trip fare and surge pricing are subject to the commission fee (which can be about 25%). It also turns out that there is a statistically significant effect for the interaction between the guaranteed tip and the employment status of drivers. Full-time drivers are more responsive to tip than their part-time counterparts.

In this experiment, the sensitivity to the pickup time and traffic congestion can be benchmarked against the three monetary variables. The values of pickup time based on the trip fare, surge pricing, and the guaranteed tip are 1.36 USD/min, 0.71 USD/min, and 0.59 USD/min, respectively. The trade-offs for the delay time due to traffic congestion are 0.28 USD/min, 0.15 USD/min, 0.12 USD/min respectively. This suggests that monetary promotions are relatively cheaper pricing strategies than the trip fare to compensate for the pickup time as well as the delay caused by a traffic jam.

To discover the relative importance of the attributes included in the choice experiments, a part-worth analysis is conducted. This decompositional method determines the utilities that each attribute and their levels add to the overall utility by calculating the part-worth utilities of each attribute level (i.e., the product between the attribute level and the estimated parameter). The relative attribute importance is obtained by calculating the ratio between the range of part-worth utilities of that attribute and the sum of ranges across all attributes. Table 7 reports the relative attribute importance based on the estimated parameters of the Primary model.

The results show that pickup time is the most important determinant in both experiments. In the AIP scenario where drivers are provided with additional (monetary) information, trip fare is the second dominant attribute. This is a plausible outcome given that this attribute determines the major portion of drivers' income. However, as stated before, drivers are more sensitive to guaranteed tip or surge pricing than trip fare per monetary unit. In other words, after pickup time, trip fare is the most crucial determinant for drivers to accept or decline a ride, but when it comes to the comparison between the monetary components, one monetary unit of guaranteed tip or surge is valued over one monetary unit in trip fare. To illustrate, a ride with a fare of, for instance, $20 and a guaranteed tip of $2 is preferred over a ride with a fare of $22 and no guaranteed tip, everything else being equal.

Due to the relatively small dataset collected in the Netherlands, we could not estimate a statistically sound separate model for the Dutch sample. Alternatively, the data from both countries were merged after unifying the attribute units, allowing the analysis of the combined sample and identifying the possible differences in drivers' behaviour by specifying dummy variables. Among the estimated models, the following differences between the two groups of drivers in the AIP-Primary model were found. Sensitivity to traffic congestion was much higher among the drivers working in the Netherlands, possibly because the level of congestion is lower in the Netherlands, according to the traffic index (Traffic Index by Country, 2021). Furthermore, the trip fare was regarded as nearly two times more important in the Netherlands than in the US. There may exist multiple underlying reasons including the currency, tipping culture (which is less customary in the Netherlands than in the US), income level, and other economic indices. However, these observations need to be further investigated with a larger sample size in the Netherlands in order to draw more conclusive results. The

Table 8
Results of the exploratory factor analysis.

Indicators	Components	
	1	**2**
I believe that the COVID-19 pandemic has negatively impacted my job as a driver.		0.659
I accept more rides than before the pandemic.	0.748	
There is no change in what I had been doing as a driver before the pandemic.	0.825	
I take preventive measures such as wearing a face mask, disinfecting my car, etc. to protect myself and my passengers.		0.720
I don't care about the COVID-19. [recoded]		0.696
I receive many more rides than before the pandemic.	0.848	
Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization. Total Variance: 58.02%		

