Towards sustainability: decoding ridehailing drivers' and passengers' behaviors

Yuanjie Tu

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Reading Committee:

Linda Boyle, Chair

Jeff Ban

Nazmul Arefin Khan

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Abstract

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Yuanjie Tu

Chair of the Supervisory Committee:
Professor Linda Boyle
Department of Civil and Urban Engineering

The goal of this dissertation is to understand and quantify the differences in behaviors between ride-hail drivers and ride-hail passengers. Ride-hailing refers to the organizations that provide on demand travel services (e.g., Uber, Lyft). The dissertation accomplishes this goal using two surveys. One that was distributed to Seattle, Washington ridehailing drivers (n=198) and another one that was distributed nationwide to ride-hail passengers (n=880). Two models were developed to examine the Seattle ridehailing drivers: a mixed discrete choice model was used to jointly model their working time choice and relocation choices, and a generalized additive mixed model (GAMM) was used to examine the drivers likelihood to accept a ride. For the nationwide survey on ridehailing passengers, an integrated choice and latent variable (ICLV) model was used to understand the passenger's choice between solo and shared rides. The research indicates that surge pricing significantly influences both the decisions of drivers regarding their working hours and their choices regarding relocation. Higher surge prices in a particular area tend to prolong the working hours of drivers there and attract drivers from other areas to relocate. Moreover, the study suggests that drivers tend to continue working when their earnings are high, while their predetermined working time target affects their decision to stop working more than their earnings target does. Regarding relocation decisions, drivers are inclined to remain in their current location, especially when trip requests are promptly received or when the relocation time is long. Concerning trip request acceptance, ride-hailing drivers display a reluctance to

accept shared rides, typically requiring at least a \$10 subsidy to do so. Similarly, passengers are hesitant to opt for shared rides, although their willingness increases with a greater level of trust in fellow passengers, a lower preference for private space, and a higher willingness to socialize during a ride. Gender does not significantly influence these tendencies. It is noted that the findings may be limited given the sampling scheme, but nonetheless, there are implications toward promoting shared rides in the future. Policy suggestions include differential taxation/fee structure for solo and shared rides, fostering public-private partnerships, refining matchmaking algorithms, and enhancing the overall experience for both drivers and passengers in shared rides.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Figure Number Page

Chapter 1

INTRODUCTION

In recent years, the advent of ride-hailing services (e.g., Uber and Lyft) has witnessed an unprecedented surge in popularity [20], marking a transformative shift in urban mobility. As major urban centers embrace the convenience and accessibility offered by these services [62], a fervent debate arises regarding their role as a cure for sustainability problems [67]. While some are optimistic about the potential of ride-hailing to ease traffic congestion and environmental concerns [62], a growing chorus of skepticism questions whether these platforms might exacerbate the very issues they purportedly aim to solve [24, 67].

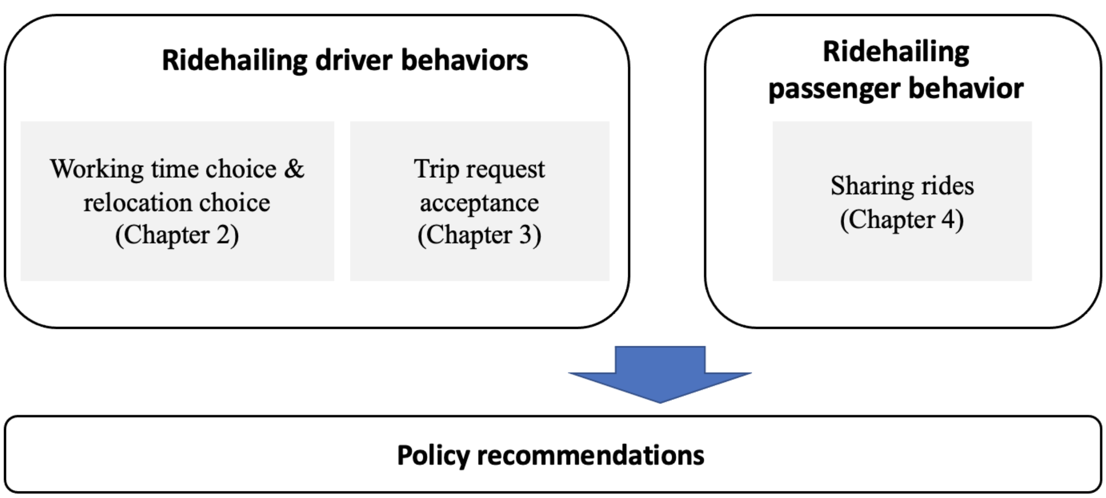
At the heart of ride-hailing services are the drivers (representing the supply side) and passengers (representing the demand side) [7, 53] - understanding their behaviors becomes pivotal in shaping relevant policies, constituting a critical step towards achieving sustainability.

On the supply side, transportation scholars have long recognized the importance of travelers' behaviors (representing the demand side) and the need to understand their preferences and motives if we are to forecast travel demand or develop effective demand management policies[12, 74]. However, the behaviors of drivers have received much less attention than those of passengers. Unlike bus drivers, ridehailing drivers are not only chauffeurs but independent contractors, which means transportation network companies (TNCs) that match drivers with passengers are limited in their ability to dictate drivers' actions [72]. Drivers provide their vehicles to transport passengers and make their own work decisions such as when to stop driving, where to relocate, and whether to accept the trip request [7]. These decisions wield substantial influence over vehicle miles traveled (VMT) and, consequently, contribute to the overall environmental impact.

This dissertation meticulously examines three key driver behaviors: working time choice, relocation choice, and trip request acceptance choice. Prolonged working hours and frequent relocation might result in drivers circulating aimlessly in the city without passengers, therefore increasing empty VMT. Of particular interest is the acceptance of shared rides, a critical factor in mitigating negative environmental effects. Rejecting shared rides may lead to an increase in empty VMT and induced solo rides, contributing to the adverse environmental impacts associated with ride hailing services. According to existing studies, a market share of pooled services of 20–50% or even larger is required to benefit the environmental effect [25, 56], while only around 20% of on-demand users request shared rides [18, 28, 5]. The study delves into how shared rides influence drivers' trip acceptance decision making.

The demand side, represented by passengers, has consistently been a focal point since the inception of ride-hailing services [12, 74]. Hence, our exploration of the demand side concentrates specifically on passengers' behaviors regarding choosing shared rides. A discussion of this analysis with drivers' acceptance of shared rides allows us to attain a comprehensive perspective on the reality and future of shared rides. This dissertation also provides policy recommendations on promoting shared rides from both drivers' and passengers' perspectives.

Figure 1.1: Dissertation framework



Through these thorough analyses, this dissertation aims to propose viable strategies to mitigate the negative environmental impact of ridehailing, thereby contributing to the development of a more sustainable and resilient urban transportation ecosystem. The dissertation framework is shown in Figure 1.1.

1.1 Driver behaviors

1.1.1 Working time choice

Drivers' working time choice is not a new question. It means how much a driver chooses to work per day/week. Economic literature has extensively addressed this aspect of drivers' choices, with discussions dating back to the 20th century, often encapsulated by the term "driver labor supply" [15].

Among the investigators who have examined drivers' working time, there is a heated argument: the neo-classical theory of labor supply states that the quantity of labor supplied increases as the wage increases, with drivers working longer hours on days when they are earning more per hour [42]. The reference dependent utility theory of labor supply suggests that the relationship is negative, as drivers tend to stop working once they reach a reference or target level of daily earnings [70]. A large pool of literature has tried to empirically test the two hypotheses, but the results are mixed. [15] and [59] used the same trip sheet dataset of New York taxi drivers and came to different conclusions. [15] found that higher earning rate, defined by daily earnings divided by daily working time, is associated with shorter expected daily working time. This result means taxi drivers might have a daily earnings target and would stop driving after the target is reached. [58], on the contrary, supports the neoclassical theory. He pointed out several econometric weaknesses of [15] and concluded that taxi drivers' probability of stopping driving mainly depends on accumulated working time that day, but not necessarily accumulated earnings. He concludes that for taxi drivers, "tomorrow is another day", so they do not worry about setting a target for a single day. The difference between [15] and [58] are mainly in their conceptual frameworks and model specifications. The intensified debate can be seen across the massive literature on this topic [3, 22, 65, 75].

Three main limitations exist in current research on drivers' working time choice. First, most work has focused on taxi drivers (Agarwal et al., 2013; Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2008, 2005), while few studies have paid attention to ridehailing drivers [6, 17, 66, 75]. Nevertheless, ridehailing and taxi drivers differ in some important ways: First, ridehailing drivers are more flexible in their working time choices than taxi drivers because they are not constrained by "switching shifts" [53, 17]. Second, the TNC platform matches ridehailing drivers with passengers more efficiently than the traditional taxi industry, which may lead to less waiting time and a higher earning rate [12, 60]. Third, the compensation models for ridehailing and taxi drivers are different. Taxi drivers pay a fixed payment independent of how much they earn to the company, while ridehailing drivers pay a proportion of their trip fares [6]. Considering these differences, ridehailing drivers' working time choices might differ significantly from those of taxi drivers. **In response to this limitation, this dissertation focuses on ridehailing drivers, instead of taxi drivers, aiming to shed light on ridehailing drivers' working time and relocation behaviors.**

A second limitation of existing studies is that they have investigated the effects of earnings targets using observational data, without explicitly measuring drivers' earnings targets [59, 75]. While there are some advantages using observational data, doing so increases the difficulty of investigating the effects of targets since those targets are not directly observed. **In response to this limitation, this dissertation collects stated preference data on drivers' earning targets and measures the impact of their earnings targets on working time and relocation choices.**

A third limitation, building on the above point, many current studies have discussed the effects of earnings targets, but none have considered time targets. Most research assumes that drivers will be less willing to continue working as their cumulative time worked increases, but no studies have discussed the possibility that drivers also have a reference level for working time. **In response to this limitation, this dissertation also collects stated preference data on ridehailing drivers' time targets, and investigate their impact on drivers' working time and relocation choices.**

1.1.2 Relocation choice

Drivers' relocation choice refers to where a driver chooses to go after finishing a trip. Before we go into the weeds, it's important to distinguish "spatial distribution of ridehailing trips" and "relocation behavior of ridehailing drivers". Many studies have investigated the spatial distribution of ridehailing trips [9, 45, 63, 71]. However, similar though they might they seem, ridehailing drivers' relocation choices are different than the spatial distribution of ridehailing trips. The spatial distribution of ridehailing trips is the result shaped by both ridehailing supply and demand, while ridehailing drivers' relocation choices only represents the supply in the space dimension (though relocation choices are, as we show, affected by the levels of demand in various locations). Therefore, understanding the spatial distribution of ridehailing trips does not by itself provide a complete understanding of ridehailing driver supply [31].

There are two main strands of studies on ridehailing drivers' relocation choices. One strand of studies is dedicated in optimizing the efficiency of drivers' searches for passengers so as to promote service quality [2, 23] to reduce traffic congestion [37]. A common limitation of this strand of studies is that they tend to assume driver behaviors are fully compliant with the platform and neglect the fact that drivers are independent contractors who freely decide where to go. Another strand of studies focuses on strategically maximizing driver earnings [32, 77]. Current studies suggest that in general, drivers earn more when they park and wait for the next trip request rather than drive to a more active location. The situation is only different if doing so saves at least 30% of trip waiting time [32]. While strategically maximizing the earnings seem "ideal", drivers in the real life might have their own decision-making mechanisms.

Few peer-reviewed studies have modeled ridehailing drivers' relocation behaviors [53]. They qualitatively investigated ridehailing drivers' relocation strategies. They found that new drivers would prefer to move around, while experienced drivers would prefer waiting in the same location to get a ride. They also found that new drivers said they would choose to chase the surge, while more experienced drivers said they would not. To my knowledge, there are no studies quantitatively modeling ridehailing drivers' relocation behaviors and related factors. **In response to this limitation, this dissertation explores and investigates the factors contributing to ridehailing drivers' relocation choices.**

In addition, current studies model drivers' working time and relocation choices separately. However, drivers' working time and relocation choices are inextricably bound up together. A driver can only choose where to go if they choose to continue working; and a driver decides whether to continue working in part based on the expected rewards in working, which in turn depend on the levels of demand in the current location and nearby locations. **In response to this, this dissertation models ridehailing drivers' working time and relocation choices jointly, aiming to provide a more accurate understanding of the two behaviors.**

1.1.3 Trip request acceptance

Trip request acceptance means whether a driver chooses to accept or reject a trip request from a passenger. A handful of studies have qualitatively analyzed and quantitatively modeled the impacts of trip features on driver response to a request [53, 52, 1, 35] investigated factors that impact ridehailing driver trip request acceptance using data from a ridehailing service provider in Beijing, China. This study discovered that ridehailing drivers are more likely to accept long trips and trips with surging prices. They also found that the number of trip requests received, and the number of trips accepted per driver have little impact on trip request acceptance.

Ashkrof Peyman et al. [53] studied driver behavior and preferences on trip request acceptance, working shift, and relocation choices. They collected data in a series of focus groups with 16 Uber drivers in the Netherlands. They found that pick-up locations, distance and time to the pick-up point, passenger ratings, surge pricing, long distance rides, destination prediction, driver's experience, and cancellation criteria may be related to a driver's decision to accept or reject a trip request. Drivers stated that they would be more likely to reject trips in risky locations, trips that require long pickup time and distance, and trips with low passenger ratings. Experienced drivers were more selective about accepting rides.

In a gray literature study, Ashkrof Peyman et al. [52] examined trip request acceptance behavior by collecting a stated preference survey of ridehailing drivers in the United States (US) (752 responses) and in the Netherlands (68 responses). By using a discrete choice model, they found that employment status of the driver, amount of time driving, working shift, travel time to the pick-up point, and surge price were important predictors of trip request acceptance.

A related study on driver attitudes towards shared rides surveyed 309 ridehailing drivers across the US [1]. Results suggested that in general, drivers dislike shared rides compared with solo rides. They discovered that ridehailing drivers are generally dissatisfied with shared rides because they are less cost-effective. That study does not link drivers' dislike towards shared rides to trip request acceptance behaviors, but it does help identify a potential factor that may affect trip request acceptance. Additional evidence in online forums and blogs shows some drivers expressing concerns about passengers with low ratings, and indicating they are less likely to accept a trip request with a low passenger rating [19, 11, 55].

So far, few peer-reviewed studies have modeled the relationship between trip request acceptance of ridehailing drivers and trip features, socio-demographics, and employment status. There are two limitations in current literature. First, no studies have comprehensively considered trip features, socio-demographics, and employment status. Second, no studies have explored the non-linear relationships between trip request acceptance and trip-features. **In response to this limitation, this dissertation examines how ridehailing drivers' responses to trip requests depend linearly and non-linearly on trip features, as well as drivers' socio-demographic and employment characteristics.**

1.2 Passenger behaviors

This section mainly discusses passenger mode choice. Ridehailing passenger mode choice means choosing a solo or shared ride. This question has been put front and center since the existence of ridehailing companies because of its potential to reduce traffic and mitigate negative environmental effects [48, 49, 13, 38].

Scholars have been exploring the factors that impact passengers' decisions of choosing shared rides, and most important factors are identified as socio-demographics, location, attitudinal variables [13]. Existing studies found out waiting time and walking distance is negatively associated with the likelihood of choosing a shared ride, and that people who are more *pro-pooling*, *pro-technology* and *anti-driving* are more likely to choose the shared ride [38, 33], monetary incentives (like discounts) increases the likelihood of choosing shared ride [33]. A study in Chicago found that areas with higher socio-economic disadvantage is correlated with more shared rides, and areas with more public transit access have more ridehailing pick-ups and drop-offs (both shared and solo rides) [64]. Another study in California found that highly educated young people who currently work or study are more likely to adopt shared rides, but longer travel time and lack of privacy decreases the likelihood of shared ride adoption [44].

The discussion on the impact of attitudinal factors on shared ride choices is mainly limited to attitudes on technology, attitudes on taking shared rides, attitudes on driving, and attitudes on private space. Fewer studies have discussed how passengers' social interaction perception, trust in other passengers would impact the decision of choosing a shared ride. Despite the modeling part, more comprehensive policy implications are needed to promote shared rides in the future. **In response to this limitation, this dissertation investigates the relationship between passengers' preference of shared rides and attitudinal factors, trip features, and socio-demographics. This dissertation also provides policy recommendations on how to promote shared rides.**

1.3 Research Goals

The goal of this dissertation is to understand and quantify the differences in behaviors between ride-hail drivers and ride-hail passengers. The dissertation accomplishes this goal using two surveys that are used to address the following research aims:

Goal 1: understanding ridehailing drivers' working time and relocation choices

By using a survey dataset distributed to Seattle, Washington ridehailing drivers (n = 198), we aim to jointly model drivers' working time choice and relocation choice simultaneously by using a mixed logit model.

Goal 2: understanding factors impacting ridehailing drivers' trip request acceptance

By using the same survey dataset as Goal 1, we aim to understand the factors affecting drivers' trip requests both linearly and nonlinearly by using a generalized additive mixed model.

Goal 3: understanding passengers' likelihood of choosing a shared ride

Using a survey dataset distributed nationwide to ridehailing passengers (n=880), we aim to understand factors affecting ridehailing passengers' likelihood of choosing a shared ride using an Integrated choice and latent variable (ICLV) model. Based on the findings, we aim to provide policy implications to promote ridesharing in the future.

This dissertation has five chapters. Chapter 1 introduces the overall dissertation framework, literature review, and research goals. Chapter 2 models ridehailing drivers' working time and relocation choices. Chapter 3 investigates ridehailing drivers' trip request acceptance choice. Chapter 4 investigates passengers' likelihood of choosing a shared ride and policy implications to improve shared rides in the future. In Chapter 5, we discuss the main takeaways and limitations.

Chapter 2

UNDERSTANDING RIDEHAILING DRIVERS' WORKING TIME AND RELOCATION CHOICES

The following chapter presents the paper that is in major revision in Transportation by Yuanjie (Tukey) Tu, Moein Khaloei, Natalia Zuniga, and Don MacKenzie.

This chapter jointly models two ridehailing driver behaviors that are central to driver supply: working time and relocation choices. These two behaviors impact driver supply through time and space: drivers can freely decide when and where to provide their labor. Relying on data from a stated choice experiment, we jointly estimate models of drivers' choices about whether to continue working and whether to relocate while working. While driver working time choices affect the overall driver supply and service quality at a given time, their relocation choices affect the distribution of service quality across different areas of a city. We modeled these two behaviors jointly because they are so intertwined that it is almost impossible to think about one without the other: a driver can only choose where to go if they first choose to continue working; a driver's decision whether to continue working depends in part on the expected rewards in working, which in turn depends on the level of demand in the current location and nearby locations. The model we propose can serve as a tool for transport agencies to predict and adjust future ridehailing driver supply.

The present study is the first to our knowledge that models ridehailing drivers' working time and relocation choices jointly. This study adds to the literature by filling the aforementioned research gaps, and the result of our study can serve as a tool for transport agencies to predict and adjust future ridehailing driver supply.

2.1 Term definitions

To aid understanding, I provide term definitions used in the rest of the chapter in Table 2.1.

Table 2.1: Term definition

Terms	**Definition**
Ride-hailing	Services are services such as Uber and Lyft, that connect passengers to local drivers to give them a ride
Working time choice	The choice of deciding when to start and stop working per workday
Relocation choice	The choice of deciding which neighborhood to go to (including staying in the same neighborhood) after finishing a ride
Earnings target	A respondent's daily earning target (could be *null* if they do not have a target)
Time target	A respondent's daily working time target (could be *null* if they do not have a target)
Surge price	The amount of price increased for a ride when there is an increase in demand

2.2 Data collection

Our primary data source is a survey of 200 ridehailing drivers in the Seattle, USA region. Two advantages stand out when using a stated preference survey in this context. First, it allows us to directly capture drivers' daily working time and earnings targets, which will furthermore help us to investigate the relationship between drivers' working time choices and these targets. Second, it enables us to investigate the causal relationship between working time choice, relocation choice, and driving characteristics we are interested in. The inclusion of a choice experiment in the survey allows us to control endogeneity, a common problem that can lead to omitted variable bias when using non-experimental data [73].