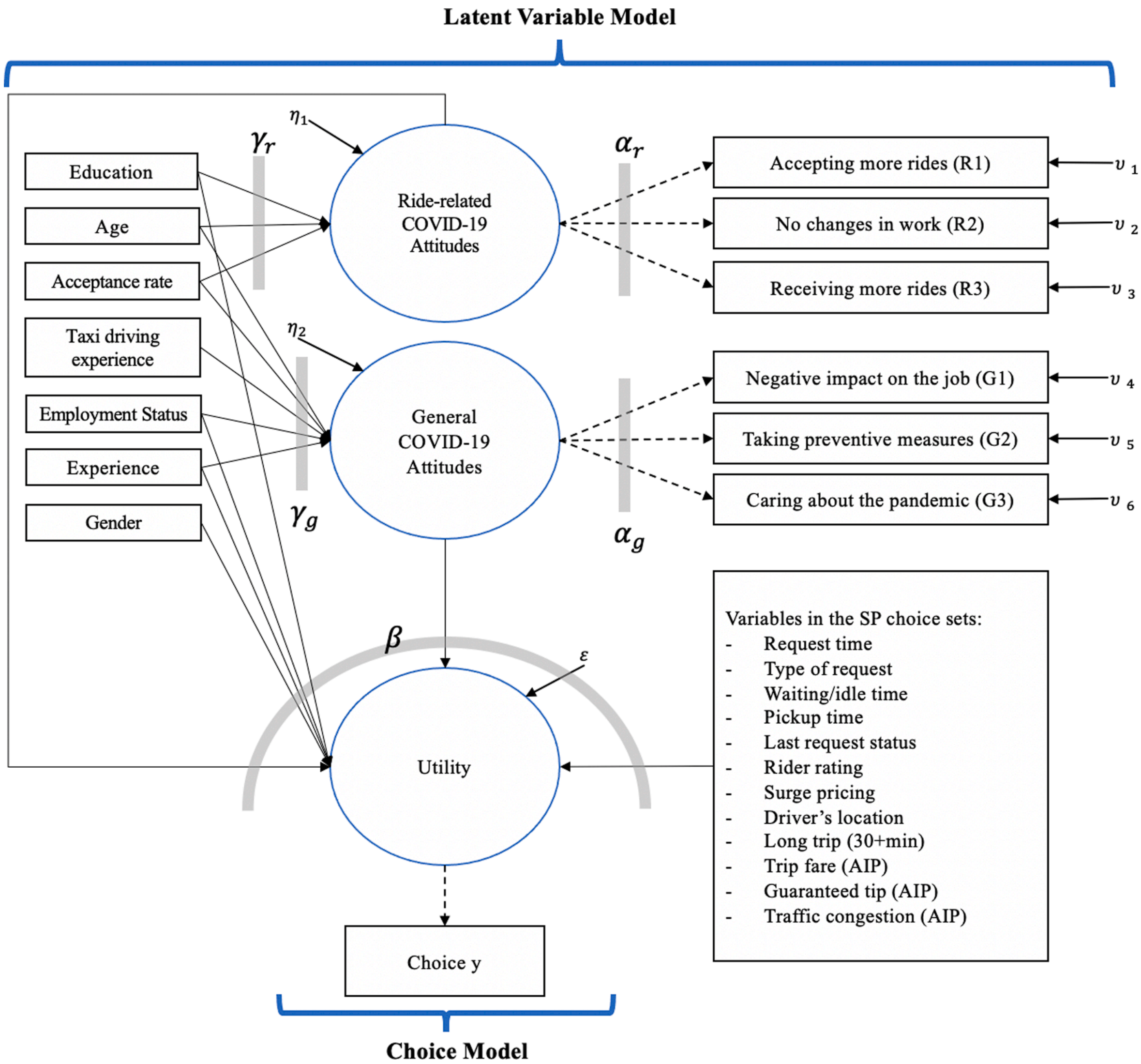

Fig. 3. Framework of the Integrated Choice and Latent Variables model.

results of the integrated model have been reported in Appendix 2.

4.3. The COVID-19 pandemic implications

To investigate the effect of the COVID-19 pandemic on ride acceptance behaviour, first an Exploratory Factor Analysis (EFA) was carried out to reduce the number of variables through merging the highly correlated observed measures (Henson and Roberts, 2006;

Table 9
Relevant results of the ICLV model.

Name	BIP		AIP	
	Value	**P-value**	**Value**	**P-value**
β _Ride-related COVID-19 attitudes	−0.579	0.000	−0.529	0.000
β _General COVID-19 attitudes	−0.418	0.000	−0.472	0.000
γ_r _Education [1 = Educated]	−0.510	0.000	−0.512	0.000
γ_r _Age	0.036	0.000	0.035	0.000
γ_r _Acceptance rate	0.639	0.000	0.625	0.000
γ_g _Age	−0.063	0.000	−0.062	0.000
γ_g _Acceptance rate	−1.100	0.000	−1.100	0.000
γ_g _Taxi driving experience [1 = Taxi driver]	−0.759	0.000	−0.697	0.000
γ_g _Employment status [1 = Part-time drivers]	0.336	0.000	0.331	0.000
γ_g _Experience [1 = Beginners]	−0.702	0.000	−0.695	0.000

Spearman, 1904). In order to ensure that the EFA is applicable, the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were performed (Kaiser, 1974). To keep a balance between parsimony and comprehensiveness, the Principal Component Analysis (PCA) model was applied (Norris and Lecavalier, 2010) and then several tests and techniques including the eigenvalues greater than 1, scree plot, and parallel analysis were deployed to ascertain the minimum number of components. Due to the superiority of the oblique rotation which takes into account the component interconnections (Flora et al., 2012; Gaskin and Happell, 2014; Price, 2017), the direct oblimin method was used to independently rotate the factor axes and situate them near the observed variables. Consequently, two components summarising the variation of the measures with the factor loading greater than 0.5 were identified using the SPSS software package (Table 8).

The first factor labelled as ride-related COVID-19 attitudes is mainly concerned with the perception of drivers on the impact of the COVID-19 outbreak on ride requests and their operations. The second component is primarily related to the drivers' attitudes towards general effects of the pandemic and is thus labelled as general COVID-19 attitudes. Following the identification of the fitted latent variables and the relevant indicators, an ICLV modelling framework is proposed for integrating the latent variables into the choice model (Fig. 3).

As shown in Fig. 3, the dashed arrows represent the relationship between the latent variables and the associated measures characterised by the measurement equations. The structural equations depicted by solid arrows represent the cause and effect relationships and connect the variables to the latent constructs. For each latent variable, one of the indicators is normalized for identification purposes (R3 and G3)[1]. To account for the panel structure, a random error component is included in the model specifications and the Monte Carlo simulation method with 10,000 draws is employed to estimate the joint model. Table 9 reports the most relevant results of the model estimation. The full model estimation is included in Appendix 3.

The results of the ICLV model show that the COVID-19 outbreak has negative effects on ride acceptance in both scenarios. The estimated parameter of ride-related COVID-19 attitudes is negative. This component is obtained from three attitudinal statements about accepting more rides that can be offset with receiving many more ride requests than before the pandemic and having the perception of no changes in work before and during the pandemic. These drivers have the impression of receiving notably more requests. While the evidence shows that the total number of requests has declined during the pandemic (Du and Rakha, 2021). However, some drivers have stopped working due to the more dramatic plunge in demand at the beginning of the pandemic, the high risk of getting infected, and the possibility of receiving unemployment benefits. This may have changed the ratio between supply and demand in the ride-hailing market so that competition between some groups of drivers has decreased and thus increasing their chance of receiving ride requests. Therefore, receiving more requests or at least having such an impression makes drivers more selective and causes more rejection. Moreover, the negative value of general COVID-19 attitudes suggests that the drivers who are prepared and protect their health by adopting preventive measures have a tendency to decline rides. This might be because of their concerns about the pandemic and the possible risks which echoes their impression of its negative impact on their job.

In the measurement model, all the indicators are significant and their signs are plausible. Based on the results of the structural model, ride acceptance rate and age are the socio-demographic variables that are relevant for both ride-related and general COVID-19 attitudes. Drivers with an acceptance rate of over 70% as well as older drivers are less concerned about the general effects of the COVID-19 pandemic but are positively linked to the ride-related COVID-19 attitudes. Moreover, educated drivers have negative ride-related COVID-19 attitudes. This attitude indirectly leads to a higher acceptance rate which reinforces the direct effect of education level on ride acceptance. Moreover, beginners and drivers with taxi driving experience are more likely to be less cautious about the pandemic and its negative effects. By definition, beginning drivers started their job during the outbreak. Thus, they are likely to be those less concerned about the pandemic amongst the pool of potential drivers with those more concerned less likely to have opted to start working as drivers during the pandemic. Conversely, part-time drivers are more sensitive to the general COVID-19 effects. This is also an intuitive result given that part-time drivers have another job that needs to be taken care of. The signs and interpretations of the other parameters estimated in the choice model are similar to those obtained in the full model.

[1] The factor loadings as well as the error term scales are normalized to 1 and the constants are set to 0.

As recommended by Vij and Walker (2016), the potential benefits of the ICLV model over the reduced choice model (i.e., a choice model without the latent components while all the observable variables are directly included in the model specifications) are discussed. We find out that the log-likelihood of the choice sub-model of the ICLV model calculated as a function of solely the observable variables (Vij and Walker, 2016), is marginally smaller than the loglikelihood of the reduced form mixed logit model in both scenarios (10 and 5 points difference in the BIP and the AIP scenarios, respectively). This implies that the ICLV model does not result in an improvement in goodness-of-fit compared to the reduced form mixed logit model. Nevertheless, some variables (e.g., Age and Acceptance rate) that are significant in the ICLV model are found to be insignificant in the choice model without latent variables. These variables are however incorporated into the structural component of the ICLV model where they are linked with the latent variables. For instance, Age and Acceptance rate that are connected to both latent variables have inverse relationships with the ride-related COVID-19 attitudes and the negative effect on general COVID-19 attitudes. Therefore, the ICLV model does help identify these links and decompose the indirect effects of these variables on ride acceptance behaviour in the context of the COVID-19 pandemic.

5. Discussion and conclusions

This research unravels the ride acceptance behaviour of ride-sourcing drivers through a stated preference experiment performed in the United States and the Netherlands. To the best of our knowledge, this is the first study attempting to comprehensively estimate the determinants of ride-sourcing drivers' ride acceptance behaviour. To this end, a set of potential attributes are identified based on the current system operations, driver-side app, existing literature, interview with drivers, and posts on drivers' forums. Then, two information-sharing policies are defined: Baseline Information Provision (BIP) and Additional Information Provision (AIP). The former scenario solely includes the variables currently shown to drivers in the most commonly used system setting, while additional information is provided in the subsequent phase of the experiment. In total, 576 and 56 qualified responses were collected in the US and the Netherlands, respectively. Subsequently, a choice modelling approach is applied to analyse the data. The focus of this study is on the US data due to the relatively small sample size in the Netherlands.

The monetary variables included in this study are surge pricing, trip fare, and guaranteed tip (i.e., the minimum amount of tip that is indicated upfront by the prospective rider). Surge pricing included in the BIP experiment is the only monetary attribute that is shared with drivers in the current system setting of the ride-sourcing platforms operating in the target area whereas trip fare and guaranteed tip are incorporated in the AIP scenario. Results reveal that guaranteed tip is the most highly valued monetary factor, especially for full-time drivers who are more financially dependent on the ride-sourcing platforms, followed closely by surge pricing. From the drivers' perspective, one monetary unit of tip or surge pricing as added income is considered about two times worthier than one monetary unit of trip fare.

In general, tipping is a pro-social consumer behaviour that is considered as an economically irrational action of customers and typically targets the low-income service providers (Azar, 2003; Elliott et al., 2018). Such a social norm has a profound economic impact on the US service industry (Shierholdz et al., 2017). In the US taxi industry in 2012, tipping comprised around 18% of the annual taxi revenue which is equal to $445 million (Bloomberg and Yassky, 2014). Currently, Uber riders can tip after they are dropped off. Analysing 40 million observations of Uber tipping behaviour in 2017, Chandar et al. (2019) concluded that more than 15% of the trips are tipped although tips are given privately (no consequences for rider rating) and the chance of having a match with the same driver is fairly low. They also found out that the average amount of tip is approximately $0.5 per trip and for those rides that have been tipped, more than $3 is tipped which is about 26% of the trip fare. In this study, we have introduced a new form of tipping that is determined in advance. When the ride is matched, the specified amount of tip must be paid and naturally, the passenger can tip more to reward the service if satisfying.