The survey was conducted from August 11 to September 9, 2021. We trialed online and in-person data collection approaches. We finally adopted an in-person computer assisted personal interview approach because we found that (1) the response rate to an online version of the survey was very low, and (2) many online respondents appeared not to be real ridehailing drivers, based on screening and quality check questions in the survey. More details on the performance of different data collection approaches can be found in [69].

We recruited participants and assisted them to complete the survey on an iPad in the Seattle-Tacoma International Airport ridehailing driver waiting area. Respondents were compensated with an $15 Amazon gift card in the indicated amount.

Anecdotally, ridehailing drivers do not seem to trust surveys and interviews. The most frequently asked questions when administering the survey were “what is the purpose of the study?” and “do you work for Lyft or Uber?”. Their major concern was that the responses would be used against them by ridehailing companies. This echoes existing evidence that drivers and companies have a tense relationship [53]. A total of 200 responses were collected from approximately 250 drivers who were invited to participate.

2.2.1 Online survey design

We conducted a series of pilot interviews with ridehailing drivers before designing the questionnaire, to ensure we captured the most important variables and used terminology familiar to the drivers. The questionnaire contained three sections: basic driving information, choice experiments, and background information.

Basic driving information

We asked respondents to provide information on which ridehailing companies they are driving for, how long they have been a ridehailing driver, whether they have another job besides ridehailing driver, the time they generally start and stop driving each day, any targets for working hours or earnings per day, and the numbers of trip requests they (1) received and (2) rejected in the past week.

To capture respondents’ working time targets, we first ask them “Do you usually try to work a certain number of hours per day?” If their answer is “yes”, we asked them “How many hours do you usually try to work per day?” Similarly, we captured their earnings target by first asking them “Do you usually try to earn a certain amount of money per day?" If they answered "yes", we asked them "How much do you usually try to earn per day?"

After capturing working time targets and earnings targets, we categorized driver respondents into four types based on whether they reported having targets of one or both types: *no-target drivers*, *time-target drivers*, *earnings-target drivers*, and *both-target drivers*. These driver types will be further used in our modeling work.

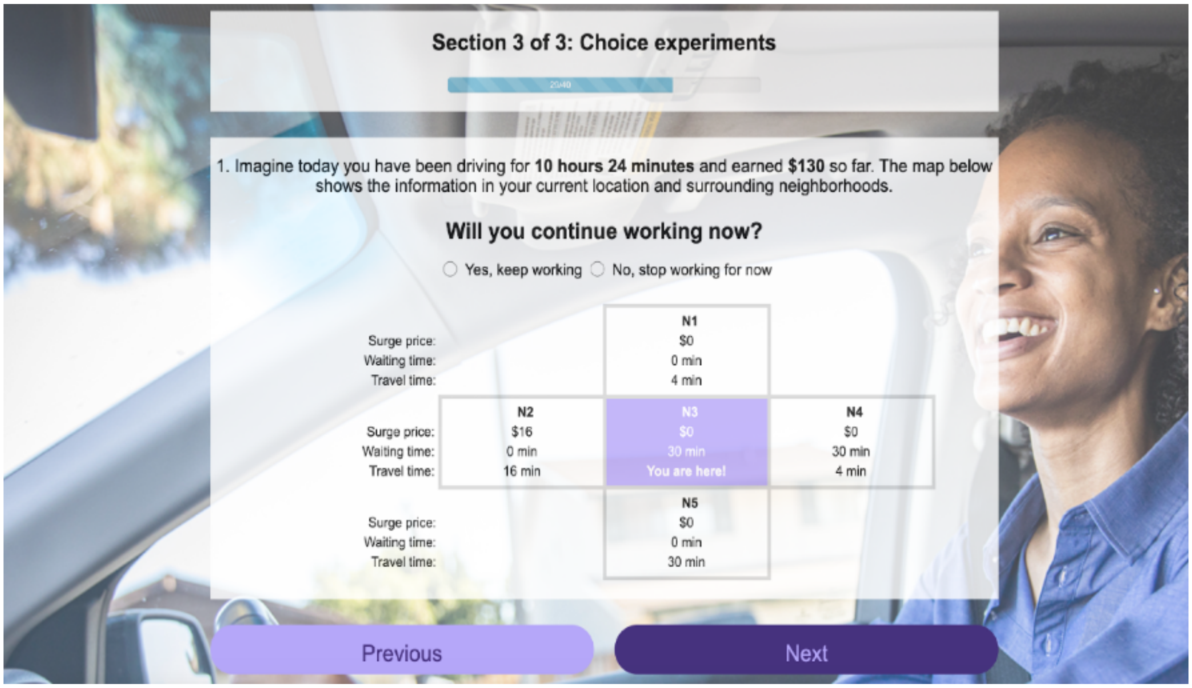
Choice experiments

To investigate the causal relationship between the drivers' working time choices, relocation choices, and driving characteristics, we adopted a blocked factorial design. The experimental design was conducted as follows. First, we chose 11 variables as experimental variables, including daily earnings, working time, ridehailing demand (represented as a combination of surge price and expected waiting time for a ride request) in the current neighborhood and four nearby neighborhoods, and the relocation time to drive to the four nearby neighborhoods. We include these variables because they are the most important variables reported by drivers in the pilot interviews. Experimental variable descriptions are shown in Table 2.1. Second, we generated levels for each experimental variable (Table 2.2). Third, we generated the full matrix of combinations of the variable levels. Next, we created blocks of six combinations (choice scenarios) for each respondent. In each scenario, she/he was asked to first choose to "stop working" or "continue working" based on different combinations of experimental variable levels; if they chose to continue working, they were asked to choose a neighborhood from among the current neighborhood they are in and four nearby neighborhoods. The four nearby neighborhoods were unlabeled alternatives, i.e. they were not identified as specific neighborhoods in the Seattle region. Figures 2.1 and 2.2 show an example of driver working time and relocation experiment.

Background information

In this section, we asked respondents questions about their socio-demographics including age, gender, race, whether born in the US, whether a student, household size, individual

Figure 2.1: An example of the choice experiments: working time choice



and household income, education level, job status (whether part time, whether have another job), and subjective health status.

2.2.2 Data quality check and cleaning

To improve data quality, we adopted multiple screening and quality check questions as follows. First, before entering the choice scenario questions, survey respondents were asked two comprehension check questions. For each comprehension check, we asked the respondent to choose the correct meaning of a highlighted number in a choice scenario. Every respondent had two chances to answer each of the comprehension questions. They were only allowed to proceed if the answers were correct, otherwise the survey was terminated. Second, we included one question to check respondents' attention. The respondents were told "this is an attention check" and were asked to choose the neighborhood with given surge price, waiting time, and travel time in the middle of choice scenario questions. Finally, we applied a logic check in the survey. In the background information section, we asked respondents

Table 2.2: Descriptions of experimental variables

Attributes	**Descriptions**
Working time choice	
Earnings	Cumulative daily earnings at the time the choice is made. Base value is the respondent's self-reported daily earnings target. If the respondent did not report a daily earnings target, we assume the base value to be $100
Working time	Cumulative daily working hours at the time the choice is made. Base value is the respondent's self reported target working hours. If the respondent did not report a target number of working hours, we assume the base value to be 8 hours
Relocation choice	
Ridehailing demand (current neighborhood)	Represents the demand for ridehailing services in the current neighborhood. Measured jointly by surge price ($) and average waiting time for a trip request if they decline the current one (minutes). Higher demand areas have lower waiting times and higher surge prices
Ridehailing demand (nearby neighborhoods)	Represents the demand for ridehailing services in each of the four nearby neighborhoods. Measured jointly by surge price ($) and average waiting time for a trip request if they decline the current one (minutes). Higher demand areas have lower waiting times and higher surge price
Relocation time	The time to drive from the current neighborhood to each of the four nearby neighborhoods, in minutes

Figure 2.2: An example of the choice experiments: relocation choice

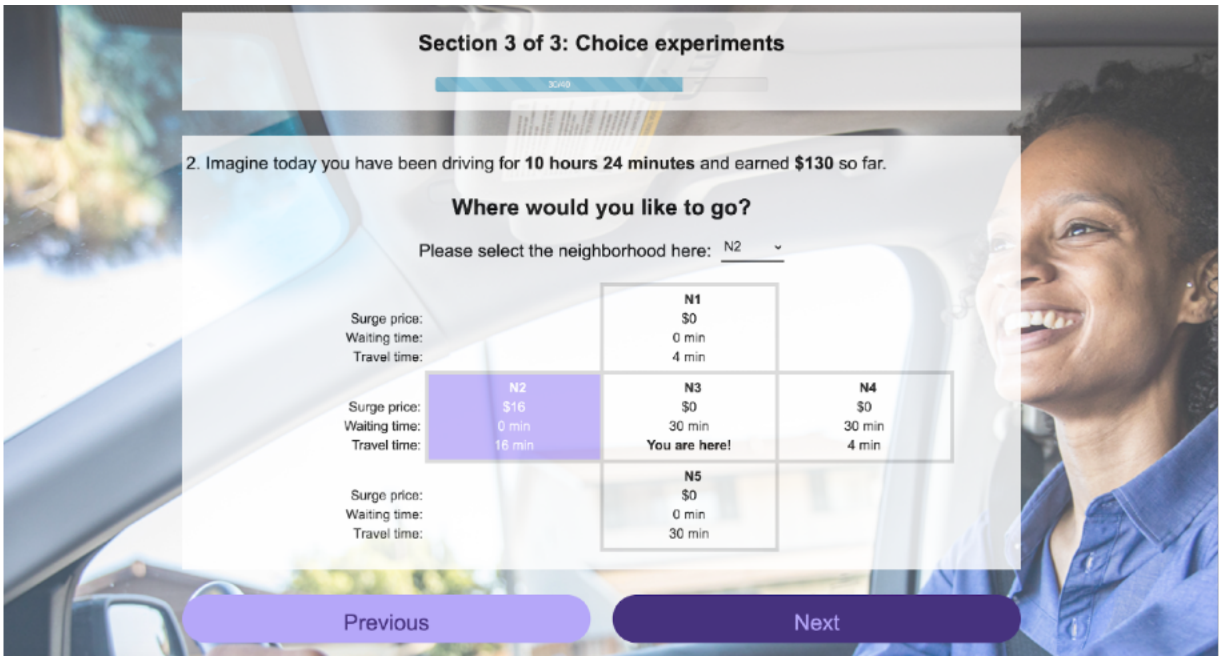


Table 2.3: Experimental attribute levels

Attributes	Levels								
Earnings Multiplier	0.4		0.7		1	1.3		1.6	
Working time multiplier	0.4		0.7		1	1.3		1.6	
Surge price ($)	16	12	8	4	0	0	0	0	0
Average waiting time (min)	0	0	0	0	0	8	16	24	30
Relocation time (min)	4		8		12	16		20	

their annual income (both household and individual). Each respondent's annual household income should be equal or larger than their individual income. We removed responses failing either the attention or logic check.

For modeling purposes, we also removed respondents who had missing data or chose "prefer not to answer" in independent variables mentioned in Section 2.4. Respondents who completed 0 trips in the prior week were also removed. After the data quality checks and cleaning, a total of 181 respondents and 1,067 choice responses were retained for analysis.

2.3 Model development

We adopted a mixed logit model to investigate ridehailing drivers' working time and relocation choices jointly. The strengths of a mixed logit model are twofold: for one, it can address the unobserved correlations between alternatives in the choice set with higher flexibility than nested logit (e.g., stay in the same place and relocate). Second, it can also account for repeated measures (e.g., each driver was presented with six hypothetical scenarios).

The model has two levels: working time choice and relocation choice. In the working time choice level, we have two alternatives: stop working and continue working. We choose whether to continue or stop working as the dependent variable following the approach of two previous studies [58, 59]. After the driver chooses to continue working, s/he can choose to stay in the same place or go to other places. If s/he decides to relocate, s/he can choose to go to one of the nearby 4 neighborhoods. The modeling structure is shown in Figure 2.3. The mixed logit model is estimated in Biogeme by maximizing the simulated likelihood [10].

2.3.1 Working time choice

The utility of driver i choosing to stop working is written in 2.4. This model structure helps distinguish the effects of different types of drivers.

Figure 2.3: Choice structure for working time and relocation choice

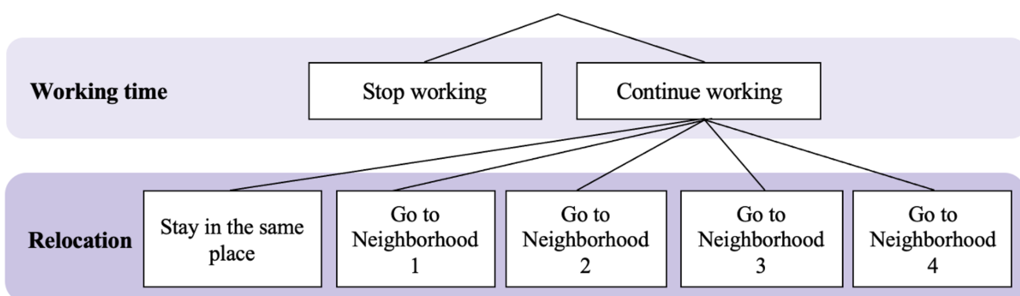


Table 2.4: The utility function of stop working

Driver Type	**Utility function**	**Driver Indicator**	**ASC**	**Earnings target**	**Time target**	**Working time**	**Earning rate**	**Covariates**	**Driver Random Effect**	**Error Term**
No targets	$U_{i-stop} =$	$D_{no}($	$\alpha_{no} +$			$\sigma_{no} W_{ij} +$	$\theta_{no} R_{ij}) +$	$\eta_s X_i$	$\mu_i +$	ϵ_{ij}
Earnings Target		$D_{et}($	$\alpha_{et} +$	$\beta_{et} E_{ij} +$		$\sigma_{et} W_{ij} +$	$\theta_{et} R_{ij}) +$	$\eta_s X_i$	$\mu_i +$	ϵ_{ij}
Time Target		$D_{tt}($	$\alpha_{tt} +$		$\gamma_{tt} T_{ij} +$		$\theta_{tt} R_{ij}) +$	$\eta_s X_i$	$\mu_i +$	ϵ_{ij}
Both Targets		$D_{bt}($	$\alpha_{bt} +$	$\beta_{bt} E_{ij} +$	$\gamma_{bt} T_{ij} +$		$\theta_{bt} R_{ij}) +$	$\eta_s X_i$	$\mu_i +$	ϵ_{ij}

Notations:

D_{no}, D_{et}, and D_{bt} are four dummy variables, representing no-target drivers, earnings-target drivers, time-target drivers, and both-target drivers. The descriptions of driver types are shown in Table 2.8.

E_{ij} is a vector of earnings target variables indicating the category of driver i's daily earnings in choice scenario j relative to their daily earnings target. β_{et}, β_{bt} are vectors of the coefficients of E_{ij} for *earnings-target drivers* and *both-target drivers*.

T_{ij} is a vector of working time target variables indicating the category of driver i's daily working hours in choice scenario j relative to their daily earnings target. γ_{tt}, γ_{bt} are vectors of the coefficient of T_{ij} for time-target drivers and both-target drivers.

W_{ij} is the cumulative working time of driver i in choice scenario j at the time the choice is being made. σ_{no}, σ_{et} are the coefficients of W_{ij} for no-target drivers and earnings-target drivers. We only include W_{ij} for no-target drivers and earnings-target drivers because they are highly correlated with time target variables for time-target drivers and both-target drivers.

R_{ij} is the earning rate of driver i in choice scenario j. θ_{no}, θ_{et}, θ_{tt}, θ_{bt} are coefficients of R_{ij} for no-target drivers, earnings-target drivers, time-target drivers, and both-target drivers respectively.

X_i is a vector of socio-demographics including gender, age, number of children, income, and job status. η_s is a vector of coefficients of X_i. The specific variables are shown in Tables 2.10.

mu_i is is an individual-specific random component assumed to be distributed as $N\{0, \sigma^2\}$ where σ is the variant component.

ϵ_{ij} is a random error term assumed to be independently and identically Gumbel distributed.

2.3.2 Relocation choice

The utility of driver i choosing relocation choice r is written as Equation 2.1.

$$U_{ir} = V_{ir} + b_i + \zeta_{ir} \tag{2.1}$$

V_{ir}, the systematic utility of driver i choosing relocation choice r is written as Equation 2.2.

$$V_{ir} = \rho S_{ir} + \omega A_{ir} + \tau L_{ir} + \phi_i \tag{2.2}$$

Where r can be the current neighborhood the driver is at, or one of the nearby 4 neighborhoods.
S_{ir} is surge price of neighborhood r. ρ is the coefficient of S_{ir}.
A_{ir} is the average waiting time of neighborhood r. ω is the coefficient of A_{ir}.
L_{ir} is the relocation time from the current neighborhood to neighborhood r. L_{ir} does not exist if driver ıchooses to stay in the current neighborhood. τ is the coefficient of L_{ir}
b_i is an individual-specific random component.
ϕ_i are the random effects used to account for unobserved correlations, including a vector of independent, standard normal distributed, random variables (continue working and relocating to other neighborhoods).
ζ_{ir} is a random error term assumed to be independently and identically Gumbel distributed.
To estimate the random effects, 500 Halton draws taken from a normal distribution were used.

2.4 Results

All supplemental materials (e.g., code, data descriptions) can be found in this GitHub repository.

Table 2.5: **Variable descriptions (part 1)**

Variable	**Definition**
Working time choice	
Working characteristics (D_i): Driver types	
No-target drivers (D_{no})	Dummy variable. If the respondent has neither working time target nor earnings target, 1, else, 0
Earnings-target drivers (D_{et})	Dummy variable. If the respondent has an earnings target but no working time target, 1, else, 0
Time-target drivers (D_{tt})	Dummy variable. If the respondent has a working time target but no earnings target, 1, else, 0
Both-target drivers (D_{bt})	Dummy variable. If the respondent has both working time target and earnings target, 1, else, 0

Table 2.6: **Variable descriptions (part 2)**

Variable	**Definition**
Working time choice	
Working characteristics (D_i): Earnings target (E_{ij}) (reference: Earnings = target)	
Earnings = 0.4*target	Dummy variable. If accumulated earnings divided by the respondent's earnings target equals 0.4, 1, else, 0. Only applicable to earnings-target drivers and both-target drivers
Earnings = 0.7*target	Dummy variable. If accumulated earnings divided by the respondent's earnings target equals 0.7, 1, else, 0. Only applicable to earnings-target drivers and both-target drivers
Earnings = 1.3*target	Dummy variable. If accumulated earnings divided by the respondent's earnings target equals 1.3, 1, else, 0. Only applicable to earnings-target drivers and both-target drivers
Earnings = 1.6*target	Dummy variable. If accumulated earnings divided by the respondent's earnings target equals 1.6, 1, else, 0. Only applicable to earnings-target drivers and both-target drivers
Working characteristics (D_i): Working time target (T_{ij}) (reference: working time = target)	
Working time = 0.4*target	Dummy variable. If accumulated working hours divided by the respondent's working time target equals 0.4, 1, else, 0. Only applicable to time-target drivers and both-target drivers
Working time = 0.7*target	Dummy variable. If accumulated working hours divided by the respondent's working time target equals 0.7, 1, else, 0. Only applicable to time-target drivers and both-target drivers
Working time = 1.3*target	Dummy variable. If accumulated working hours divided by the respondent's working time target equals 1.3, 1, else, 0. Only applicable to time-target drivers and both-target drivers
Working time = 1.6*target	Dummy variable. If accumulated working hours divided by the respondent's working time target equals 1.6, 1, else, 0. Only applicable to time-target drivers and both-target drivers
Working time (W_{ij})	Accumulated working hours, in hours. Only applicable to no-target drivers and earnings-target drivers
Earning rate (earnings/working time) (R_{ij})	Accumulated daily earnings/accumulated working hours

Table 2.7: **Variable descriptions (part 3)**

Variable	**Definition**
Working time choice: socio-demographics (X_i)	
Age	The age of the respondent. 18 – 39: 0 40 – 64: 1 ¿=65: 2
Female	If 1, gender = female, 0, otherwise
Num. of children	Number of children (under 18 years old) in the household
Above median income	If household income equal or higher than King County median household income in 2019 ($99,158) (U.S. Census Bureau, 2021), 1; else, 0.
Another job	Whether the respondent has another job other than the ridehailing driver 0: has another job, full-time (35+ hours/week) 1: has another job, part-time (fewer than 35 hours/week) 2: doesn't have another job
Relocation choice	
Surge price (S_{ir})	An additional surge amount to the trip fare if go to other places, in dollars
Average waiting time (A_{ir})	Expected waiting time until next request if the respondent reject the current one if go to other places, in minutes
Relocation time (L_{ir})	Driving time to the nearby neighborhood, in minutes

2.4.1 Descriptive analysis

Socio-demographics and employment characteristics

The socio-demographics and employment characteristics are shown in Table 2.5 and 2.6. Compared to the general population, ridehailing drivers in our sample have some unique characteristics. They are overwhelmingly male (96%), Black American (75%), and born outside the US (95%). The finding is consistent with a report by City of Seattle, that 93% of TNC drivers identified themselves as non-white (City of Seattle, 2020). Since the response rate to our survey was very high (~80%), we are confident that it is fairly representative of ridehailing drivers picking up passengers at SeaTac airport (all of whom pass through the waiting lot).