This feature can be used when a rider highly disvalues waiting time (e.g., being in a hurry) and intends to persuade nearby drivers to quickly accept the ride. It is effectively a self-determined discriminatory pricing scheme that allows riders to signal their willingness to pay and thereby potentially influence the level of service received. This is in line with the study conducted by Flath (2012) which suggests that passengers with a strong aversion to waiting would tip taxi drivers to reduce the time needed to find a taxi. As opposed to trip fare and surge pricing, tipping is not directly imposed on riders by the platform which makes it less unfavourable from the rider's perspective. The results of this study suggest that such a feature can significantly impact drivers' ride acceptance behaviour. This can also be part of the platform pricing strategy through developing an algorithm that optimally calculates the trip fare and surge pricing based on the guaranteed tip determined by riders. This may lead to a higher acceptance rate and level of service which is beneficial for riders, drivers, and the platform.

Surge pricing is a spatial–temporal pricing strategy that is introduced to address an imbalanced supply–demand relation. However, surge pricing is one of the most controversial topics in the ride-sourcing literature given its enormous implications for all stakeholders involved. On one hand, it is argued that surge pricing is a near-optimal solution that decreases match failure as well as system inefficiency through suppressing the excessive demand and also increases the platform profit (Cachon et al., 2017; Nourinejad and Ramezani, 2019). Using machine learning techniques, Battifarano et al. (2019) propose that surge pricing can generate more profit if the value is predicted and disseminated to both riders and drivers in advance. On the other hand, surge pricing may lead to strategic waiting for both riders who seek normal price and drivers looking for higher prices which results in inefficient performance due to forward-looking behaviour (Ashkrof et al., 2020; Chen and Hu, 2020; Zhong et al., 2020). The results of this study indicate that surge pricing is an important determinant of ride acceptance behaviour. This is in line with the findings of Chen and Sheldo (2015). They found that drivers work longer and flexibly adjust their working shift when surge pricing is present even if they have already hit their daily target. Based on the findings of this research, surge pricing is the second most important monetary attribute that can strongly incentivise drivers to accept rides. The value of pickup time for surge pricing is estimated to be 0.5–0.71 USD/min. This has important consequences for determining the expected response of drivers to the introduction of surge pricing as a function of their travel time from the surge location and the surge price level. Unlike the guaranteed tip, no difference in perspectives of part-time and full-time drivers concerning surge pricing is found.

Nevertheless, employment status is a crucial attribute influencing the choice of drivers. Part-time drivers, who have other sources of income, show a strong preference for accepting ride offers compared to their full-time counterparts. This might be because part-time drivers supplement their revenue from other jobs and also have limited available time restricting their degrees of freedom. Hence, the opportunity costs of part-time drivers are potentially higher which leads to a higher acceptance rate (Baron, 2018).

Furthermore, the experience level of drivers with the ride-sourcing platforms and their operational strategies has been identified as a determinant that influences their choices in various aspects (Miranda et al., 2008; Rosenblat and Stark, 2015; Chu et al., 2018; Noulas et al., 2019; Wang and Yang, 2019). Based on the findings of this study, beginning drivers who have one year or less of experience with ride-hailing tend to accept more rides. Lack of sufficient experience and knowledge to evaluate the characteristics of ride requests and having higher trust in the system performance might be the underlying reasons for this tendency (Ashkrof et al., 2020). In both BIP and AIP experiments, pickup time, especially for part-time drivers, has a negative impact on ride acceptance due to the disutility of driving without a passenger, i.e. unpaid time. Therefore, in order to have a higher acceptance rate, a new matching algorithm can be developed that can calculate the response likelihood of nearby drivers and then offer the request to the driver with the highest probability of acceptance. For instance, less attractive requests can be matched with part-time beginning drivers. The introduction of such measures should consider their potential acceptance amongst drivers.

The COVID-19 crisis has hit many sectors including transportation and specifically ride-sourcing system as a form of shared mobility. Recent studies highlight the immediate and long-term effects of the pandemic on user's behaviour due to hygienic considerations and the financial consequences of the outbreak (Serafimova, 2020; Morshed et al., 2021). This may also apply to the supply side where drivers need to adopt hygienic and preventive measures such as using barriers between passengers and driver, equipping the car with disinfectant, and so forth. The findings of the ICLV model suggest that drivers with a higher sensitivity to the ride-related and the general COVID-19 effects tend to have a lower acceptance rate with the extent of which depending on their personal characteristics. For instance, beginners and full-time drivers are more likely to be less sensitive to the COVID-19 impacts on their job and particularly ride acceptance.

While the small sample collected in the Netherlands does not allow for estimating a full-fledged model, it has been observed that drivers working in the Netherlands are more sensitive to the trip fare as well as traffic congestion. These findings should be further investigated with a larger sample size from the Netherlands and possibly from other European countries. Another limitation of this research refers to the inherently typical bias of stated preference surveys in which respondents face a limited number of attribute levels and may not accurately grasp the choice experiments, especially the AIP scenario that includes several hypothetical new components. It can be insightful to validate the findings of this study through analysing a set of revealed preferences data concerning drivers' behaviour in ride-sourcing environments or field observation of drivers if possible. Moreover, the insights gained in this study can be integrated into ride-hailing analysis models (Kucharski and Cats, 2020) and used to assess the possible effects of driver's ride acceptance behaviour based on various information-sharing policies on the ride-sourcing system performance, including efficiency, level-of-service and profitability. Future research may investigate other aspects of ride-sourcing drivers' decisions such as registration to the platform at the strategic level, selecting working shift at the tactical level, and relocation strategies at the operational level.