Driving characteristics

Driver types

Most respondents were both-target drivers (57%), with the remainder of the sample split fairly evenly among no-target drivers (14%), time-target drivers (17%), and earnings-target drivers (13%).

Target characteristics

Figure 2.4 shows the distributions of daily target earnings (Figure 2.4 A) and working time (Figure 2.4 B). The variability of driver earnings targets is large, ranging from $100 to $400. The mean earnings target is $221. The variability of daily working hour targets is also large across drivers, with a minimum of 4 hours and a maximum of 12 hours. The mean target is 9 hours. We compared the daily working hour target we collected with actual daily working time of taxi drivers [3, 59]. They are very similar: New York taxi drivers' working hours per shift ranges from 7 to 9 hours [59], and Singapore drivers mainly drive between 8 to 10 hours [3].

For both-target drivers, the working time targets and earnings targets are moderately correlated: the correlation coefficient is 0.39. This is consistent with the intuition that drivers who expect to work longer would also expect to earn more.

Table 2.8: Data characteristics (part 1) (N = 181)

Characteristic	**This sample**	**Characteristics**	**This sample**
What is your gender?		Are you currently a student?	
Male	96%	Yes, full time (35+ hours/week)	3%
Female	4%	Yes, part time (<35 hours/week)	7%
What is your race?		No, not a student	90%
White	7%	Are you of Hispanic, Latino, or Spanish origin?	
Asian	11%	Yes, Hispanic origin	3%
African American	75%	No, non-Hispanic origin	94%
Another	5%	Prefer not to answer	3%
Prefer not to answer	2%	Were you born in the United States?	
What is your age?		Yes, born in the US	4%
18-39	51%	No, born outside the US	95%
40-64	45%	Prefer not to answer	1%
65 and above	4%	Do you have another job besides ride-sharing driver?	
Which ride-sharing companies are you driving for?		Yes, full time (35+ hours/week)	9%
Uber only	14%	Yes, part time (<35 hours/week)	12%
Lyft only	35%	No, no another job	79%
Uber and Lyft	51%		

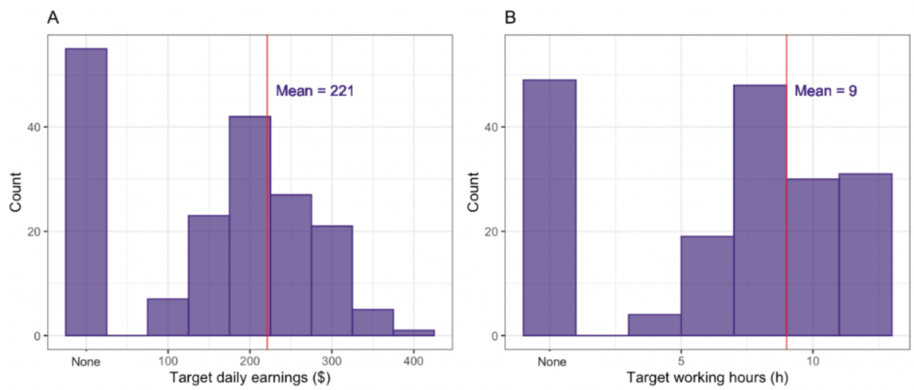
Table 2.9: Data characteristics (part 2) (N = 181)

Characteristic	**This sample**	**Characteristics**	**This sample**
What is the highest degree or level of school you have completed?		Which category best describes your household income before taxes from the last calendar year?	
Less than high school	5%	Less than 10,000 dollars	3%
High school	46%	10,000 to 14,999 dollars	2%
College	44%	15,000 to 19,999 dollars	3%
Graduate school or higher	5%	20,000 to 24,999 dollars	9%
How long have you been an active ride-sharing driver? *"Active" means the time between two rides should be no longer than a month.*		25,000 to 34,999 dollars	10%
Less than 6 months	5%	35,000 to 49,999 dollars	20%
6 months - less than 1 year	5%	50,000 to 74,999 dollars	33%
1 year - less than 1.5 years	2%	75,000 to 99,999 dollars	11%
1.5 years - less than 2 years	7%	100,000 to 199,999 dollars	7%
2 years or more	80%	200,000 to 249,999 dollars	1%
Prefer not to answer	1%		

Table 2.10: Data characteristics (part 3) (N = 181)

Characteristic	**This sample**	**Characteristics**	**This sample**
How many people live in your household including yourself?		Which ride-sharing companies are you driving for?	
1	29%	Uber only	14%
2	17%	Lyft only	35%
3	13%	Uber and Lyft	51%
4	15%	Within your household, how many are children under the age of 18?	
5	12%	0	58%
6	6%	1	14%
>=7	8%	2	10%
Do you start driving at around the same time every day?		3	8%
Yes	63%	4	4%
No	37%	5	3%
Do you stop driving at around the same time every day?		>=6	3%
Yes	50%		
No	50%		

Figure 2.4: Target daily earnings and working hours



2.4.2 Inferential analysis

Table 2.11 - 2.13 present the mixed logit model estimation results for both working time and relocation choices. Key features of these results are examined in the sections that follow.

Working time choice

Earning rate

Overall, ridehailing drivers are more likely to continue working when their earning rate is higher. However, the magnitude and significance of this effect vary across different types of drivers. Earning rate has the largest impact for no-target drivers, followed by time-target drivers and earnings-target drivers. However, the effect of earning rate on the working time choices of both-target drivers is small and non-significant.

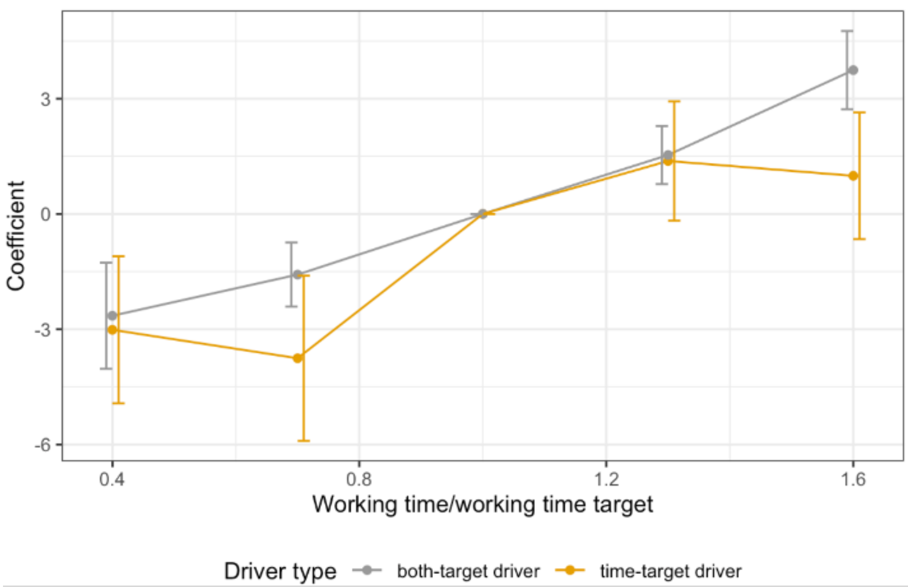
Working time

We only include the working time variable for no-target drivers and earnings-target drivers. For time-target drivers and both-target drivers, the working time variable is not included because its physical meaning is very similar to working time target variables. Overall, having already worked more hours in a day leads to a higher probability of stopping working. However, the effect is statistically significant only for no-target drivers.

Working time target

We only include working time target variables for time-target drivers and both-target

Figure 2.5: Working time target effect for time-target drivers and both-target drivers



Note: error bar represents 95% confidence interval

drivers. The coefficients of the working time target variables are shown in Figure 2.5. The level "working time = target" is used as the reference level, and so its coefficient is fixed to 0 by definition. Both time-target drivers and both-target drivers are most likely to continue working when they are below their working time targets, and they become more likely to stop working after reaching the target.

Earnings target

We only include earnings target variables for earnings-target drivers and both-target drivers. Both earnings-target drivers and both-target drivers are more likely to stop working when they reach 160% of their earnings target. However, the earnings target variables are all non-significant and thus should be interpreted with caution.

Socio-demographics

Female drivers and drivers with more children are more likely to continue working, all else equal. We found no significant differences in working time choice across age groups or other employment status.

Relocation choice

The $ASC_{stay\ in\ the\ same\ place}$ is positively associated with staying in the same place. This means that drivers are more likely to stay in the same neighborhood, everything else being equal. The result is consistent with a study by Henao and Marshall [32]. They found that drivers earn more if they wait for the next trip request in the same place rather than driving to other places, unless they can save at least 30% of trip waiting time.

Neighborhood characteristics

Surge price is significant for both staying in the same place and relocating to other places, meaning that drivers prefer a neighborhood with a higher surge price.

Average trip waiting time has a negative impact on both staying in the same place and relocating to other places, meaning that drivers are less likely to work in a place where there is a long expected wait to get a trip request.

Relocation time is negatively associated with relocating to other places, suggesting that drivers are less likely to relocate to places when it takes a long time to drive there.

Error components

Both error components (continue working and relocate to other places) are significant, meaning that our assumption on the model structure is valid by capturing both unobserved correlations between different options involving continuing to work, and between different neighborhoods to which the driver could relocate.

Table 2.11: **Modeling results (part 1) (N = 1067). Standard errors are in parentheses**

Variable	**Drivers without targets (N = 140)**	**Drivers with time target only (N = 174)**	**Drivers with earnings target only (N = 144)**	**Drivers with both targets (N = 609)**
Working time choice: stop working				
Working characteristics				
$ASC_{stop\ working}$	1.888 (1.637)	3.853 (0.788)***	2.123 (1.836)	2.629 (0.618)***
Earning rate	-0.194 (0.059)***	-0.090 (0.044)**	-0.041 (0.020)**	-1.4×10^{-5} (0.015)
Working time	0.452 (0.129)***	–	0.188 (0.130)	–
Earnings target (reference: Earnings = target)				
Earnings = 0.4*target	–	–	-0.152 (0.847)	-0.201 (0.509)
Earnings = 0.7*target	–	–	-0.572 (0.970)	-0.671 (0.455)
Earnings = 1.3*target	–	–	-0.667 (0.815)	-0.151 (0.426)
Earnings = 1.6*target	–	–	1.741 (1.072)	0.174 (0.506)
Working time target (reference: working time = target)				
Working time = 0.4*target	–	-3.016 (0.977)***	–	-2.650 (0.705)***
Working time = 0.7*target	–	-3.756 (1.097)***	–	-1.579 (0.425)***
Working time = 1.3*target	–	1.379 (0.792)*	–	1.534 (0.385)***
Working time = 1.6*target	–	0.992 (0.840)	–	3.744 (0.519)***

*Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level*

Table 2.12: **Modeling results (part 2) (N = 1067). Standard errors are in parentheses**

Variable	**Drivers without targets (N = 140)**	**Drivers with time target only (N = 174)**	**Drivers with earnings target only (N = 144)**	**Drivers with both targets (N = 609)**
Working time choice: stop working				
Socio-demographics				
Age (reference: 40-64)				
Young adults (18-39)	-0.193 (0.376)			
Older adults (>=65)	0.182 (0.898)			
Gender (reference: male)				
Female	-3.383 (1.051)***			
Num. of children	-0.305 (0.109)***			
Household annual income				
Higher than city median	-0.909 (0.644)			
Do you have another job? (reference: No, I don't have another job)				
Yes, I have another job	-0.760 (0.560)			

*Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level*

Table 2.13: **Modeling results (part 3) (N = 1067). Standard errors are in parentheses**

Variable	**Drivers without targets (N = 140)**	**Drivers with time target only (N = 174)**	**Drivers with earnings target only (N = 144)**	**Drivers with both targets (N = 609)**
Relocation choice: stay in the same place				
Neighborhood characteristics				
$ASC_{stay\ in\ the\ same\ place}$	0.306 (0.157)*			
Surge price	0.184 (0.012)***			
Average trip waiting time	-0.038 (0.008)***			
$Error\ component_{continue\ working}$	1.935 (0.214)***			
Relocation choice: relocate to other places				
Surge price	0.184 (0.012)***			
Average trip waiting time	-0.038 (0.008)***			
Relocation time relocate to other places	-0.124 (0.012)***			
Error component$_{continue\ working}$	1.935 (0.214)***			
Error component$_{relocate\ to\ other\ places}$	0.466 (0.228)**			
Model performance				
Log Likelihood	-970			

*Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level*

2.5 Surge price effect

In our model structure, surge price has a direct impact on relocation choices, and an indirect impact on working time choices. First, the characteristics of each neighborhood determine the utility of relocating to that neighborhood. In turn, the expected utility over all neighborhoods affects the utility of continuing to work. For example, increasing surge price of the current neighborhood increases utility of staying in the same neighborhood. The higher expected utility at the relocation level in turn increases the utility of continuing to work.

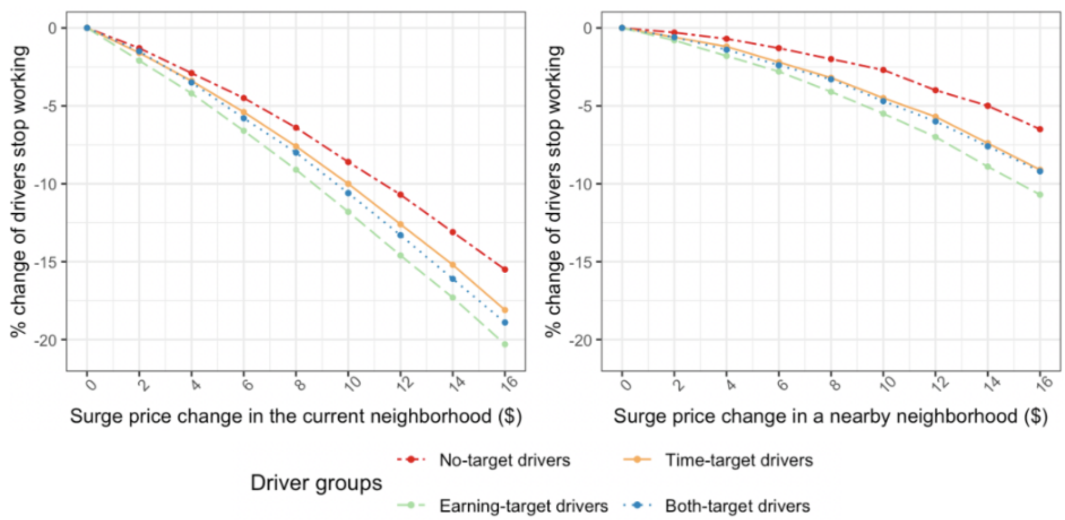
Via a sensitivity analysis, we can understand how surge price would impact both working time and relocation choices. We show the surge price elasticity of drivers stopping working (Figure 2.6) and relocating (Figure 2.7). We vary the surge price in the current neighborhood and a nearby neighborhood and observe the percentage change of the market share of drivers that choose to stop working (Figure 2.6) and to stay in the same place/go elsewhere (Figure 2.7).

2.5.1 Working time choice

Overall, increasing the surge price in either the current or a nearby neighborhood encourages drivers to continue working (Figure 2.6). This pattern is consistent among all types of drivers. Earnings-target drivers are most sensitive to the change of surge price, followed by both-target drivers, time-target drivers, and no-target drivers. This suggests that increasing the same amount of surge price would encourage a larger share of earnings-target drivers to continue working compared with other types of drivers.

However, changing the surge price in the current neighborhood almost doubles the impact decisions to stop working, compared with changing the surge in a nearby neighborhood. The result suggests that drivers would be more likely to stay in the same place than going elsewhere if increasing the same amount of surge price in the current neighborhood and a nearby one.

Figure 2.6: Predicted working time choice under future scenarios

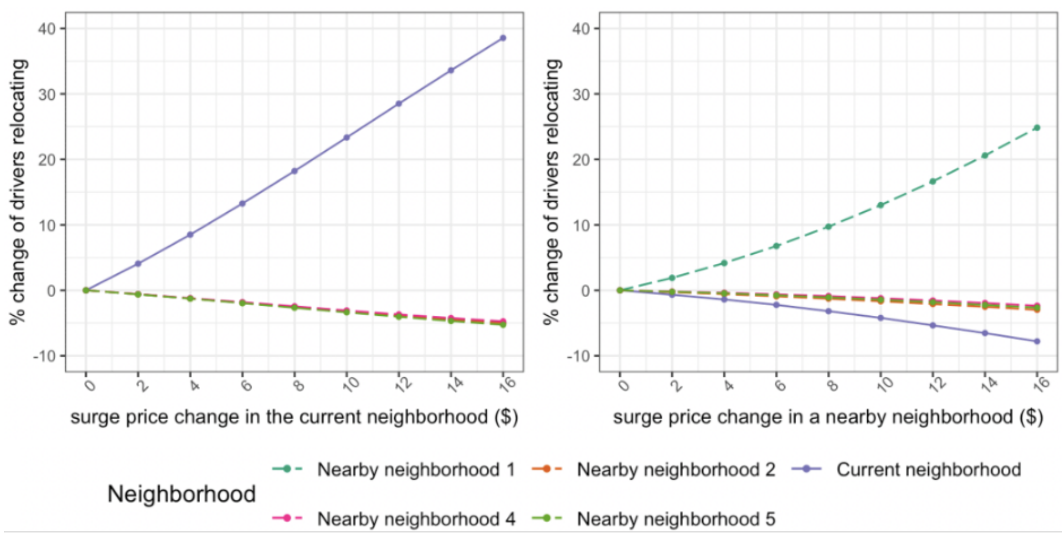


2.5.2 Relocation choice

Increasing the surge price in the current neighborhood encourages drivers to stay where they are. The horizontal axis in Figure 2.7 represents the surge price change, while the vertical axis represents the absolute difference between current percentage and original percentage of drivers relocating. For example, increasing surge price in the current neighborhood by $16 would first increase the share of drivers continuing to work by 19%. Among those who continue working, 40% more drivers would choose to stay in the same place than before, while 5% less drivers would choose to relocate to another neighborhood on average. This result suggests that increasing the surge price in the current neighborhood increases driver supply in that neighborhood in two ways: first, it encourages drivers to continue working; second, it discourages drivers from relocating to other neighborhoods.

If we increase surge price in a nearby neighborhood, we observe more drivers going there. For example, increasing surge price in a nearby neighborhood by $16 would first encourage 10% of drivers to continue working. Among those who continue working, the surge price would encourage 25% of drivers to go there; 7% drivers who otherwise would have stayed in their current neighborhood, 2% drivers who would have relocated to a different neighborhood would instead go to the neighborhood with the $16 surge price.

Figure 2.7: Predicted relocation choice under future scenarios



Changing the surge price in the current neighborhood has larger impact on drivers' relocation choice than changing it in a nearby neighborhood.

2.6 Conclusions

Using 1,067 stated choice responses, our study first identified four types of ridehailing drivers based on their working time and earnings targets, then jointly modeled their working time choice and relocation choices. Based on the modeling results, we simulated the impact of surge price on both working time and relocation choices.

Working time choice Our finding mainly echoes the neo-classic theory of driver labor supply: all types of drivers choose to continue working as their earning rate increases [42]. We see little evidence of an earnings threshold effect that the reference dependent theory postulates [70], even when the driver reported having an earnings target in the survey. However, there is evidence of reference dependent behavior with respect to the working time variable: time-target drivers and both-target drivers are less likely to continue working after hitting their working time targets.

Relocation choice Relocation choice is mainly impacted by surge price, average trip waiting time, and relocation time: higher surge price in the current neighborhood encourages the driver to stay, while higher surge price in a nearby neighborhood attracts the driver to relocate. Drivers are more likely to stay in a neighborhood where the average trip waiting time is low. Longer relocation time discourages drivers to relocate. In addition, drivers are more likely to stay in the same place, everything else being equal.

Future research There are several future directions in which our work can be improved: First, future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. The sample in our study only comes from the airport waiting area. Future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. However, our experience shows that ridehailing drivers are a notoriously difficult community to reach and recruit for survey research. Second, future efforts should identify and consider other important factors such as pay rates of different cities to have a better understanding of the relationship between trip features and drivers' behavior.

Chapter 3

WHAT IMPACTS RIDEHAILING DRIVERS' TRIP REQUEST ACCEPTANCE?

The following chapter presents the paper that is in print on International Journal of Sustainable Transportation by Yuanjie (Tukey) Tu, Moein Khaloei, Nazmul Arefin Khan, and Don MacKenzie.

This chapter modeled the relationship between trip features and drivers' trip request acceptance using data from a stated choice experiment. Trip request acceptance means the likelihood a ridehailing driver accepts a trip request sent to them by a passenger. Trip features represent the features of the requested trip, including passenger star ratings, trip length, pick-up time, average waiting time, surge price, and shared/pooled ride. Based on our findings, we have further provided policy recommendations for promoting trip request acceptance rates by calculating drivers' willingness to accept compensation for undesired trip features.

To the authors' knowledge, this is the first study applying a generalized additive mixed model (GAMM) to examine how ridehailing drivers' responses to trip requests depend linearly and non-linearly on trip features, as well as drivers' socio-demographic and employment characteristics. This study advances the current research area by quantifying the linear and nonlinear impact of trip features on drivers' trip request acceptance. The findings and proposed policy implications can also be used to improve ridehailing service efficiency, better fulfill urban mobility needs, narrow the mobility disparities across different races and neighborhoods, and reduce negative environmental impacts.

3.1 Term definitions

To aid understanding, I provide term definitions used in the rest of the chapter in Table 3.1.

Table 3.1: Term definition

Terms	**Definition**
Ride-hailing	Services are services such as Uber and Lyft, that connect passengers to local drivers to give them a ride
Solo ridehailing	Services provide a ride-hailing service under your request only. Other users cannot make requests to share the ride with you
Shared ridehailing	Services match you with riders heading in the same direction, so you can share the ride and cost
Trip request acceptance	The choice of deciding when to start and stop working per workday
Trip features	Features of a specific ridehailing trip, such as passenger ratings, pick-up time, trip distance, and surge price.

3.2 Data collection

Our primary data source is a stated preference survey completed by 200 ridehailing drivers in the Seattle metropolitan area. Using a stated preference survey enables us to investigate the causal relationship between trip features and trip request acceptance rate. The inclusion of an experimental design in the survey allows us to control endogeneity, a common problem that can lead to omitted variable bias when using non-experimental data [73]

The study was identified as human subjects research that qualifies for exempt status from Institutional Review Board (IRB) approval by Human Subjects Division, University of Washington (IRB ID: STUDY00013095). The survey was conducted from August 11 to September 9, 2021 in Seattle, USA. We trialed online and in-person data collection approaches. An in-person approach was finally adopted because (1) the online response rate was low and (2) many online respondents appeared not to be real ridehailing drivers, based on screening and quality check questions in the survey. More details on performance of different data collection approaches can be found in [69].

We recruited participants and assisted them to complete the survey on an iPad in the Seattle-Tacoma International Airport ridehailing driver waiting area. Respondents were compensated with an $15 Amazon gift card in the indicated amount.

Anecdotally, ridehailing drivers do not seem to trust surveys and interviews. The most frequently asked questions when administering the survey were "what is the purpose of the study?" and "do you work for Lyft or Uber?". Their major concern was that the responses would be used against them by ridehailing companies. This echoes existing evidence that drivers and companies have a tense relationship [53]. A total of 200 responses were collected from approximately 250 drivers who were invited to participate.

3.2.1 Survey design

We conducted a series of pilot interviews with ridehailing drivers before designing the questionnaire, to ensure we captured the most important variables and used terminology familiar to the drivers. The questionnaire contained three sections: basic driving information, choice experiments, and background information.

Basic driving information

We asked respondents to provide information on which ridehailing companies they are driving for, how long they have been a ridehailing driver, whether they have another job besides ridehailing driver, the time they generally start and stop driving each day, any targets for working hours or earnings per day, and the numbers of trip requests they (1) received and (2) rejected in the past week.

To capture respondents' working time targets, we first ask them "Do you usually try to work a certain number of hours per day?" If their answer is "yes", we asked them "How many hours do you usually try to work per day?" Similarly, we captured their earnings target by first asking them "Do you usually try to earn a certain amount of money per day?" If they answered "yes", we asked them "How much do you usually try to earn per day?"

After capturing working time targets and earnings targets, we categorized driver respondents into four types based on whether they reported having targets of one or both types: *no-target drivers*, *time-target drivers*, *earnings-target drivers*, and *both-target drivers*. These driver types will be further used in our modeling work.

Choice experiments

To investigate the causal relationship between the trip features and trip request acceptance, a blocked factorial design was adopted. The experimental design was conducted as follows. First, 5 variables were chosen as experimental variables, including ridehailing demand, passenger pick-up time, passenger ratings, solo/shared trip, and whether the trip is over 45 minutes. These variables included the information commonly provided to drivers when they receive a trip request. Variable descriptions are shown in Table 3.1. Second, levels were generated for each experimental variable (Table 3.2). Third, the full matrix of combinations of the variable levels was generated. Next, we created blocks of 6 combinations (choice scenarios) for each respondent. Each respondent was asked to make choices for 6 choice scenarios. In each scenario, she/he was asked to choose to "accept" or "reject" a trip request based on different combinations of experimental variable levels. Figure 1 shows an example of driver trip request acceptance experiment.

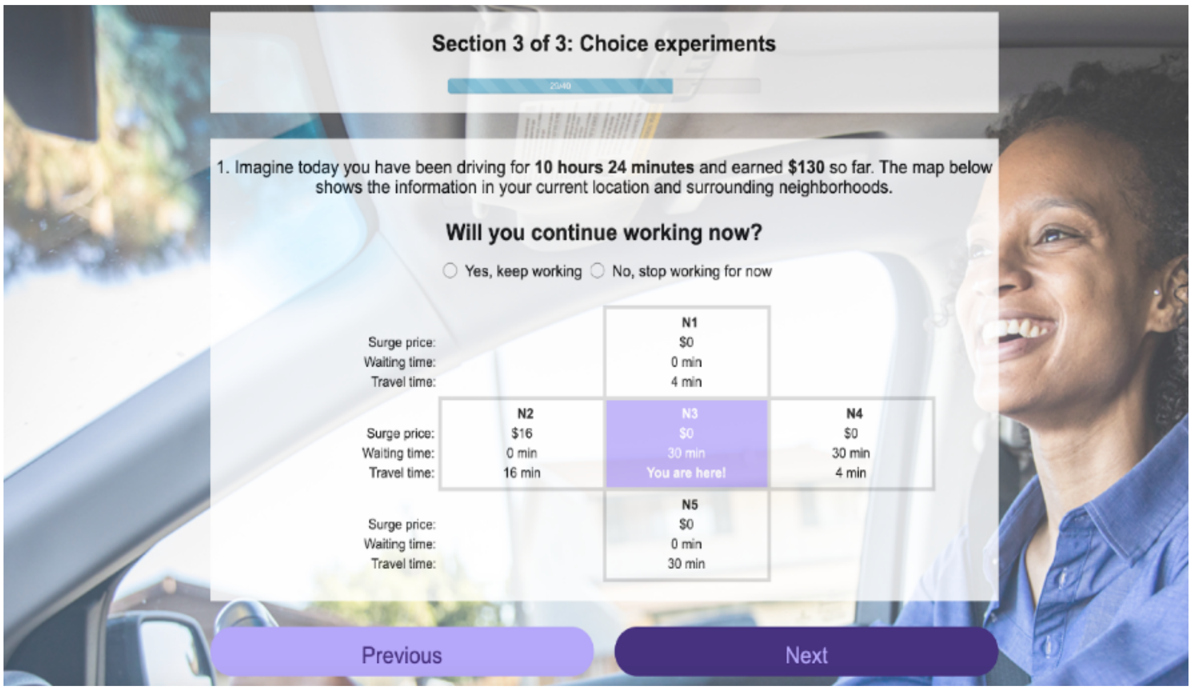
Background information

In this section, respondents were asked questions about their socio-demographics including age, gender, race, whether born in the US, whether a student, household size, individual and household income, education level, job status (whether part time, whether have another job), and subjective health status.

3.2.2 Data quality

To improve data quality, multiple screening and quality check questions were adopted as follows. First, before entering the choice scenario questions, survey respondents were asked two comprehension check questions. For each comprehension check, the respondent were asked to choose the correct meaning of a highlighted number in a choice scenario. Every

Figure 3.1: An example of the choice experiments: working time choice



respondent had the chance to answer each of the comprehension questions twice. They were only allowed to proceed if the answers were correct, otherwise the survey was terminated. Second, one question was included to check respondents' attention. The respondents were told "this is an attention check" and were asked to choose the neighborhood with given surge price, waiting time, and travel time in the middle of choice scenario questions. Finally, a logic check was applied in the survey. In the background information section, respondents were asked to provide their annual income (both household and individual). Each respondent's annual household income should be equal or larger than their individual income. Responses failing either the attention or logic check, were removed.

For modeling purposes, we also removed respondents who have null inputs or choosing "prefer not to answer" in independent variables mentioned in Section 3. Respondents who completed 0 trips in the prior week were also removed.

After data quality check and data cleaning, a total of 181 respondents and 1,085 choice responses were retained for analysis.

Figure 3.2: An example of the choice experiments: relocation choice

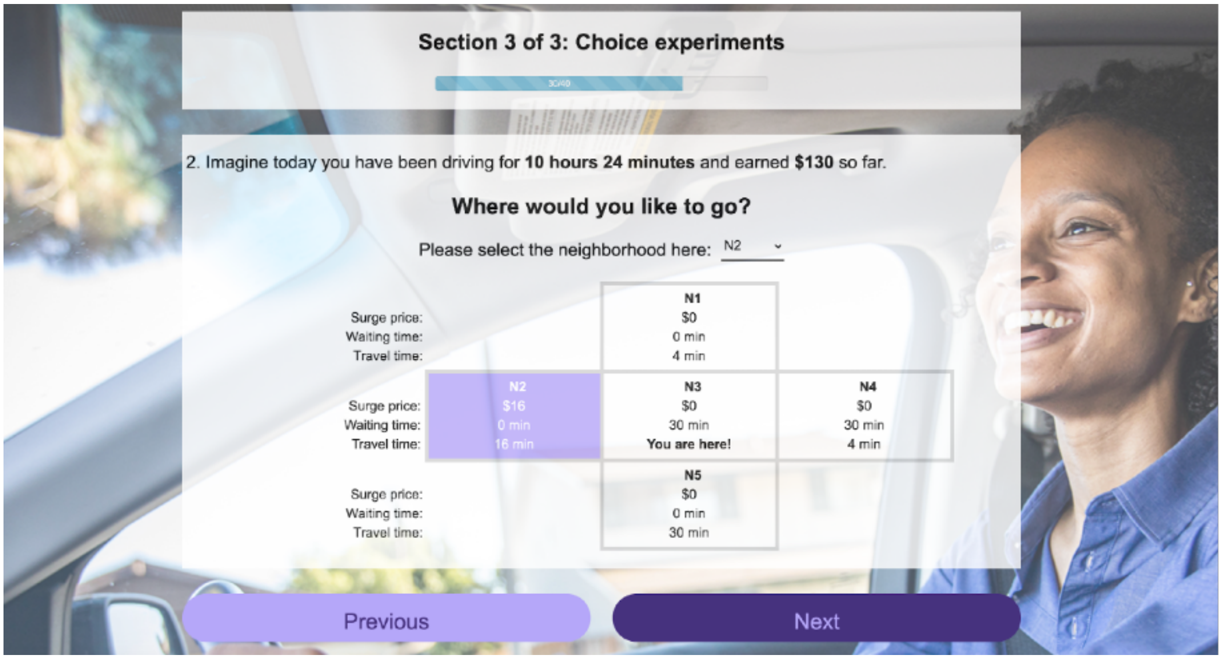


Table 3.2: Experimental variables

Attributes	Definition
Ridehailing demand	Represents the demand for ridehailing services. Measured jointly by *surge price ($)* and *average waiting time for a trip request if they decline the current one (min).* Higher demand areas have lower waiting times and higher surge price and vice versa.
Passenger pick-up time	The time to drive from the current location to the pickup location (minutes).
Passenger ratings	Average rating the passenger received from drivers, ranging from 4.1 to 4.9. We chose 4.1 as the lower bound because we learned from driver interviews that very few passengers have ratings below 4 stars.
Solo/shared trip	Whether the trip is a solo or shared trip. A shared trip means picking up unrelated passengers or groups of passengers with different origins and destinations. A solo trip means an individual or group traveling together.
Long trip	If the trip is over 45 minutes, 1; otherwise, 0. We choose the 45-minute threshold because the pilot driver interviewees mentioned ridehailing companies provide 45 minutes as a threshold for “long trip”.

Table 3.3: Experimental attribute levels

Attributes	Levels								
Surge price ($)	16	12	8	4	0	0	0	0	0
Average waiting time (min)	0	0	0	0	0	8	16	24	30
Passenger pick-up time (min)	4		8		12	16		20	
Passenger ratings	4.1		4.3		4.5	4.7		4.9	
Solo/shared trip	Solo				Shared				
Long trip	Yes, long trip				No, not a long trip				

3.3 Methods

To understand the relationship between trip features and ridehailing drivers' behavior towards trip request, a generalized additive mixed model (GAMM) was adopted.

The dependent variable is a binary variable, meaning that a respondent can "accept" or "reject" the trip request based on the given choice scenarios. Independent variables include driving habits (trip rejection rate), trip features (e.g., pick-up time, long trip, surge price), socio-demographics (e.g., age, gender) and employment characteristics (e.g., whether they have another job besides ridehailing driver). To account for multicollinearity, variables with variance inflation factors (VIF) larger than 5 were excluded. The variable descriptions are shown in Table 3.3.

To explore how trip requests depend linearly and nonlinearly on trip features, we applied a generalized additive mixed model (GAMM). A GAMM is a semi-parametric statistic modeling approach widely used in detecting nonlinear relationships [51]. The nonlinear effects represented by nonparametric functions shown in 3.1 are represented by smooth splines and estimated by restricted maximum likelihood. In addition to including nonlinear effects, a GAMM includes a random effect for each individual driver. The R package "mgcv" was used to estimate the model [47]. Notation descriptions are shown in 3.6.

$$g(\mu_i k) = \alpha + \beta X_{i,k} + \gamma Z_i + f(r_{i,k}, l_{i,k}) + f(wr_i) + b_i \quad (3.1)$$

Table 3.4: Variable descriptions: Driving characteristics

Variable	**Definition**
Dependent variable	
Response to a request	If the respondent accepts the trip request, 1, else, 0
Driving habits	
Trip rejection rate	Number of trip requests rejected divided by number of total trip requests received last week, in %
Trip features	
Pick-up time	Driving time to pick up a passenger, in minutes
Long trip	If the trip is longer than 45 minutes (does not include pick-up time), 1; else, 0
Average trip waiting time	Expected waiting time until next request if the respondent rejects the current one, in minutes
Surge price	An additional surge amount to the trip fare, in dollars
Passenger ratings	The average of the ratings that a passenger has received from drivers
Shared/pooled ride	The trip is shared with other passengers who are heading in the same direction. If it's a shared trip, 1; else, 0

Table 3.5: Variable descriptions: Socio-demographics

Variable	**Definition**
Socio-demographics	
Age	The age of the respondent. 18 – 39: 0, 40 – 64: 1, ¿=65: 2
Gender	If 1, female; 0, male
Household size	The number of people (including the respondent) in the household.
City median household income	If household income equal or higher than Seattle median household income in 2019 ($102,500), 1; else, 0.
Education level	The education level of a respondent, 0: less than high school, 1: high school or GED, 2: college, including some college, professional degree, associate degree and bachelor's degree, 3: graduate school or above, including master's degree and doctoral degree
Employment characteristics	
Uber	If Uber driver, 1; else, 0
Lyft	If Lyft driver, 1; else, 0
Another job	Whether the respondent has another job other than the ridehailing driver, 0: has another job, full-time (35+ hours/week), 1: has another job, part-time (fewer than 35 hours/week), 2: doesn't have another job

Table 3.6: Notation descriptions

Notations	**Descriptions**
$g(\cdot)$	a logit function
$\mu_{i,k}$	$E(y_{i,k})$, where $y_{i,k}$ represents response to a request of driver i and choice scenario k
α	the constant
$X_{i,k}$	a vector of attributes of choice situation k faced by driver i
Z_i	a vector of observable attributes of driver i
$f(\cdot)$	a smooth function (we use low-rank thin plate splines in this study)
$r_{i,k}$	pick-up time
$l_{i,k}$	a dummy variable representing whether the trip presented to driver i in scenario k is a long trip
$f(r_{i,k}, l_{i,k})$	nonlinear interactions between pick-up time and long trip
wr_i	the weekly trip rejection rate of driver i
$f(wr_i)$	a smooth function between trip rejection rate and trip request acceptance. In this study, we only included two nonlinear terms because other variables were found to have a linear relationship with $g(\mu_{i,k})$
b_i	an individual-specific random component assumed to be distributed as $N0, \sigma^2$ where σ is the variance component

3.4 Results

All supplemental materials (e.g., code, data descriptions) can be found in this GitHub repository.

3.4.1 Descriptive analysis

Socio-demographics and employment characteristics

The data characteristics are shown in Table 3.5. Compared to the general population, our sample of ridehailing drivers has some unique characteristics. They are overwhelmingly male (95%), African American (75%), and born outside the US (94%). Most of the respondents are working age, with only 4% being 65 years or older. In terms of education background, a vast majority of respondents – 46% and 44% graduated from high school and college, respectively. Only a small proportion of respondents have an education background less than high school or higher than college (graduate school).

Most respondents (75%) have a small household size (¡= 4 members). 30% of respondents live by themselves. Most respondents (58%) do not have children, followed by 1 4 children. Over half of respondents (52%) have a household income between $35,000 and $74,999. 28% have a household income less than $35,000. Only 17% have a household income higher than $75,000.