CRediT authorship contribution statement

Peyman Ashkrof: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Gonçalo Homem de Almeida Correia:** Conceptualization, Project administration, Supervision, Writing – review & editing. **Oded Cats:** Funding acquisition, Conceptualization, Project administration, Resources, Supervision, Writing – review & editing. **Bart van Arem:** Conceptualization, Supervision, Writing – review & editing.

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.

Acknowledgements

This research was supported by the CriticalMaaS project (grant number 804469), which is financed by the European Research Council and the Amsterdam Institute for Advanced Metropolitan Solutions.

Appendix

See Table A1-A3.

Table A1
Primary model estimation with main-effects-only.

Name	BIP			AIP		
	Value	**T-value**	**P-value**	**Value**	**T-value**	**P-value**
ASC_Accept	1.620	6.810	0.000	1.340	4.820	0.000
Pickup time [min]	−0.044	−5.890	0.000	−0.050	−5.600	0.000
Idle time [min]	−0.020	−3.060	0.002	−0.005	−0.561	0.575
Working time [1 = Peak hours]	−0.570	−5.490	0.000	−0.067	−0.557	0.577
Working day [1 = Weekend/Friday]	−0.443	−5.700	0.000	−0.511	−5.970	0.000
Shift segment [1 = At the beginning of the shift]	−0.208	−2.520	0.012	−0.115	−1.230	0.217
Driver's location [1 = City centre]	−0.115	−1.490	0.137	−0.041	−0.923	0.356
Last request status [1 = Declined]	0.150	1.850	0.065	−0.022	−0.242	0.809
Long trip [1 = 30 + min]	0.114	1.290	0.197	0.188	1.830	0.067
Rider rating [star]	0.030	0.581	0.561	0.060	1.040	0.296
Type of request [1 = UberX]	0.108	1.270	0.204	0.090	0.867	0.386
Surge pricing [USD]	0.090	2.580	0.010	0.049	1.120	0.262
Trip fare [USD]	–	–	–	0.038	4.250	0.000
Guaranteed tip [USD]	–	–	–	0.068	1.890	0.059
Traffic congestion [min]	–	–	–	−0.010	−2.700	0.007
Initial Log-Likelihood		−2395.517			−2395.517	
Final Log-Likelihood		−2031.219			−1751.637	
Rho-square		0.152			0.269	
AIC		4086.438			3533.274	
BIC		4160.212			3625.492	

Table A2
Results of the integrated Dutch-US model for the AIP scenario.

Name	Value	T-value	P-value
ASC_Accept	1.180	8.040	0.000
Pickup time [min]	−0.049	−6.110	0.000
Idle time [min]	−0.001	−0.106	0.916
Driver's location * Shift segment [1 = City centre and Beginning of the shift]	−0.135	−1.400	0.161
UberX*Long ride*Rating*Declined ride	0.009	0.896	0.370
Surge pricing [USD]	0.063	1.810	0.070
Trip fare_NL [USD]	0.074	5.260	0.000
Trip fare_US [USD]	0.045	5.650	0.000
Guaranteed tip [USD]	0.060	1.780	0.075
Traffic congestion_NL [min]	−0.079	−6.840	0.000
Traffic congestion_US [min]	−0.008	−2.240	0.025
Initial Log-Likelihood		−2636.732	
Final Log-Likelihood		−1956.091	
Rho-Square		0.258	
AIC		3934.181	
BIC		4002.863	

NL and US refer to the Netherlands and the US, respectively.

Table A3
Full estimation of the ICLV model.