Table 3.7: Data characteristics (N = 181)

Characteristics	This sample	Characteristics	This sample
What is your gender?		***Are you currently a student?***	
Male	96%	Yes, full time (35+ hours/week)	3%
Female	4%	Yes, part time (<35 hours/week)	7%
What is your race?		No, not a student	90%

Continued on next page

Table 3.7 – continued from previous page

Characteristics	This sample	Characteristics	This sample
White	7%	***Are you of Hispanic, Latino, or Spanish origin?***	
Asian	11%	Yes, Hispanic origin	2%
African American	75%	No, non-Hispanic origin	95%
Another	5%	Prefer not to answer	3%
Prefer not to answer	2%	***Were you born in the United States?***	
What is your age?		Yes, born in the US	4%
18-39	51%	No, born outside the US	95%
40-64	45%	Prefer not to answer	1%
65 and above	4%	***Do you have another job besides ride-sharing driver?***	
Do you have another job besides ride-sharing driver?		Yes, full time (35+ hours/week)	9%
Less than high school	5%	Yes, part time (¡35 hours/week)	12%
High school	46%	No, no another job	79%

Continued on next page

Table 3.7 – continued from previous page

Characteristics	This sample	Characteristics	This sample
College	44%	***Which category best describes your household income before taxes from the last calendar year? (in dollars)***	
Graduate school or higher	5%	Less than 10,000	4%
How long have you been an active ride-sharing driver? *"Active" means the time between two rides should be no longer than a month.*		$10,000 to $14,999	3%
Less than 6 months	6%	15,000 to 19,999	4%
6 months - less than 1 year	5%	20,000 to 24,999	9%
1 year - less than 1.5 years	2%	25,000 to 34,999	9%
1.5 years - less than 2 years	6%	35,000 to 49,999	20%
2 years or more	80%	50,000 to 74,999	33%
Prefer not to answer	1%	75,000 to 99,999	10%
How many people live in your household including yourself?		100,000 to 199,999	7%
1	30%	200,000 to 249,999	1%

Continued on next page

Table 3.7 – continued from previous page

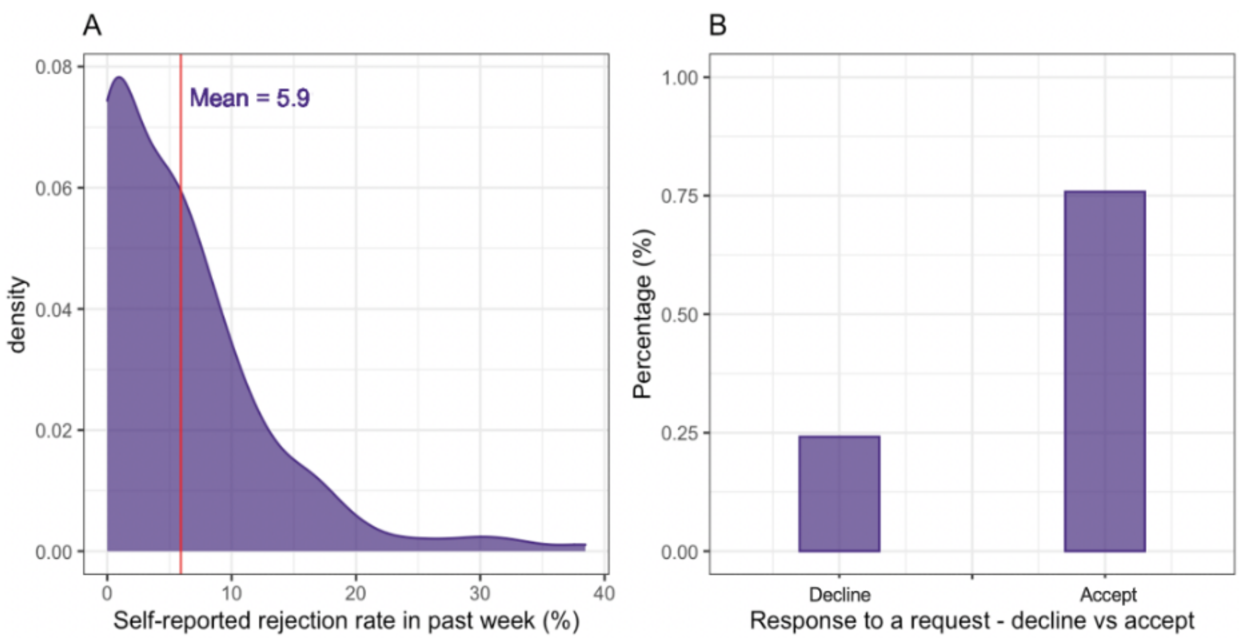
Characteristics	This sample	Characteristics	This sample
2	17%	***Which ride-sharing companies are you driving for?***	
3	13%	Uber only	14%
4	15%	Lyft only	35%
5	11%	Uber and Lyft	51%
6	6%	***Within your household, how many are children under the age of 18?***	
>= 7	8%	0	58%
0-49	42%	2	10%
50-99	47%	3	8%
100-149	10%	4	4%
>= 150	1%	>= 5	6%

Response to a request

Overall, respondents reported accepting most of the trip requests they receive. 32% respondents said they had accepted all trips in the past week, and the average rejection rate in the past week was 5.9%. Only 10% respondents said they had rejected more than 15 trips in the prior week. In the stated choice scenarios, 24% of the hypothetical trip requests were rejected 3.3.

Driver respondents mentioned four reasons for accepting trips in the pilot interviews and the survey comment area: (1) rejecting trips brings punishment – driver ratings could decrease, there could be up to a 15-minute timeout with no trips, and there is a risk of account deactivation if they reject too many trips; (2) their income mainly comes from driving for TNCs, and they would be unable to make profit if they reject a lot of trips; (3) they are given approximately only 5 seconds to make the decision, hence it is difficult to be thoughtful and selective; and (4) the information provided to drivers is limited. Important information such as trip destination, estimated distance and time, and trip fare are not shown to the drivers with the trip request, which makes it difficult to turn down a request.

Figure 3.3: Distribution of response to a request



3.4.2 Modeling results

The modeling results are shown in Table 3.8, 3.9 and 3.10. The model results include two sections: model performance and coefficients. In terms of the model performance, the final log likelihood is -278, with 53.5% deviance explained.

The coefficient section is composed of two parts: parametric coefficients and smooth terms. The parametric coefficient section shows the linear terms and their significance. The smooth term section exhibits the nonlinear terms and their estimated degrees of freedom. A variable with an estimated degree of freedom of 1 indicates a linear relationship, while estimated degrees of freedom significantly higher than 1 indicates nonlinearity.

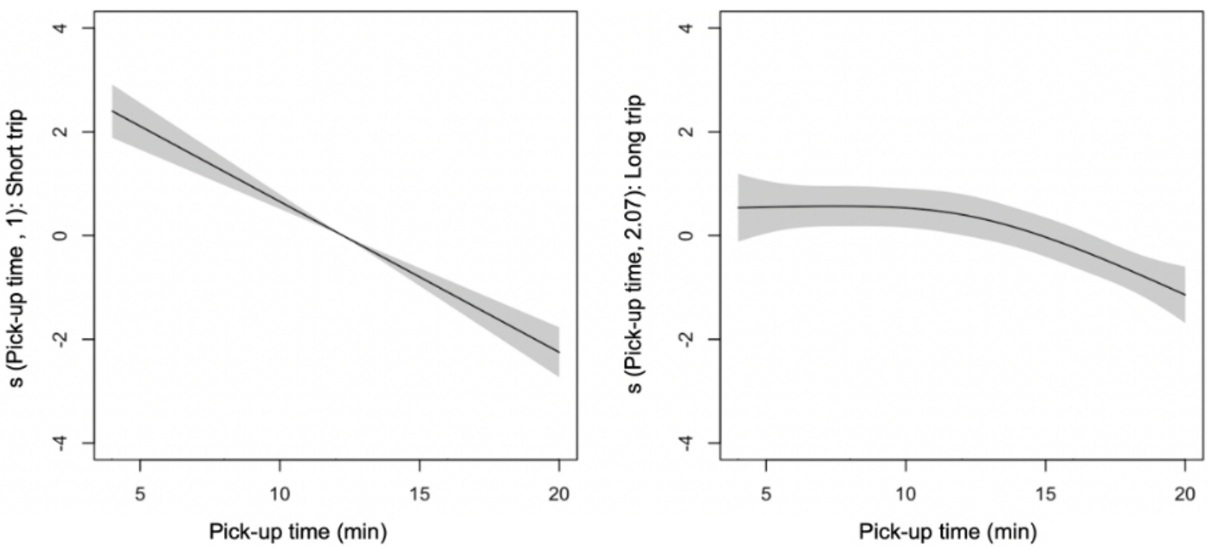
Trip features

(1) Nonlinear terms: pick-up time

3.4 shows the nonlinear effects of pick-up time and its interactions with long trip from the GAMM. The horizontal axis represents pick-up time, while the vertical axis represents the effects on the log odds of accepting a trip versus rejecting a trip, everything else being equal. In both conditions, a driver is less likely to accept a trip request if s/he needs to drive a long time to pick up the passenger. A possible explanation is that trips with long pickups are commonly not cost-effective since drivers must cover the cost (e.g., the opportunity cost of getting another ride, fuel, mileage) by him/herself. This echoes the finding of another study, which found that a few drivers in a focus group said they tend to not take trips with long pickups [53].

However, the interaction between pick-up time and long trip requests (over 45 minutes) reveals richer information. The relationship between pick-up time and trip request acceptance is linear when the trip is short. For short trips, the log odds of trip request acceptance decline linearly with pick-up time, even for short values of pick-up time. For long trips, however, the story is quite different: drivers appear to be insensitive to changes in pick-up time up to about 12 minutes. Once pick-up time exceeds 12 minutes, a driver's odds of accepting a long trip begin to decline.

Figure 3.4: Nonlinear effects: pick-up time and long trip in GAMM model



(2) Linear terms

Surge price is positively associated with response to a request. It's reasonable since surge price means higher trip earnings. The result is also consistent with other studies [52] [35]. However, surge pricing may also have downsides: one study mentioned that surge pricing may result in more rejected trips without surge prices because drivers were on the way to the surge pricing areas [53].

Shared trip has a negative relationship with response to a request, which is consistent with a recent study [1]. Shared trips might indicate lower trip fares, frequent pickups and drop-offs, and potentially complicated interactions between passengers [1]. Another survey also discovered that drivers are generally dissatisfied with UberPool [30].

Long trip (trip over 45 minutes) is significant and positively correlated with trip request acceptance. The result means ridehailing drivers are more likely to accept long trips than short ones. This is intuitive since overall, long trips mean a higher fare and less time lost on pickups and drop-offs [53]. However, some drivers mentioned a mixed feeling about long rides: a long trip risks leaving the driver in "the middle of nowhere" with no prospects for a return trip [40].

Passenger rating demonstrates a positive relationship with trip request acceptance, however, it the parameter is statistically significant only at 10% significance level. Generally, it is expected that ridehailing drivers may favor trips with higher passenger ratings. A few respondents in our survey mentioned in the comment area that they would not take passengers with ratings lower than a certain threshold (e.g., 4.5). However, when a spline term for passenger ratings was included, it failed to indicate any threshold or non-linear effects. This also echoes existing evidence [19, 55]. Drivers dislike low passenger ratings because such passengers might be late for the ride, disrespectful to the driver, and neglecting road safety (thus ask the driver to pick up/drop off in the middle of the road), among other reasons [11].

Finally, average waiting time for a trip is negatively associated with trip request acceptance but is non-significant.

Socio-demographics and employment characteristics

The parameter estimation results of socio-demographics and employment status are found to be non-significant. This result is also confirmed by the results of a generalized likelihood ratio test [34]. This contrasts with another study, which finds gender, employment status and amount of years driving are significant predictors of trip request acceptance [52]. They found males, part-time drivers, and those who have better education more likely to accept the trip request. However, the coefficients of these variables in our study are directionally different and all of them are non-significant. The other study also used stated preference experiments but did not account for repeated measures for the same individual [52]. To compare with this study, we re-estimated our model without accounting for repeated measures (by omitting the random effects). When we did so, the socio-demographics and employment characteristics were found to be statistically significant. This may suggest individual-level characteristics (including socio-demographics and employment status) appear overly significant when repeated measures are not accounted for within the modeling framework.

Table 3.8: Modeling results (trip features): coefficients (N = 1085). Dependent variable is decision to accept (y=1) or decline (y=0) a trip request.

Trip feature variables	**Coefficients**	**Standard errors**
Intercept	-0.371	2.844
Long trip	1.259***	0.224
Average waiting time for a trip (minutes)	-0.008	0.011
Surge price ($)	0.082***	0.025
Star rating of passenger	0.668*	0.385
Shared/pooled	-0.889***	0.222
Note: '***' refers to 0.01 significance level; '**' refers to 0.05 significance level; '*' refers to 0.1 significance level.		

Table 3.9: Modeling results (socio-demographics): coefficients (N = 1085). Dependent variable is decision to accept (y=1) or decline (y=0) a trip request.

Socio-demographics	**Coefficients**	**Standard errors**
What is your age? (reference: < 40)		
40-64	0.567	0.695
>= 65	1.687	1.637
Household size	-0.138	0.157
Household income (reference: less than city median)		
Equal or higher to city median	0.807	1.148
Gender (reference: male)		
Female	1.848	1.664
What is the highest degree or level of school you have completed? (reference: less than high school)		
High school	-1.813	1.759
College	-1.918	1.754
Graduate school and above	-3.216	2.143
What platforms do you drive for?		
Uber	-0.160	0.708
Lyft	-0.083	0.920
Do you have another job? (reference: yes, full time)		
Yes, part time	1.152	1.432
No other jobs	1.212	1.179
Note: '***' refers to 0.01 significance level; '**' refers to 0.05 significance level; '*' refers to 0.1 significance level.		

Table 3.10: Modeling results (non-linear effects): coefficients (N = 1085). Dependent variable is decision to accept (y=1) or decline (y=0) a trip request.

Smooth item	**EDF**	**Chi. Sq.**
s (Pick-up time): Long trip	2.065***	18.145
s (Pick-up time): Short trip	1.001***	87.354
s (Trip rejection rate)	4.469	1.863
Random effect	**EDF**	**Standard Dev.**
ID	130.362***	1.925
Model performance		
Deviance explained	53.5%	
Final Log likelihood	-278	
Note: '***' refers to 0.01 significance level; '**' refers to 0.05 significance level; '*' refers to 0.1 significance level.		

3.5 Implications

A lack of understanding on how drivers respond to a trip request impairs the development of effective interventions for promoting trip request acceptance rates. To prevent drivers from rejecting the trip requests, TNCs have adopted strategies like hiding most trip information from the drivers, giving up to a 15 minutes timeout, or deactivating driver accounts when they frequently reject too many trips [55, 46]. These "stick" strategies have been criticized as rough and neglecting drivers' rights [46]. One critical downside of adopting such strategies is, it makes ridehailing drivers unhappy, and might hurt drivers' willingness to stay in the labor market [1, 14].

In this section, possible positive "carrot" interventions for increasing trip request acceptance rates were discussed. Based on the model estimation results, trip features are the most significant factors that affect drivers' trip request acceptance decisions. Therefore, understanding drivers' willingness to accept (WTA) compensation for main trip features are warranted. Drivers' WTA compensation in this section was presented based on the GAMM estimation results. WTA equations used in our study are shown in equations (2 4). Other possible interventions were also briefly discussed.

3.5.1 Willingness to accept (WTA) compensation

Shared trip

Compared with solo trips, a shared trip decreases the total utility by β_m, in this case, 0.889. To compensate for the same amount of utility lost caused by the shared trip, the surge price needs to increase by ΔS, in this case, \$10.84. This result means that drivers need to be compensated by an extra \$10 to accept a shared trip! This result paints a negative picture for the financial sustainability of pooling, especially since other research shows that travelers want to pay less, not more, for a pooled trip [36].

$$\Delta\mu_m = \beta_m \Delta M = -\beta_s \Delta S_m \tag{3.2}$$

Where $\Delta\mu_m$ is the utility difference between a solo and a shared trip; β_m and β_s are the coefficients of the shared/pooled ride and surge price, respectively; ΔM represents shifting from a solo to a shared ride. Δs_m refers to the WTA to compensate for $\Delta\mu_m$.

Passenger rating

Decreasing the passenger rating by 0.10 decreases the total utility by β_p, in this case, 0.067. The surge price needs to increase by \$0.81 to compensate for the utility lost caused by passenger rating decrease. This result means that drivers would be willing to accept a trip with lower passenger ratings when compensated by an extra \$0.81.

$$\Delta\mu_p = \beta_p \Delta P = -\beta_s \Delta S_p \tag{3.3}$$

Where $\Delta\mu_p$ is the utility change when the passenger rating decreases by ΔP; β_p is the coefficient of passenger ratings; ΔP represents passenger rating change, in this case, 0.10.

Δs_p refers to the WTA needed to compensate for $\Delta \mu_p$.

Pick-up time

Since the relationship between pick-up time and WTA changes is nonlinear, WTA of pick-up time was calculated by simulation (3.5).

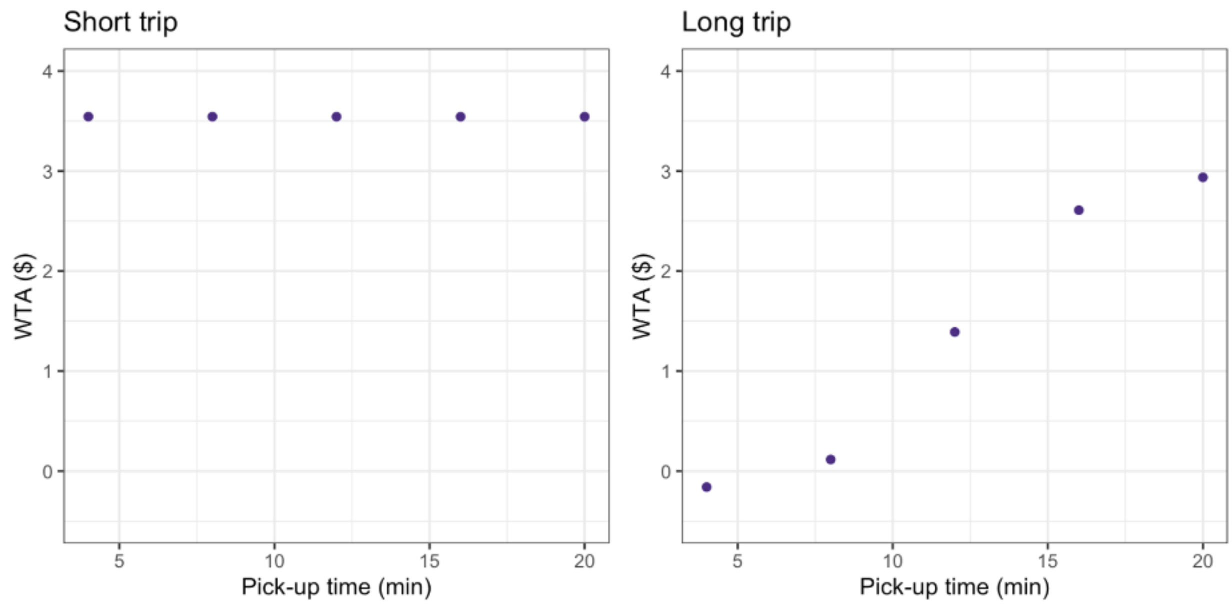
$$\Delta \mu_r = g(y) - g(y_\Delta R) = -\beta_s \Delta S_r \tag{3.4}$$

Where Δmu_r is a vector of utility changes when every element in the pick-up time vector decreases by ΔR; $g(\cdot)$ is a logit function; y means the vector of driver responses to a trip request of the collected data; $g(y_\Delta R)$ represents the simulated vector of driver responses when pick-up time increases by ΔR. In this case, ΔR equals 1 minute. ΔS_r refers to a vector of prices needed to compensate for ΔR with different pick-up times.