Name	BIP		AIP	
	Value	**P-value**	**Value**	**P-value**
ASC_Accept	−0.351	0.084	−0.475	0.069
β _Ride-related COVID-19 attitudes	−0.579	0.000	−0.529	0.000
β _General COVID-19 attitudes	−0.418	0.000	−0.472	0.000
β _Pickup time*Full-time drivers [min]	−0.027	0.011	−0.021	0.102
β _Pickup time*Part-time drivers [min]	−0.072	0.000	−0.076	0.000
β _Idle time [min]	−0.018	0.004	−0.005	0.575
β _Working time [1 = Peak hours]	−0.347	0.001	0.046	0.711
β _Working day [1 = Weekend/Friday]	−0.247	0.005	−0.350	0.000
β _Uberx*Long ride*Rating*Declined ride	0.099	0.000	0.081	0.016
β _Driver's location*shift segment [1 = City centre and Beginning of the shift]	−0.295	0.005	−0.159	0.184
β _Surge pricing [USD]	0.108	0.001	0.068	0.077
β _Trip fare [USD]	–	–	0.040	0.000
β _Guaranteed tip*Full-time drivers [USD]	–	–	0.211	0.000
β _ Guaranteed tip *Part-time drivers [USD]	–	–	0.016	0.737
β _Traffic congestion [min]	–	–	−0.012	0.001
β _Employment status [1 = Part-time drivers]	1.230	0.000	1.150	0.000
β _Experience [1 = Beginners]	0.072	0.546	−0.029	0.824
β _Gender [1 = Male]	0.361	0.000	0.072	0.470
β _Satisfaction level [1 = Fully satisfied]	0.543	0.000	0.140	0.112
β _Education [1 = Educated]	−0.203	0.025	0.243	0.014
γ_{0r} _Ride-related COVID-19 attitudes	−1.740	0.000	−1.730	0.000
γ_r _ Education [1 = Educated]	−0.510	0.000	−0.512	0.000
γ_r _Age	0.036	0.000	0.035	0.000
γ_r _Acceptance rate	0.639	0.000	0.625	0.000
η_1^* _Ride-related COVID-19 attitudes	0.900	0.000	0.895	0.000
α_{0r} _Accepting more rides	−0.230	0.000	−0.228	0.000
α_r _Accepting more rides	0.827	0.000	0.829	0.000
υ_1^* _Accepting more rides	1.270	0.000	1.260	0.000
α_{0r} _No changes in work	0.035	0.253	0.036	0.236
α_r _No changes in work	0.930	0.000	0.932	0.000
υ_2^* _No changes in work	1.100	0.000	1.100	0.000
γ_{0g} _General COVID-19 attitudes	1.510	0.000	1.460	0.000
γ_g _Age	−0.063	0.000	−0.062	0.000
γ_g _Acceptance rate	−1.100	0.000	−1.100	0.000
γ_g _Taxi driving experience [1 = Taxi driver]	−0.759	0.000	−0.697	0.000
γ_g _ Employment status [1 = Part-time drivers]	0.336	0.000	0.331	0.000
γ_g _ Experience [1 = Beginners]	−0.702	0.000	−0.695	0.000
η_2^* _General COVID-19 attitudes	−1.530	0.000	−1.520	0.000
α_{0g} _Negative impact	−1.250	0.000	−1.250	0.000
α_g _Negative impact	0.258	0.000	0.258	0.000
υ_4^* _Negative impact	1.440	0.000	1.430	0.000
α_{0g} _Taking preventive measures	−1.210	0.000	−1.200	0.000
α_g _Taking preventive measures	0.302	0.000	0.304	0.000
υ_5^* _Taking preventive measures	1.050	0.000	1.050	0.000
delta_1*	0.564	0.000	0.561	0.000
delta_2*	1.300	0.000	1.290	0.000
ec_sigma*	0.823	0.000	0.820	0.000
Initial Log-Likelihood	−44567.850		-44567.850	
Final Log-Likelihood	−28734.390		-28497.320	
Rho-Square	0.355		0.361	
AIC	57554.780		57088.630	
BIC	57819.130		57377.580	

η^*, υ^* are the scale of the error terms of the structural and measurement equations.
δ_1 and δ_2 are two positive parameters used to account for the 5-point Likert scale of the measures.
ec_sigma is an error component capturing the panel effects.

References

Ashkrof, P., Correia, G.H. de A., Cats, O., van Arem, B., 2020. Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis. Res. Transp. Bus. Manag. 37, 100516. https://doi.org/10.1016/j.rtbm.2020.100516.

Azar, O.H., 2003. The implications of tipping for economics and management. Int. J. Soc. Econ. 30, 1084–1094. https://doi.org/10.1108/03068290310492878.

Baron, D.P., 2018. Disruptive Entrepreneurship and Dual Purpose Strategies: The Case of Uber. Strateg. Sci. 3, 439–462. https://doi.org/10.1287/stsc.2018.0059.

Battifarano, M., Qian, Z.(Sean), 2019. Predicting real-time surge pricing of ride-sourcing companies. Transp. Res. Part C Emerg. Technol. 107, 444–462. https://doi.org/10.1016/j.trc.2019.08.019.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of Choice and Latent Variable Models. In Perpetual Motion. https://doi.org/10.1016/b978-008044044-6/50022-x.

Beojone, C.V., Geroliminis, N., 2021. On the inefficiency of ride-sourcing services towards urban congestion. Transp. Res. Part C Emerg. Technol. 124, 102890 https://doi.org/10.1016/j.trc.2020.102890.

Bierlaire, M., 2020. A Short Introduction to PandasBiogeme. Ec. Polytech. Fed. Lausanne 13–43.

Bierlaire, M., Lurkin, V., 2020. Introduction to choice models [WWW Document]. URL https://www.edx.org/course/introduction-to-discrete-choice-models.

Bliemer, M.C.J., Rose, J.M., 2010. Construction of experimental designs for mixed logit models allowing for correlation across choice observations. Transp. Res. Part B Methodol. https://doi.org/10.1016/j.trb.2009.12.004.

Bloomberg, M.R., Yassky, D., 2014. 2014 Taxicab Factbook. Taxicab Factb. 1–13.

Cachon, G.P., Daniels, K.M., Lobel, R., 2017. The role of surge pricing on a service platform with self-scheduling capacity. Manuf. Serv. Oper. Manag. 19, 368–384. https://doi.org/10.1287/msom.2017.0618.

Chandar, B., Gneezy, U., List, J.A., Muir, I., 2019. The Drivers of Social Preferences : Evidence from a Nationwide Tipping Field Experiment.

Chen, M.K., Sheldon, M., 2015. Dynamic Pricing in a Labor Market : Surge Pricing and Flexible Work on the Uber. Ssrn 1–19.

Chen, X., Chen, X., Zheng, H., Xiao, F., 2021. Efficient dispatching for on-demand ride services : Systematic optimization via Monte-Carlo tree search. Transp. Res. Part C 127, 103156. https://doi.org/10.1016/j.trc.2021.103156.

Chen, Y., Hu, M., 2020. Pricing and matching with forward-looking buyers and sellers. Manuf. Serv. Oper. Manag. 22, 717–734. https://doi.org/10.1287/msom.2018.0769.

ChoiceMetrics, 2018. Ngene 1.2 USER MANUAL & REFERENCE GUIDE The Cutting Edge in Experimental Design End-User License Agreement 241.

Chu, L.Y., Wan, Z., Zhan, D., 2018. Harnessing the Double-Edged Sword via Routing: Information Provision on Ride-Hailing Platforms. SSRN Electron. J. https://doi.org/10.2139/ssrn.3266250.

Du, J., Rakha, H., 2021. Impact of COVID-19 on Ridehailing and Other Modes of Transportation [WWW Document]. URL https://www.morgan.edu/school_of_engineering/research_centers/urban_mobility_and_equity_center/research/new_research/covid_and_ridehailing.html (accessed 5.13.21).

Elliott, D., Tomasini, M., Oliveira, M., Menezes, R., 2018. Tippers and stiffers: An analysis of tipping behavior in taxi trips. 2017 IEEE SmartWorld Ubiquitous Intell. Comput. Adv. Trust. Comput. Scalable Comput. Commun. Cloud Big Data Comput. Internet People Smart City Innov. SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI 2017 - 1–8. https://doi.org/10.1109/UIC-ATC.2017.8397523.

Flath, D., 2012. Why Do We Tip Taxicab Drivers? Japanese Econ. 39, 69–76. https://doi.org/10.2753/jes1097-203x390304.

Flora, D.B., LaBrish, C., Chalmers, R.P., 2012. Old and new ideas for data screening and assumption testing for exploratory and confirmatory factor analysis. Front. Psychol. 3, 1–21. https://doi.org/10.3389/fpsyg.2012.00055.

Gaskin, C.J., Happell, B., 2014. On exploratory factor analysis: A review of recent evidence, an assessment of current practice, and recommendations for future use. Int. J. Nurs. Stud. 51, 511–521. https://doi.org/10.1016/j.ijnurstu.2013.10.005.

Hall, J.V., Krueger, A.B., 2018. An Analysis of the Labor Market for Uber's Driver-Partners in the United States. ILR Rev. 71, 705–732. https://doi.org/10.1177/0019793917717222.

Hamilton, I., Hernbroth, M., 2019. Uber drivers across the world are striking about pay, conditions, and the firm's "orgy of greed" [WWW Document]. businessinsider. URL https://www.businessinsider.nl/photos-uber-drivers-go-on-strike-around-the-world-2019-5?international=true&r=US (accessed 5.6.21).

Hensher, D.A., Rose, J.M., Rose, J.M., Greene, W.H., 2005. Applied Choice Analysis. Cambridge University Press.

Henson, R.K., Roberts, J.K., 2006. Use of Exploratory Factor Analysis in Published Research. Educ. Pschological Meas. 66, 11–14. https://doi.org/10.1177/0013164405282485.

Kaiser, H.F., 1974. An index of factorial simplicity. Psychometrika 39, 31–36. https://doi.org/10.1007/BF02291575.

Ke, J., Zheng, Z., Yang, H., Ye, J., 2021. Data-driven analysis on matching probability, routing distance and detour distance in ride-pooling services. Transp. Res. Part C Emerg. Technol. 124, 102922 https://doi.org/10.1016/j.trc.2020.102922.

Kucharski, R., Cats, O., 2020. Exact matching of attractive shared rides (ExMAS) for system-wide strategic evaluations. Transp. Res. Part B Methodol. 139, 285–310. https://doi.org/10.1016/j.trb.2020.06.006.

Leng, B., Du, H., Wang, J., Li, L., Xiong, Z., 2016. Analysis of taxi drivers' behaviors within a battle between two taxi apps. IEEE Trans. Intell. Transp. Syst. 17, 296–300. https://doi.org/10.1109/TITS.2015.2461000.

McFadden, D., 1974. Conditional Logit Analysis of Qualitative Choice Behaviour, in: Frontiers of Econometrics.

Miranda, F., Muñoz, J.C., De dios Ortúzar, J., 2008. Identifying transit driver preferences for work shift structures: An econometric analysis. Transp. Sci. 42, 70–86. https://doi.org/10.1287/trsc.1070.0199.

Morshed, S.A., Khan, S.S., Tanvir, R.B., Nur, S., 2021a. Impact of COVID-19 pandemic on ride-hailing services based on large-scale Twitter data analysis. J. Urban Manag. https://doi.org/10.1016/j.jum.2021.03.002.

Morshed, S.A., Khan, S.S., Tanvir, R.B., Nur, S., 2021b. Impact of COVID-19 pandemic on ride-hailing services based on large-scale Twitter data analysis. J. Urban Manag. 10, 155–165. https://doi.org/10.1016/j.jum.2021.03.002.

Norris, M., Lecavalier, L., 2010. Evaluating the use of exploratory factor analysis in developmental disability psychological research. J. Autism Dev. Disord. 40, 8–20. https://doi.org/10.1007/s10803-009-0816-2.