Simulation results suggest that compared to short trips, WTA compensation for long trips is generally lower. For a short trip, it needs an additional \$3.60 to accept a trip if the pick-up time increases by 1 minute, regardless of the initial pick-up time. However, for a long trip, drivers only need compensation if the pick-up time goes beyond 8 minutes. For instance, when the pick-up time increases from 20 to 21 minutes, ridehailing drivers would need an extra \$3 to keep the utility of the trip the same.

One thing to note is that although we investigated drivers' willingness to acceptance surge prices, surge price may not function entirely the same as higher trip fare. For example, some drivers mentioned surge pricing cannot be trusted since it only lasts for several minutes. They do not chase surge prices since it often disappears when they arrive at an area that moments before had a high surge price. A higher fare that is guaranteed for each trip may have a larger impact on promoting trip request acceptance. Future research may test the effect of higher trip fare on trip request acceptance.

Figure 3.5: WTA compensation for pick-up time



Other interventions

Aside from monetary compensation, some other interventions could promote ridehailing drivers' trip request acceptance rates. This may include, better passenger training, more satisfying driver protection mechanisms, and more efficient algorithms to match passengers. Such interventions may improve passenger ratings, decrease pick-up times, and reduce drivers' cost of accepting shared ride trips and trips with lower passenger ratings.

3.5.2 Why do ridehailing drivers hate shared rides?

Why are drivers less likely to accept pooled rides? I summarized the main reasons based on the ridehailing driver behavior survey that was described in Chapter 2 and 3, and the existing studies in the field.

(1) Pooled rides are cheaper

First and foremost, drivers are paid less per ride for a pooled ride than a solo ride. According to a study in Netherlands, ridehailing drivers are paid based on the trip distance, regardless the number of passengers [53]. According to [53], they would be more likely to accept pooled rides if the trip fare takes the number of passengers into consideration. Our survey results show that pooled rides tend to provide smaller tips for the drivers as well – this is intuitive because passengers choose pooled rides because it's cheaper therefore it's more unlikely for them to pay extra tips.

(2) Pooled rides take more effort

Another reason drivers do not like accepting pooled rides is that they need to put higher efforts per ride (make frequent stops) than solo rides. According to our survey data, coordinating multiple pickups and drop-offs can place higher demand on the driver and be more stressful. This echoes an existing study in Netherland, that "every stop increase the operational costs as well as the risk of getting fined" [53].

(3) Greater uncertainty

Pooled rides can boost risks on lower driver ratings, trip cancellation, passengers' inappropriate behaviors, etc.

Some driver respondents during our survey expressed their frustration about getting lower driver ratings when taking pooled rides. There is a risk that passengers would blame other passengers' bad behaviors on the driver and therefore give lower driver ratings. In addition, since drivers need to make multiple pickups and drop-offs during a pooled ride, it's likely that passengers will need to wait longer to be picked up and the trip might be longer. Some driver respondents expressed that passengers may give a lower rating for a pooled ride since they have the same expectation as when they are hailing a solo ride. More passengers might also increase the change of having conflicts between driver and passengers and therefore lead to lower driver ratings [53].

At the same time, more passengers would increase the risk of trip cancellation, and passengers' inappropriate behaviors.

Overall, drivers dislike pooled rides because they are higher cost (lower driver ratings, more efforts), greater uncertainty yet lower rewards (lower trip fare).

3.6 Conclusions and discussions

Understanding trip request acceptance of ridehailing drivers is significant for improving ridehailing service efficiency, promoting equal access, and easing negative environmental impacts. This study explored the non-linear relationship between trip request acceptance and trip features, socio-demographics and employment characteristics using a generalized additive mixed model (GAMM).

The model results confirm that, firstly, nonlinear effects between trip features and trip request acceptance are necessary to explore, and secondly, it is important to account for repeated measures by including random effects in the model.

Among all the variables, trip features have the most significant effects. Results suggested that longer pick-up time is negatively associated with trip request acceptance. The relationship between pick-up time and trip request acceptance is linear when the trip is short (not over 45 minutes), while nonlinear otherwise. When the trip is short, drivers are more likely to accept trips with shorter pick-up times, and less likely to accept trips with longer pick-up times compared to when the trip is long. When the trip is long, the pick-up time has smaller positive effect on the trip request acceptance when the trip is less than 12 minutes. Once the pick-up time goes beyond 12 minutes, the trip request acceptance drops rapidly. It was also found that long trips (over 45 minutes) are positively associated with trip request acceptance. With an increase in surge price, drivers are more likely to accept trip requests. Furthermore, passenger ratings are positively associated with trip request acceptance. However, drivers are less likely to accept shared trips than solo ones.

Drivers' socio-demographic and employment status impacts were statistically non-significant in our model. However, their impacts became significant when repeated measure effects were no longer controlled. This points to the importance of controlling for repeated measures and highlights an important limitation of some of the extant literature that found socio-demographic predictors to be significant, but failed to control for repeated measures.

As for corresponding policy interventions to promote trip request acceptance, we concluded that the most effective approach might be adjusting trip features (e.g., increase surge price, improve matching algorithms to decrease pick-up time) or compensating for undesired trip features. However, designing policies targeting drivers with different socio-demographics may not work, since their impacts on trip request acceptance are non-significant after accounting for repeated measures.

There are several future directions in which our work can be improved. First, future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. The sample in our study only comes from the airport waiting area. The ridehailing drivers that were allowed to be at SeaTac airport waiting area for trip requests had two characteristics: (1) they have a King County for-hire driver's permit; (2) they have an electric or hybrid car. Those whose permit number was expired or those who had conventional gasoline cars were excluded from the sample. Future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. However, our experience shows that ridehailing drivers are a notoriously difficult community to reach and recruit for survey research. Second, certain factors were not accommodated within the modeling frameworks that may influence drivers' response to a trip request. For example, the City of Seattle has a higher pay rate than surrounding cities such as Tacoma and Renton, thus drivers might prefer trips within the city of Seattle. Another example is that the COVID-19 pandemic may have an impact on ridehailing drivers' trip acceptance behaviors (Shokoohyar et al., 2022; Shokouhyar et al., 2021, p.). In addition, it's worthwhile to explore the relationship between trip length and trip acceptance in a more granular scale (we use short vs long trip in this manuscript). Future efforts should identify and consider such factors to have a better understanding of the relationship between trip features and drivers' behavior. Third, future studies might consider collecting revealed preference data (e.g., trip records) from TNC companies to supplement the stated preference data in our study. Nevertheless, this study provides critical insights on ridehailing drivers' behavior towards passenger trip requests. Findings from this research would assist the transportation planners and policymakers to create policy interventions that would focus on improving ridehailing driver behaviors and develop more efficient transportation systems.

Chapter 4

PASSENGERS PERCEPTION OF RIDESHARE

In this chapter, we shift focus to ridesharing from the passengers' perspective to explore the demand side of ride-hailing. Through an examination of factors associated with passengers' likelihood to choose a shared ride, using data from a stated choice experiment, I considered trip features (travel time, waiting time, and travel cost), attitudinal factors (social interaction perception, personal space preference, and trust in other passengers), and socio-demographic variables (gender, age, income, education levels, working from home, travel disability, employment status, and race).

By integrating the insights from Chapter 3 (supply side) and Chapter 4 (demand side), a more comprehensive understanding of the current state and future prospects of ridesharing emerges. Building on these findings, I have formulated policy recommendations aimed at promoting shared rides, addressing perspectives from both drivers and passengers.

4.1 Term definitions

To aid understanding, I provide term definitions used in the rest of the chapter in Table 4.1.

Table 4.1: Attributes and levels of the attributes in experimental design

Terms	**Definition**
Ride-hailing	Services are services such as Uber and Lyft, that connect passengers to local drivers to give them a ride
Solo ride-hailing	Services provide a ride-hailing service under your request only. Other users cannot make requests to share the ride with you
Shared ride-hailing	Services match you with riders heading in the same direction, so you can share the ride and cost
Trip features	Features of a specific ridehailing trip, such as travel cost, travel time, and waiting time
Attitudinal factors	Respondents' attitudes related to choosing a ridehailing trip, such as "trust in other passengers during shared rides" and "social interaction perceptions". Attitudinal factors are latent variables, meaning they can only be inferred in a statistic model from other observable variables that can be directly observed and measured

4.2 Nationwide Survey on ride-hail passengers

To answer the question, "what factors are associated with passengers' likelihood to select a shared ride", a questionnaire was designed that comprise of four sections: (1) socio-demographic questions; (2) questions about details of a recent trip made by respondents; (3) choice experiment that collects respondents' binary choices between a solo ridehailing service and a shared ridehailing service; (4) psychometric questions that provide indicators of latent constructs for hybrid choice modeling.

4.2.1 Section 1. Socio-demographics

The socio-economic information included in this section is age, gender, racial group, education, disability status, and occupation. They were also asked about their individual and household's income, size, numbers of full-time and part-time workers, number of members younger than 18.

4.2.2 Section 2. Trip diary

We asked respondents about the most recent trip they had made for a specific purpose, which was selected at random. The purpose of this approach was to create more realistic choice scenarios, to obtain responses that are more likely to reflect their true preferences and behavior [43]. We asked respondents to provide the approximate time, people they traveled with, trip mode, and duration of their most recent trip (defined as traveling for more than 1 mile and stopping at a new location) for the specified trip purpose.

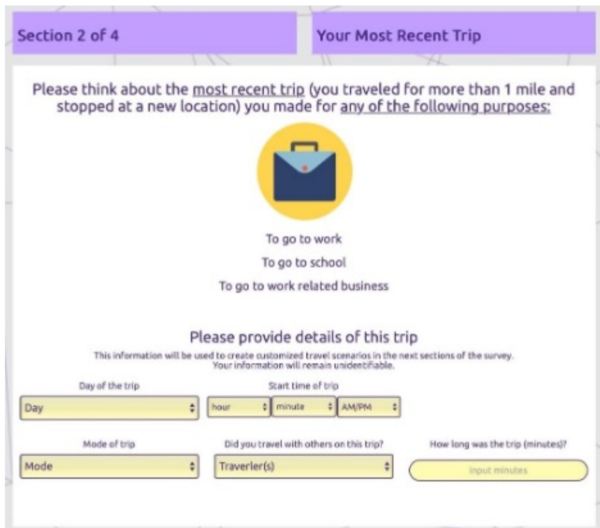
The trip purpose (destination) was randomly selected from six categories: work/school, shopping, meal, social/recreation, errands, and home. Based on the answers to the socio-economic questions in previous section, people who do not go to work/school outside their home were not shown the work/school category. For the home category, they were also asked about the place from which they were returning. Figure 4.1 provides examples of the questions for the most recent trip for work and home purposes.

Section 3. Choice experiments

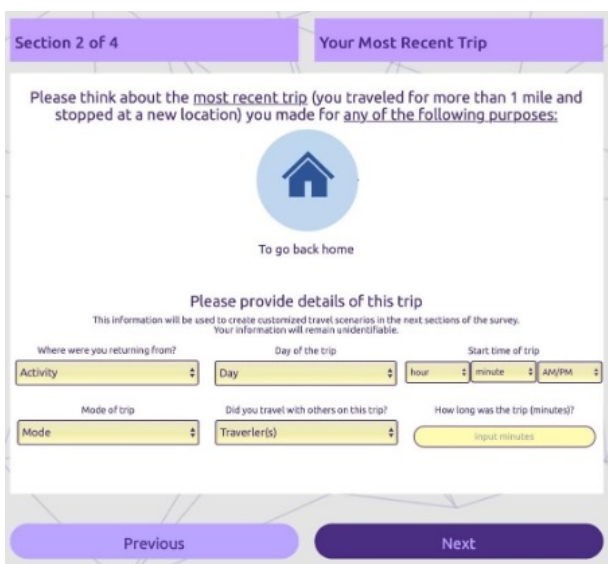
We asked respondents to choose between a solo ridehailing service and a shared ridehailing service for a trip similar to their previously reported most recent trip. For each alternative, the attributes of interest were orthogonally designed and levels of the attributes are summarized in Table 4.2. We have three experimental variables, including vehicle type (human driven car, driverless car accompanied by staff, and driverless car without staff), travel cost ($0.7 * basecost$, $basecost$, $1.3 * basecost$), waiting time (1 min, 3 min, and 5 min), and travel time ($0.7 * basetime$, $basetime$, $1.3 * basetime$).

Base cost for the experimental variable *travel cost* are calculated based on travel mode and travel duration reported by respondents about their most recent trip. We assumed a speed of 25 mph for automobile-based modes, 17 mph for bus, 30 mph for rail, 9.6 mph for cycling, and 3.1 for walking. Multiplying the speed and reported travel duration, we

Figure 4.1: Examples of the section asking about the respondent's most recent trip



(a) Most recent trip information (trip purpose)



(b) Most recent trip information (travel time, mode, etc.)

obtain an approximate distance of the reported trip. Adapting the price scheme published by Uber, we calculate the base travel cost using the formula below:

Base cost $= \$2.20(bookingfee) + \$1.60(additionalcostpermile) * distance$

Base time for the experimental variable *ride time* is calculated by dividing the distance by the assumed speed of 25 mph for automobile-based modes. Both the travel cost and the ride time shown to respondents in the choice set pivot around the base values with 30% variation. 4.2 presents an example of the choice scenario.

Both solo ridehailing and shared ridehailing options have the same set of attributes and levels. Respondents made a binary choice based on these attributes, assuming solo and shared ridehailing were the only two options for the trip. Each respondent completed six scenarios/choice tasks, all of which were associated with the same trip purpose.

Note: Since the focus of this Chapter is on human-driven cars, I only kept responses with the attribute "Human driven car" and filtered out "Driverless car accompanied by staff" and "Driverless car without staff".

Table 4.2: Attributes and levels of the attributes in experimental design

Attribute	**Level 1**	**Level 2**	**Level 3**
Vehicle Type	Human driven car	Driverless car accompanied by staff	Driverless car without staff
Travel Cost	$0.7 * basecost$	$basecost$	$1.3 * basecost$
Waiting time	1 min	3 min	5 min
Travel time	$0.7 * basetime$	base time	$1.3 * basetime$

psychometric questions

In the last section of the questionnaire, we presented respondents with a series of psychometric questions aimed at measuring latent variables identified by [27, 29, 76]. We prepared

Figure 4.2: An example of a choice scenario displayed to a respondent

a set of latent constructs and indicator questions that were most relevant to ridehailing and autonomous vehicles, and were intended to measure attitudes towards using solo and shared rides (both human driven cars and driverless cars). The total of 41 psychometric questions included a combination of Likert scaled and semantic differential scaled responses. The full categories of questions are displayed in Appendix 2.

Note: Since the focus of this study is on human driven cars, I only selected attitudinal variables related to human driven cars, including social interactions, networking opportunities, personal space preference during travel, and trust on other passengers.

4.2.3 Quality check questions

In order to control data quality, we applied established quality-control techniques to identify and filter out data of low quality. In our experiment, low-quality data may result from several concerns. A particular concern with respondents being paid to complete a survey is that some may respond without giving adequate consideration to questions, or even clicking mindlessly. To address these concerns, quality metrics in three categories were applied: Concept checks, logic checks, and response time checks.

During the survey, concept questions followed the section in which the concepts of ride-hailing and driverless ridehailing were defined for the respondents. Respondents were only allowed to proceed if they had answered every concept check question correctly.

After the survey, responses that failed any of the two logic checks were removed. First, a respondent's individual income must be equal/less than his/her household income. Second, in the respondent's household information, the number of children must be fewer than the total number of people in the household including the respondent. Also, a response time check was applied to flag the respondents with very long or very short survey completion times relative to the 16 minutes average completion time. The allotted time to take the survey was 60 minutes and the minimum threshold to pass the check was about 4 minutes specified by timekeeping of just reading the questions and randomly answering/checking the answer and going forward.

4.3 Survey distribution

The survey was distributed in January 2021 nationwide via Facebook ads. They were placed on all available Facebook services, and respondents who completed the survey were compensated with a $5 digital gift card. We obtained 880 responses and a total of 5,280 stated choice observations.

4.4 Hypothesis

The survey variables were separated into three categories - trip features, attitudinal factors, and socio-demographics. The hypothesis based on the research questions focus on trip features and attitudinal factors.

4.4.1 Trip features

Trip features include travel cost, travel time, and waiting time (for the ridehailing driver to pick up).

(1) Respondents are less likely to choose either a travel mode (either solo or shared ride) when the travel cost is higher.

(2) Respondents are less likely to choose either a travel mode (either solo or shared ride) when the travel time is longer. In addition, respondents are less likely to choose a shared ride when the travel time is the same for solo and shared rides.

(3) Respondents are less likely to choose either a travel mode (either solo or shared ride) when the waiting time is longer.

4.4.2 Attitudinal factors

Attitudinal factors include social interaction perception, personal space preference during travel, trust in other passengers during shared rides, and networking opportunities during shared rides.

(1) Respondents who are more comfortable with social interactions with other passengers are more likely to choose shared rides.

(2) Respondents who valued personal space might be less likely to choose shared rides – shared rides have less personal space.

(3) Respondents who are concerned about inappropriate passenger behaviors might be less likely to choose shared rides.

4.4.3 Socio-demographics

Social-demograhics include age, gender, student status, travel disability, work from home, employment status, and race.

(1) Females will be less willing to choose shared rides – females might perceive it less safe when interacting with strangers in a shared ride.

(2) Respondents with lower income might be more likely to choose shared rides – shared rides are cheaper.

(3) Younger respondents might be more likely to opt for shared rides.

(4) Students might be more willing to take shared rides.

(5) Respondents with travel disability might be less willing to choose shared rides.

(6) Respondents who work from home might be less likely to choose shared rides.

(7) Unemployed respondents might be more willing to choose shared rides.

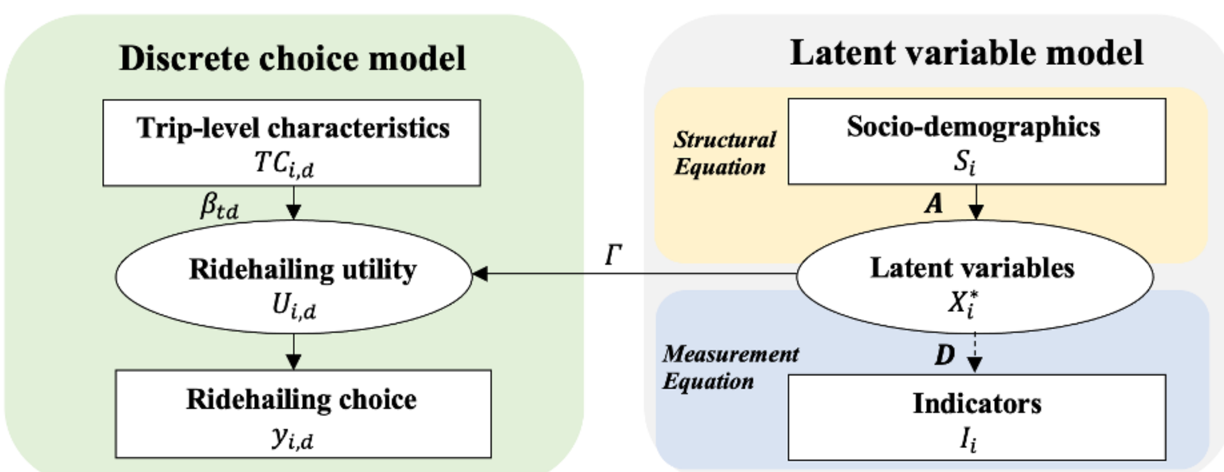
4.5 Methods

4.5.1 Integrated choice and latent variable (ICLV) model

I adopted the integrated choice and latent variable (ICLV) modeling framework [50] to explore the cognitive processes underlying ridehailing choices. Traditional discrete choice models aim at understanding how people make decisions based on observable variables, but ignored ”why we want what we want” [4]. ICLV bridges the gap by allowing for the incorporation of latent behavior constructs employed by traditional discrete choice models. I chose ICLV model for this study because it accommodats the effects of various utilities and attitudinal factors on vehicle ownership choices by integrating (1) a discrete choice model and (2) a latent variable model within the modeling framework (Figure 4.3).