Noulas, A., Salnikov, V., Hristova, D., Mascolo, C., Lambiotte, R., 2019. Developing and deploying a taxi price comparison mobile app in the wild: Insights and challenges. Proc. - 2018 IEEE 5th Int. Conf. Data Sci. Adv. Anal. DSAA 2018, 424–430. https://doi.org/10.1109/DSAA.2018.00055.

Nourinejad, M., Ramezani, M., 2019. Ride-Sourcing Modeling and Pricing in Non-Equilibrium Two-Sided Markets. Transp. Res. Part B 00, 24–26. https://doi.org/10.1016/j.trb.2019.05.019.

Price, L.R., 2017. Psychometric Methods: Theory into Practice [WWW Document]. Meas. Interdiscip. Res. Perspect. URL https://lccn.loc.gov/2016013346 (accessed 4.14.21).

Romanyuk, G., 2016. Ignorance Is Strength : Improving Performance of Matching Markets by Limiting Information. Job Mark. Pap. 1–43.

Rose, J.M., Bliemer, M.C.J., 2009. Incorporating model uncertainty into the generation of efficient stated choice experiments: A model averaging approach, in: International Choice Modelling Conference, March 30-April 1, Yorkshire U.K.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transp. Res. Part B Methodol. 42, 395–406. https://doi.org/10.1016/j.trb.2007.09.002.

Rosenblat, A., Stark, L., 2015. Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers. Ssrn 10, 3758–3784. https://doi.org/10.2139/ssrn.2686227.

SAE International, 2018. Surface Vehicle Recommended Practice.

Serafimova, T., 2020. Covid-19: An Opportunity to Redesign Mobility Towards Greater Sustainability and Resilience? 8.

Shierholdz, H., Cooper, D., Wolfe, J., Zipperer, B., 2017. Employers would pocket $5.8 billion of workers' tips under Trump administration's proposed 'tip stealing' rule [WWW Document]. A Rep. by Econ. Policy Institute, Washingt. DC. URL https://www.epi.org/publication/employers-would-pocket-workers-tips-under-trump-administrations-proposed-tip-stealing-rule/ (accessed 4.29.21).

Smart, R., Rowe, B., Hawken, A., 2015. Faster and Cheaper: How Ride-Sourcing Fills a Gap in Low-Income Los Angeles Neighborhoods.

Spearman, C., 1904. " General Intelligence ," Objectively Determined and Measured Author (s): C . Spearman Source : The American Journal of Psychology , Vol . 15 , No . 2 (Apr ., 1904), pp . 201-292 Published by : University of Illinois Press Stable URL : http://www.jsto. Am. J. Psychol. 15, 201–292.

Traffic Index by Country, 2021. Traffic Index by Country 2021 [WWW Document]. URL https://www.numbeo.com/traffic/rankings_by_country.jsp (accessed 5.13.21).

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transp. Res. Part B Methodol. 90, 192–217. https://doi.org/10.1016/J.TRB.2016.04.021.

Walker, J.L., Wang, Y., Thorhauge, M., Ben-Akiva, M., 2018. D-efficient or deficient? A robustness analysis of stated choice experimental designs. Theory Decis. 84, 215–238. https://doi.org/10.1007/s11238-017-9647-3.

Wang, H., Yang, H., 2019. Ridesourcing systems: A framework and review. Transp. Res. Part B Methodol. 129, 122–155. https://doi.org/10.1016/j.trb.2019.07.009.

Wang, S., Smart, M., 2020. The disruptive effect of ridesourcing services on for-hire vehicle drivers' income and employment. Transp. Policy 89, 13–23. https://doi.org/10.1016/j.tranpol.2020.01.016.

Wang, Z., Fu, K., Ye, J., 2018. Learning to estimate the travel time. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min. 858–866 https://doi.org/10.1145/3219819.3219900.

Wentrup, R., Nakamura, H.R., Ström, P., 2019. Uberization in Paris – the issue of trust between a digital platform and digital workers. Crit. Perspect. Int. Bus. 15, 20–41. https://doi.org/10.1108/cpoib-03-2018-0033.

Xu, K., Sun, L., Liu, J., Wang, H., 2018. An empirical investigation of taxi driver response behavior to ride-hailing requests: A spatio-temporal perspective. PLoS ONE 13, 1–17. https://doi.org/10.1371/journal.pone.0198605.

Xue, Z., Zeng, S., Ma, C., 2021. Economic modeling and analysis of the ride-sourcing market considering labor supply. Res. Transp. Bus. Manag. 38, 100530 https://doi.org/10.1016/j.rtbm.2020.100530.

Zha, L., Yin, Y., Xu, Z., 2018. Geometric matching and spatial pricing in ride-sourcing markets. Transp. Res. Part C Emerg. Technol. 92, 58–75. https://doi.org/10.1016/j.trc.2018.04.015.

Zhong, Y., Wan, Z., Shen, Z.-J.-M., 2020. Queueing Versus Surge Pricing Mechanism: Efficiency, Equity, and Consumer Welfare. SSRN Electron. J. https://doi.org/10.2139/ssrn.3699134.

Zuniga-Garcia, N., Tec, M., Scott, J.G., Ruiz-Juri, N., Machemehl, R.B., 2020. Evaluation of ride-sourcing search frictions and driver productivity: A spatial denoising approach. Transp. Res. Part C Emerg. Technol. 110, 346–367. https://doi.org/10.1016/j.trc.2019.11.021.