In this section, I'll first give a brief introduction of discrete choice models and random utility models so that readers can have a basic idea of the modeling framework. Next, I'll introduce the application of discrete choice model in this study (left part of the modeling framework in Figure 4.3). Then, I'll describe the latent variable (right part of the modeling framework Figure 4.3). The full model is specified in Equation 4.3 to 4.6.

Figure 4.3: Modeling framework



Discrete choice model

(1) Brief introduction of discrete choice models

Discrete choice models investigate how people make decisions [68]. The assumption behind discrete choice models is utility-maximizing behavior by an individual, meaning an individual chooses the alternative that has the largest utility; therefore, these models are often called random utility models (RUMs). Specifically, when an individual needs to choose from alternative j, where $j = 1, ..., J$. The utility of the individual choosing alternative j is U_j. Since the individual chooses the greatest utility, the behavior model is therefore: choose alternative i over j if and only if $U_i > U_j, \forall j \neq i$.

The utility of an individual choosing alternative j, U_j depends on systematic utility V_j and unobserved utility ε_j. V_j means the utility that depends on some observable attributes, and ε_j means the aspects of utility that are not observed.

Therefore, the probability of an individual choosing alternative j is shown in Equation 4.1.

$$P_j = Prob(U_j > U_i \; \forall j \neq i) = Prob(V_j + \varepsilon_j > V_i + \varepsilon_i \forall j \; \neq i) \tag{4.1}$$

(2) Application in solo and shared mode choice

In this study, the discrete choice model describes the mode choice y_i of individual i choosing alternative d (solo and shared rides), d is described in Equation 4.2.

$$y_{i,d} = \{1 \, if \, U_{i,d} >= U_{i,d}' \; for \; d' \; \in \; solo, shared \, 0 \, otherwise\} \tag{4.2}$$

$y_{i,d}$ is the choice indicator, and it equals to 1 if individual i chooses alternative d, 0 otherwise. d' refers to the choice set, which are solo rides and shared rides in this case.

The utility of individual i choosing mode choice alternative d (solo and shared rides), $U_{i,d}$, is shown in Equation 4.3.

$$U_{i,d} \; = \; V_{i,d} \; + TX_i^* \; + \; \varepsilon_{i,d} \tag{4.3}$$

Where $V_{i,d}$ is the systematic utility of individual i choosing alternative d (Equation 4.4). X_i^* is a vector of latent explanatory variables affecting mode choices, including *trust on other passengers during shared rides*, *social interaction perception*, and *travel space preference during travel* (Equation 4.5). T is a vector of the coefficients describing the relationship between the latent variables and $U_{i,d}$. $\varepsilon_{i,d}$ is the random component of the utility of a mode choice level d, assumed to be independently and identically Gumbel distributed [4].

The systematic utility $V_{i,d}$ of individual i choosing mode choice alternative d, solo or shared rides, can be described in Equation 4.4.

$$V_{i,d} = ASC_{i,d} + \beta_{i,d} TC_{i,d} \tag{4.4}$$

Where $TC_{i,d}$ is the trip characteristics, including *travel time*, *waiting time*, and *travel cost* for solo and shared rides, which are the experimental variables shown in Table 4.2. $\beta_{i,d}$ is the coefficient on $TC_{i,d}$. The alternative-specific constant (ASC) for an alternative (shared rides or solo rides in this case) captures the average effect on utility of all factors that are not included in the model. An ASC is added to shared rides alternative for convenient purposes. It's common practice to set $J-1$ alternative-specific constants with J alternatives in specifying a discrete choice model - the other constants are interpreted as being relative to whichever one is set to zero [68].

Latent variable model

The structural equation of the latent variable model [4] can be written as Equation 4.5. It measures the structural relationship between latent variables and a list of explanatory variables, based on the research hypothesis I listed in Section 4.4.

$$X_i^* = \mathbf{A}S_i + v_i \tag{4.5}$$

X_i^* represents a vector of latent variables including *trust on other passengers during shared rides*, *social interaction perception*, and *travel space preference during travel* 4.4. The latent variables are derived from the psychometric indicators in the survey data via factor analysis [36] and also put in this GitHub repository (https://github.com/yuanjietu/ridehailing _passenger_shared_rides). S_i is a vector of socio-demographics including *age*, *gender*, *income*, *education levels*, *travel disability*, *race*, *work from home*, and *student status* 4.5. **A** refers to a matrix of coefficients describing the structural relationship between latent variables and socio-demographics. v_i is a vector of stochastic components of the measurement equation.

The latent variables themselves cannot be observed directly - they are assumed to be measured by multiple indicators [4], in this case response to Likert-scale survey questions. There might be multiple latent variables impacting how an individual chooses an indicator. The measurement model represents the relationship between the vector of indicators I_i and latent variables X_i^*, can be specified as Equation 4.6.

$$I_i = \mathbf{D}X_i^* + \eta_i \tag{4.6}$$

D is a matrix of coefficients that indicate the relationship between the latent variables and indicators, η_i is a vector of independently and identically distributed error items. $\varepsilon_{i,d}$, v_i, and η_i are assumed to be mutually independent.

The discrete model, latent variable model and measurement model are estimated simultaneously using maximum simulated likelihood estimation with the software package Python Biogeme with 200 random draws [10].

Table 4.3: Variable description: trip level variables

Variable	**Description**
Travel time (solo ride)	Solo ridehailing travel time of a trip, in minutes
Wait time (solo ride)	Solo ridehailing waiting time of a trip, in minutes
Travel cost (solo ride)	Solo travel cost of a trip, in minutes
Travel time (shared ride)	Shared ridehailing travel time of a trip, in minutes
Wait time (shared ride)	Shared ridehailing waiting time of a trip, in minutes
Travel cost (shared ride)	Shared travel cost of a trip, in minutes

Table 4.4: Variable description: latent variables

Variable	**Description**
Social interaction perception	Latent variable describing social interaction perceptions in a ridehailing trip
Personal space preference during travel	Latent variable describing network opportunity perceptions in a ridehailing trip
Trust on other passengers during shared rides	Latent variable describing how much a respondent trusts other passengers during a shared ride

Table 4.5: Variable description: socio-demographics

Variable	**Description**
Age: younger adults	(Dummy) If respondent is younger than 40 years old, 1; otherwise, 0
Age: older adults	(Dummy) If respondent is equal to or older than 65 years old, 1; otherwise, 0
Gender: male	(Dummy) If respondent is male, 1; otherwise, 0
Race: white	(Dummy) If respondent is white, 1; otherwise, 0
Higher education	(Dummy) If respondent has an education higher than high school, 1; otherwise, 0
Higher income	(Dummy) If respondent has an income equal to or higher than $70 k, 1; otherwise, 0
Travel disability	(Dummy) If respondent has a disability that makes it hard to travel outside home, 1; otherwise, 0
Student	(Dummy) If respondent is a full-time student, 1; otherwise, 0
Employment status	(Dummy) If respondent is employed full-time (35+ hours per week), 1; otherwise, 0
Work from home	(Dummy) If respondent only works or attend school from home in normal times, 1; otherwise, 0

4.6 Results

In this section, I'll first introduce the descriptive analysis (including the demographics and statistic summary of solo and shared rides), and then I'll present the modeling results of the discrete choice model and latent variable models.

4.6.1 Descriptive analysis

Socio-demographics of the sample is shown in Table 4.6. Among all respondents, 50% are females, similar to the female proportions in the Census (2019). More than 80% of the respondents are between age 18 to 44, while less than 15% and around 5% respondents are between 45 to 64 and older than 65 years old. Compared to the Census (2019), Facebook respondents are in general much younger. Facebook respondents seem to have more Asian population and fewer others than the Census population. In terms of education, Facebook respondents are much higher educated than that of Census population. In the stated choice scenarios, 50% respondents chose hypothetical shared rides (Figure 4.4).

Figure 4.4: Distribution of respondents' solo and shared ride choices

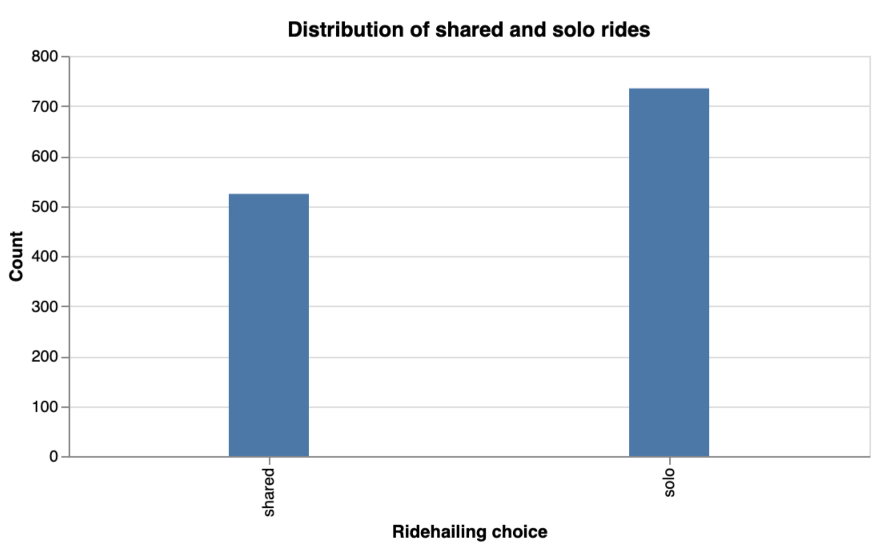


Table 4.6: Summary of the Demographic Statistics of the Final Sample

Demographics	**Facebook**	**Census** (2019)
Gender		
Female	51.0%	50.8%
Male	49%	49.2%
Age		
18-44	81.1%	46.0%
45-64	13.9%	32.9%
>= 65	5.0%	21.1%
Race		
White	69.2%	76.3%
Black	11.6%	13.4%
American Indian or Alaska native	1.5%	1.3%
Asian	15.4%	5.9%
Other	0.3%	3.1%
Hispanic origin		
Yes	12.1%	18.3%
Education		
Less than high school	1.0%	10.6%
High school degree	5.6%	28.3%
Bachelor's degree	34.9%	21.3%
Master's degree	30.8%	9.0%
Doctoral degree	4.8%	1.8%
Professional degree	3.5%	1.3%

4.6.2 Discrete choice model

The mode choice model (Table 4.7) shows that travel time, travel cost, waiting time are negatively associated with choosing solo rides and pooled rides. This means the longer the travel time and waiting time are, respondents are less likely to choose a solo or shared ride. Higher travel cost will decrease the respondents' likelihood to choose a solo or shared ride. ASC for shared rides is negative, suggesting that respondents are less likely to choose shared rides compared to solo rides, everything else being equal. However, it's non-significant, so it should be interpreted with caution.

In terms of attitudinal factors, social interaction perception is positively associated with choosing a shared ride, meaning respondents are more likely to share a ride with others if they are willing to interact with other passengers. Trust in other passengers is positively correlated with choosing a shared ride, meaning respondents are more likely to share a ride if they trust other passengers' behaviors. Personal space preference is positively correlated with choosing a shared ride, meaning respondents are more likely to choose a shared ride if they prefer personal space during travel.

Table 4.7: Discrete choice likelihood if sharing a ride

Variable	**Coefficients**	**P-value**
Solo ride		
Travel time	-0.011***	0.004
Travel cost	-0.037***	2.25×10^{-7}
Waiting time	-0.043*	0.067
Personal space preference during travel	0.946***	3.30×10^{-4}
Shared ride		
ASC	-0.431	0.633
Travel time	-0.011***	0.004
Travel cost	-0.037***	2.25×10^{-7}
Waiting time	-0.043*	0.067
Social interaction perception	0.351***	2.16×10^{-5}
Trust on other passengers	0.631***	2.41×10^{-4}
Model performance		
Initial loglikelihood	-25652.2	
Final likelihood	-24764.6	
Akaike Information Criterion (AIC)	49653.2	
*Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level. ASC = Alternative-specific constant*		

4.6.3 Latent variable model

Table 4.8, 4.9, 4.10 and 4.11 show the latent variable model results (including the structural equation model and the measurement equation model). The structural equation model illustrates the relationship between socio-demographics and the chosen latent variables (including social interaction perception, trust in other passengers during shared rides, and personal space preference during travel). The results suggest that respondents with higher incomes are more comfortable interacting with other passengers compared to respondents with lower incomes, while Asian and White respondents are less likely to feel comfortable interacting with other passengers compared to other races. As for personal space preference, respondents with higher education and travel disability tend to put higher emphasis on having personal space during travel, while young people are less likely to have personal space preference when traveling. In terms of trust in other passengers, younger respondents, respondents with travel disabilities, Asians, and Whites are found to have less trust in other passengers, while people with higher incomes have higher trust in other passengers.

The measurement equation model connects the attitudinal factors and the indicators, including social interaction perception (Table 4.9), personal space preference during travel (Table 4.11), and trust in other passengers (Table 4.10). I fix the coefficient for the first indicator (for social interaction perception and personal space preference) to be 1 and estimate the other indicators relative to them.

Table 4.8: Structural equation model results

	Coefficients	**P-value**	**Coefficients**	**P-value**	**Coefficients**	**P-value**
Variables	*Social interaction perception*		*Personal space preference during travel*		*Trust in other passengers during shared rides*	
Intercept	0.447**	0.0374	0.928***	2.41×10^{-8}	0.87***	1.03×10^{-11}
Female	-0.113	0.145	0.075	0.237	-0.059	0.224
Younger adults	0.003	0.971	-0.162**	0.0125	-0.168***	0.004
Older adults	0.567	0.207	-0.046	0.829	-0.002	0.99
Higher income	0.653***	1.55×10^{-14}	-0.03	0.621	0.196***	0.3×10^{-4}
Higher education	-0.154	0.269	0.183	0.134	-0.14	0.111
Work from home	-0.173**	0.031	0.060	0.385	-0.035	0.519
Travel disability	-0.050	0.803	0.326**	0.023	-0.237*	0.058
Employed: full-time	-0.072	0.597	0.044	0.653	0.00020	0.998
Employed: part-time	-0.083	0.583	-0.208**	0.042	-0.102	0.336
Race: Asian	-0.56***	7.17×10^{-5}	-0.075	0.505	-0.298***	0.002
Race: White	-0.376**	9.67×10^{-5}	0.078	0.315	-0.123***	0.004

Table 4.9: Measurement equation model: social interaction perception

Attitudinal indicators	**Coefficients**
I feel ( ) when strangers try to talk to me in a pooled ride hailing vehicle. *1. Very uncomfortable, 2. Uncomfortable, 3. Slightly uncomfortable, 4. Slightly comfortable, 5. Comfortable, 6. Very comfortable*	1
I feel ( ) when no one is talking in a pooled ride hailing vehicle. *1. Very uncomfortable, 2. Uncomfortable, 3. Slightly uncomfortable, 4. Slightly comfortable, 5. Comfortable, 6. Very comfortable*	0.239***
Talking and being with strangers during a shared ride is ( ). *1. Very uncomfortable, 2. Uncomfortable, 3. Slightly uncomfortable, 4. Slightly comfortable, 5. Comfortable, 6. Very comfortable*	0.931***
Sharing a ride with strangers is ( ). *1. Very dangerous, 2. Dangerous, 3. Slightly dangerous, 4. Slightly safe, 5. Safe, 6. Very safe*	0.929***
I enjoy talking and being with strangers during a shared ride. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	1.050***
Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level.	

Table 4.10: Measurement equation model: Trust on other passengers during shared rides

Attitudinal indicators	**Coefficients**
I would trust other ridesharing participants to show up on time. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	1
I would trust other ridesharing participants to behave themselves. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	1.48***
I would trust other ridesharing participants to avoid physical contact with me. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	1.58***
Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level.	

Table 4.11: Measurement equation model: Personal space preference during travel

Attitudinal indicators	Coefficients
I try to travel in a calm, non-noisy environment. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	1
I try to use transportation options that allow me to avoid contact with other people. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	0.608***
I try to use transportation options that allow me to rest or read. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	0.404***
I don't have enough personal space in a pooled ride hailing vehicle. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	0.449***
I don't mind traveling on a crowded bus. *1. Strongly disagree, 2. Disagree, 3. Slightly disagree, 4. Slightly agree, 5. Agree, 6. Strongly agree*	-0.218***
Note: * significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level.	

4.7 Policy implications

In Chapter 3 and 4, I looked at shared rides acceptance from perspectives of both ridehailing drivers and passengers, and here a gloomy result haunts us: Neither drivers nor passengers are likely to accept shared rides. For ridehailing drivers in particular, they would like a $10 compensation to take a shared ride! This presents a challenging scenario, especially considering the collective desire of transportation engineers and urban planners for increased shared rides, benefiting both the environment and urban traffic management. This prompts the question: How can we effectively promote shared rides in the future?

In this section, I will explore potential strategies to encourage shared rides, drawing insights from both the modeling results and existing literature, which could also serve as potential future studies.

Ridehailing is a complex system. Improving shared rides goes beyond ridehailing drivers and passengers themselves. The most important stakeholders are in fact government and ridehailing companies as Uber and Lyft. This section will discuss possible ways to promote shared rides from a system thinking perspective.

4.7.1 Government policy

1. **Pricing strategies:** Most cities and states set fees on TNCs for congestion and emissions. The most widely adopted format is a flat fee per ride. In most cities/states the fee is not different between solo and shared rides. This disproportionately taxed shared rides, making shared rides unattractive compared to solo ones. If the regulator's objective is to mitigate emissions resulting from ride-hailing services, it might be a good idea to apply lower fees/taxes to shared rides. In addition, the difference should be large enough that users would be willing to shift to shared rides. Only New York city, Chicago, New Jersey, and San Francisco are taxing solo rides more than shared ones [26]. For example, New York city imposes a surcharge of $2.75 for a solo ride, while $0.75 for a shared ride [21]. In San Francisco, the city imposes a 3.25% surcharge on all individual rides and a 1.5% surcharge on shared rides that originate in San Francisco [8].

2. **Public-Private Partnerships:** Foster collaborations between ride-hailing platforms, local governments, and public transportation authorities. Joint initiatives can lead to integrated transportation solutions that combine ride-hailing with public transit, promoting shared mobility.

3. **Other Support:** Except for pricing and monetary incentives, it would help if the policies support drivers in other ways, such as dedicated lanes, reduced tolls for shared vehicles, or other regulatory measures to create a favorable environment. Some cities have already been implementing supplementary policies. For example, Singapore's Electronic Road Pricing (ERP) system offers reduced fees during specific hours for ride-hailing vehicles engaged in shared rides, encouraging the use of shared mobility options [57].

4.7.2 Company strategies

1. **Dynamic Matchmaking Algorithms:** Develop and implement advanced algorithms that dynamically match compatible passengers with similar routes. This ensures efficient and convenient shared rides for both drivers and passengers. Existing studies and our interview and survey results show that drivers are frustrated by shared rides partly because the extra work that they have to put in to pick up and drop off multiple users [53]. It's likely that drivers will be less reluctant to accept shared rides if the amount of extra work is decreased.

2. **Incentive Programs:** Implement incentive programs that reward passengers for requesting shared rides and drivers for accepting shared rides. For drivers, this could include financial bonuses, priority access to high-demand areas, or other perks to motivate drivers to choose shared options. For passengers, offering discount or coupons for shared rides, such as "book 1 shared ride and get 1 free" might be an option to encourage shared rides. In particular, offering a discount for transit fare when taking a shared ride to transit stations might be a good idea to increase transit ridership via pooling-transit connections [39].

3. **Enhanced Driver and User Experience:** Enhance driver and user experience could promote shared rides. For drivers, improving driver experience could include drivers' minimizing extra effort (e.g., to pick up/drop off multiple passengers), regulating passenger behaviors during a shared ride. (2) Improving the overall experience

for passengers using shared rides. This could include minimizing waiting times and travel time, regulating driver and passenger behaviors, and ensuring a safe, comfortable shared ride experience.

4.8 Conclusions

Understanding how passengers choose solo and shared rides is pivotal for promoting ridesharing in the future. Using a nationwide stated preference survey data collected from Facebook, this chapter first found that 58% of respondents would choose solo rides over shared rides. Next, this chapter explored the relationship between passengers' solo and shared ride choice and trip features (travel time, waiting time, and travel cost), socio-demographics (age, gender, race, and so on), and attitudinal factors (personal space preference during travel, social interaction perception, and trust in other passengers) using the same dataset.

The model results show that everything being equal, passengers are less likely to choose shared rides, but the relationship is non-significant so it needs to interpret with caution. Travel cost, travel time, and waiting time are negatively associated with both solo and shared rides, and their impacts are the same. Among three attitudinal factors, personal space preference during travel is non-significant, while social interaction perception and trust in other passengers contribute positively to choosing a shared ride.

Based on the model results and existing literature, I also discussed possible policy strategies to promote shared rides from the perspectives of the government and rdehailing companies.

There are several future directions in which our work can be improved. First, future models could consider controlling repeated measures. The discrete choice model in this chapter, did not control repeated measures because of limited computing power. In addition, the data was administrated on Facebook, and future studies could consider collecting data from multiple sources to improve its representativeness of the population. Third, more waves of data can be collected to see the change in passenger attitudes over time.

Chapter 5
CONCLUSIONS

5.0.1 Main takeaways

This dissertation first investigated three main ridehailing driver behaviors including working time choice, relocation choice, and trip request acceptance by using 1,067 stated choice responses. The results show that

Working time choice: all types of drivers (no matter their daily earnings target and working time target) choose to continue working as their earning rate increases. We see little evidence of an earnings threshold effect that the reference dependent theory postulates [70], even when the driver reported having an earnings target in the survey. However, there is evidence of reference dependent behavior with respect to the working time variable: time-target drivers and both-target drivers are less likely to continue working after hitting their working time targets.

Relocation choice: relocation choice is mainly impacted by surge price, average trip waiting time, and relocation time: higher surge price in the current neighborhood encourages the driver to stay, while higher surge price in a nearby neighborhood attracts the driver to relocate. Drivers are more likely to stay in a neighborhood where the average trip waiting time is low. Longer relocation time discourages drivers to relocate. In addition, drivers are more likely to stay in the same place, everything else being equal.

Trip request acceptance: longer pick-up time is negatively associated with trip request acceptance. The relationship between pick-up time and trip request acceptance is linear when the trip is short (not over 45 minutes), while nonlinear otherwise. When the trip is short, drivers are more likely to accept trips with shorter pick-up times, and less likely to accept trips with longer pick-up times compared to when the trip is long. When the trip is long, the pick-up time has smaller positive effect on the trip request acceptance when the trip is less than 12 minutes. Once the pick-up time goes beyond 12 minutes, the trip request acceptance drops rapidly. It was also found that long trips (over 45 minutes) are positively associated with trip request acceptance. With an increase in surge price, drivers are more likely to accept trip requests. Furthermore, passenger ratings are positively associated with trip request acceptance. However, drivers are less likely to accept shared trips than solo ones.

This dissertation also explored passengers' likelihood of choosing shared rides by using 5,280 stated choice responses. The model results show that everything being equal, passengers are less likely to choose shared rides, but the relationship is non-significant so it needs to interpret with caution. Travel cost, travel time, and waiting time are negatively associated with both solo and shared rides, and their impacts are the same. Among three attitudinal factors, personal space preference during travel is non-significant, while social interaction perception and trust in other passengers contribute positively to choosing a shared ride.

Based on the research results from both the drivers' and passengers' perspectives, we provide policy recommendations on promoting shared rides in the future.

5.0.2 Dissertation structure change

The structure of this dissertation went through some changes before landing in its current form. The first two sections (Chapter 2 & Chapter 3) on (1) modeling ridehailing driver working time and relocation choices, and (2) modeling trip request acceptance were always in the plan. However, the content in Chapter 4 has changed over time. The original plan was to integrate the two driver behavior models in Chapter 2 and 3 into the POLARIS model developed in Argonne national lab, US Department of Energy, to simulate the total carbon emissions generated by ridehailing services under different driver decision making scenarios. However, a series of complications arose: I was no longer in the same lab and therefore cannot adhere to the original plan.

Then, I started to focus on investigating passengers' likelihood to choose shared rides, and discussing policy implications to promote sharing rides in the future by combining perspectives of both ridehailing drivers and passengers.

5.0.3 Limitations and future research

Several promising directions for future enhancement and exploration arise from this dissertation.

First, future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. The sample in our study only comes from the airport waiting area. The ridehailing drivers that were allowed to be at SeaTac airport waiting area for trip requests had two characteristics: (1) they have a King County for-hire driver's permit; (2) they have an electric or hybrid car. Those whose permit number was expired or those who had conventional gasoline cars were excluded from the sample. Future studies might consider including drivers from other channels (e.g., hailing rides) to provide a more representative view of ridehailing drivers. However, our experience shows that ridehailing drivers are a notoriously difficult community to reach and recruit for survey research.

Second, the data used in this dissertation were solely from surveys, capturing ridehailing drivers' and passengers' stated choices. Future research could benefit from supplementing this survey data with observational data from ridehailing companies such as Uber and Lyft [41]. This additional data could provide deeper insights into drivers' decisions regarding working hours, relocation, and trip request acceptance, as well as passengers' decisions on accepting rides.

Third, the current findings on drivers' decision making could be integrated to the POLARIS model to simulate the total carbon emissions produced by ridehailing services under different driver decision making scenarios, and generate relevant transportation policies that could decrease future negative environmental impacts.

Interesting future questions could be raised based on our findings. For instance, how can we maximize ridehailing drivers' work hours once their vehicles are fully electric? Drivers may lose significant work time if they need to charge their cars frequently. To address this, providing personalized charging recommendations could be an effective strategy to optimize their work hours. We could use the result of driver preferences, to detect the potential "cold spot" of ridehailing service areas, meaning the area where drivers are not likely to go, to promote equitable access of ridehailing services.

5.0.4 Broader research impact

There are some broader impact of this dissertation beyond in the field of transportation engineering.

Contribution to gig economy studies

The gig economy, particularly the ridehailing sector, is a rapidly growing area of study [54, 16, 61]. This research enriches the academic discourse on gig work by providing detailed analysis of the operational behaviors of ridehailing drivers. It opens avenues for further exploration into the implications of gig work on labor markets, worker well-being, and economic productivity. The study's findings can also inform the development of policies and interventions aimed at improving the sustainability and fairness of gig work arrangements.

Policy and planning impact

The findings from this study can inform urban planning and transportation policies, helping cities better integrate ridehailing services into their overall transportation infrastructure. By understanding the dynamics of driver behavior, policymakers can design more effective regulations and incentives that balance the needs of ridehailing drivers, passengers, and the urban environment. This can lead to more equitable and efficient transportation systems, enhancing mobility for all city residents.

Social equity impact

The study sheds light on the daily operational challenges faced by ridehailing drivers, offering a pathway to enhance their job satisfaction and well-being. By addressing issues related to working time and relocation stress, ridehailing platforms can implement support systems that reduce driver fatigue and promote work-life balance. Additionally, understanding trip request acceptance behaviors can lead to better matching algorithms, reducing wait times for passengers and improving overall customer satisfaction. This, in turn, can help develop a more reliable and user-friendly transportation network.

Environmental impact

Optimizing driver relocation and trip acceptance decisions has the potential to reduce unnecessary vehicle miles traveled (VMT), leading to lower fuel consumption and decreased emissions. By minimizing idle driving and ensuring more efficient routes, the study contributes to the broader goal of reducing the environmental footprint of urban transportation. Enhanced ridehailing operations can thus play a crucial role in promoting sustainable urban mobility and mitigating the adverse effects of traffic congestion and pollution.

Appendices

Appendix 1

DRIVER BEHAVIOR QUESTIONNAIRE

This attachment presents the questionnaire for passenger mode choice survey. Only driving habits and socio-demographic questions are shown. More choice experiment information in Section 2 and Section 3.

A.1 Driving habits

1. Which ride-sharing companies are you driving for

   Ø Uber

   Ø Lyft

   Ø Both

2. How long have you been an active ride-sharing driver?

   Ø Less than 6 months

   Ø 6 months - less than 1 year

   Ø 1 year - less than 1.5 years

   Ø 1.5 years - less than 2 years

   Ø 2 years or more

3. Do you work as a ride-sharing driver during COVID-19 pandemic?

   Ø No, I stopped working during the pandemic, and I am not working now

   Ø Yes, I work during the pandemic

   Ø I stopped working at the beginning, but start working again after getting vaccinated

4. Do you start driving at around the same time every day?

   Ø No

   Ø Yes

5. When do you start driving every day? ....

6. Do you stop driving at around the same time every day?

   Ø No

   Ø Yes

7. When do you stop driving every day? ....

8. Do you usually try to work a certain number of hours per day?

   Ø No

   Ø Yes

9. How many hours do you usually try to work per day? ....

10. Do you usually try to earn a certain amount of money per day?

    Ø No

    Ø Yes

11. How much do you usually try to earn per day? $...........................

12. How many trip did you get last week? ....

13. How many did you reject last week? ....

A.2 Socio-demographics

1. What is your age? ....

2. What is your gender?

   Ø female

   Ø male

   Ø another

3. Are you of Hispanic, Latino, or Spanish origin?

   Ø Yes, of Hispanic, Latino or Spanish Origin

   Ø No, Not of Hispanic, Latino or Spanish Origin

4. What is your race?

   Ø White

   Ø Black or African American

   Ø American Indian or Alaska Native

   Ø Asian

   Ø Native Hawaiian or Other Pacific Islander

   ØAnother

5. Were you born in the United States?

   Ø yes

   Ø no

6. What is the highest degree or level of school you have completed?

   Ø Less than High School

   Ø High School Graduate or GED

   Ø Some College/Technical school training

   Ø 2-Year College Degree (Associates)

   Ø 4-Year College Degree (BA, BS)

   Ø Master's Degree

   ØDoctoral Degree

   Ø Professional Degree (MD, JD)

7. Are you currently a student?

   Ø No, not a student

   Ø Part-time student

   Ø Full-time student

8. Ø Which of the following best describes your current employment status?
   Employed, Full-time (35+ hours/week)
   Ø Employed, Part-time (Fewer than 35 hours/week)
   Ø Homemaker
   Ø Looking for work
   Ø Unable to work due to a disability
   Ø Retired
   Ø Unemployed
   Ø Other

9. What is the zip code where you currently live?
   ....

10. How many people live in your household (including yourself)?
    ....

11. Your household includes yourself, people living with you and sharing income with you (e.g. spouse, partner, or dependents).
    ....

12. Of these, how many are children under the age of 18?
    ....

13. Which category best describes your household income before taxes from the last calendar year? (including yourself)
    Ø Under $10,000
    Ø $10,000 — $14,999
    Ø $15,000 — $19,999
    Ø $20,000 — $24,999
    Ø $25,000 — $34,999
    Ø $35,000 — $49,999

Ø $50,000 — $74,999

Ø $75,000 — $99,999

Ø $100,000 — $149,999

Ø $150,000 — $199,999

Ø $200,000 — $249,999

Ø $250,000 or more

14. Which category best describes your individual income before taxes from the last calendar year?

Ø Under $10,000

Ø $10,000 — $14,999

Ø $15,000 — $19,999

Ø $20,000 — $24,999

Ø $25,000 — $34,999

Ø $35,000 — $49,999

Ø $50,000 — $74,999

Ø $75,000 — $99,999

Ø $100,000 — $149,999

Ø $150,000 — $199,999

Ø $200,000 — $249,999

Ø $250,000 or more

15. What is your health status?

Ø Very good

Ø Good

Ø Fair

Ø Poor

Ø Very poor

Ø I don't know

Ø Prefer not to answer

Appendix 2

PASSENGER BEHAVIOR QUESTIONNAIRE

This attachment presents the questionnaire for passenger mode choice survey. Only socio-demographic and attitudinal questions are shown. More choice experiment information in Section **??**.

B.1 Social demographics

1. What is your age?

   ....

2. What is your gender?

   Ø female

   Ø male

   Ø another

3. Are you of Hispanic, Latino, or Spanish origin?

   Ø Yes, of Hispanic, Latino or Spanish Origin

   Ø No, Not of Hispanic, Latino or Spanish Origin

4. What is your race?

   Ø White

   Ø Black or African American

   Ø American Indian or Alaska Native

   Ø Asian

   Ø Native Hawaiian or Other Pacific Islander

   ØAnother

5. Were you born in the United States?

   Ø yes

   Ø no

6. What is the highest degree or level of school you have completed?

   Ø Less than High School

   Ø High School Graduate or GED

   Ø Some College/Technical school training

   Ø 2-Year College Degree (Associates)

   Ø 4-Year College Degree (BA, BS)

   Ø Master's Degree

   ØDoctoral Degree

   Ø Professional Degree (MD, JD)

7. Are you currently a student?

   Ø No, not a student

   Ø Part-time student

   Ø Full-time student

8. Ø Which of the following best describes your current employment status?

   Employed, Full-time (35+ hours/week)

   Ø Employed, Part-time (Fewer than 35 hours/week)

   Ø Homemaker

   Ø Looking for work

   Ø Unable to work due to a disability

   Ø Retired

   Ø Unemployed

   Ø Other

9. What is the zip code where you currently live?

   ....

10. How many people live in your household (including yourself)?

    ....

11. Your household includes yourself, people living with you and sharing income with you (e.g. spouse, partner, or dependents).

    ....

12. Of these, how many are children under the age of 18?

    ....

13. Which category best describes your household income before taxes from the last calendar year? (including yourself)

    Ø Under $10,000

    Ø $10,000 — $14,999

    Ø $15,000 — $19,999

    Ø $20,000 — $24,999

    Ø $25,000 — $34,999

    Ø $35,000 — $49,999

    Ø $50,000 — $74,999

    Ø $75,000 — $99,999

    Ø $100,000 — $149,999

    Ø $150,000 — $199,999

    Ø $200,000 — $249,999

    Ø $250,000 or more

14. Which category best describes your individual income before taxes from the last calendar year?

    Ø Under $10,000

    Ø $10,000 — $14,999

    Ø $15,000 — $19,999

    Ø $20,000 — $24,999

Ø $25,000 — $34,999

Ø $35,000 — $49,999

Ø $50,000 — $74,999

Ø $75,000 — $99,999

Ø $100,000 — $149,999

Ø $150,000 — $199,999

Ø $200,000 — $249,999

Ø $250,000 or more

15. Do you have a condition or disability that makes it difficult to travel outside home?

Ø Yes

Ø No

16. Do you only work or attend school from home in normal times?

Ø Yes

Ø No

B.2 Attitudinal factors

1. I feel ( ) when strangers try to talk to me in a pooled ride hailing vehicle.

Ø Very uncomfortable

Ø Uncomfortable

Ø Slightly uncomfortable

Ø Slightly comfortable

Ø Comfortable

Ø Very comfortable

2. I feel ( ) when no one is talking in a pooled ride hailing vehicle.

Ø Very uncomfortable

Ø Uncomfortable

Ø Slightly uncomfortable

Ø Slightly comfortable

Ø Comfortable

Ø Very comfortable

3. Sharing a ride with a stranger is ( ).

   Ø Very dangerous

   Ø Dangerous

   Ø Slightly dangerous

   Ø Slightly safe

   Ø Safe

   Ø Very safe

4. Talking and being with strangers during a shared ride is ( ).

   Ø Very uncomfortable

   Ø Uncomfortable

   Ø Slightly uncomfortable

   Ø Slightly comfortable

   Ø Comfortable

   Ø Very comfortable

5. Sharing a ride would seem like a ( ) risk choice.

   Ø Very high

   Ø High

   Ø Slightly high

   Ø Slightly low

   Ø Low

   Ø Very low

6. Widespread use of self-driving vehicles would result in ( ) crashes.

   A lot fewer

   Fewer

   Slightly fewer

Slightly more

More

A lot more

7. Sharing a ride with strangers is ( ).

   Ø Very uncomfortable

   Ø Uncomfortable

   Ø Slightly uncomfortable

   Ø Slightly comfortable

   Ø Comfortable

   Ø Very comfortable

8. I am ( ) self-driving vehicles can drive as well as human drivers in general.

   Ø Extremely confident

   Ø Confident

   Ø Sort of confident

   Ø A little doubtful

   Ø Doubtful

   Ø Extremely doubtful

9. Most people would feel ( ) to chat with strangers in a shared ride.

   Ø Very uncomfortable

   Ø Uncomfortable

   Ø Slightly uncomfortable

   Ø Slightly comfortable

   Ø Comfortable

   Ø Very comfortable

10. I would trust other ridesharing participants to show up on time.

    Ø Strongly disagree

    Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

11. I try to travel in a calm, non-noisy environment.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

12. I would feel ( ) when strangers try to talk to me in a shared ride where there is no driver/staff in the driverless vehicle.

    Ø Very uncomfortable

    Ø Uncomfortable

    Ø Slightly uncomfortable

    Ø Slightly comfortable

    Ø Comfortable

    Ø Very comfortable

13. It is ( ) for me to build new job connections in a shared ride.

    Very unlikely

    Unlikely

    Slightly unlikely

    Slightly likely

    Likely

    Very likely

14. Most people would feel ( ) to say hi to strangers in a shared ride.

Ø Very uncomfortable

Ø Uncomfortable

Ø Slightly uncomfortable

Ø Slightly comfortable

Ø Comfortable

Ø Very comfortable

15. The opportunity to meet people when traveling by pooled ride-hailing (e.g. Uber Pool or Lyft Share) is ( ) to me.

    Ø Extremely valuable

    Ø Very valuable

    Ø Somewhat valuable

    Ø Not so valuable

    Ø Not valuable

    Ø Not at all valuable

16. Travelling by pooled ride-hailing (e.g. UberPool or Lyft Share) provides me opportunity to meet new people.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

17. Driverless cars generally will be ( ) than I am as a driver.

    Much more dangerous

    Ø More dangerous

    Ø A little more dangerous

    Ø A little safer

Ø Safer

Ø Much safer

18. I enjoy talking and being with strangers during a shared ride.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

19. I try to use transportation options that allow me to avoid contact with other people.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

20. I would trust other ridesharing participants to behave themselves.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

21. Driverless cars generally will be ( ) compared with most drivers on the road.

    Ø Much safer

    Ø Safer

    Ø A little safer

Ø Somewhat more dangerous

Ø More dangerous

Ø Much more dangerous

22. It is ( ) for me to meet new friends in a shared ride.

    Ø Very unlikely

    Ø Unlikely

    Ø Slightly unlikely

    Ø Slightly likely

    Ø Likely

    Ø Very likely

23. I try to use transportation options that allow me to rest or read.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

24. My family/friends would feel ( ) to say hi to strangers in a shared ride.

    Ø Very uncomfortable

    Ø Uncomfortable

    Ø Slightly uncomfortable

    Ø Slightly comfortable

    Ø Comfortable

    Ø Very comfortable

25. Most people say hi to strangers in a shared ride.

    Ø Strongly disagree

    Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

26. My family/friends ( ) say hi to strangers in a shared ride.

    Ø Definitely would

    Ø Probably would

    Ø Maybe would

    Ø Maybe would not

    Ø Probably would not

    Ø Definitely would not

27. I would trust other ridesharing participants to avoid physical contact with me.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

28. Sharing a ride with strangers when there is no driver/staff in the driverless vehicle would be ( ).

    Ø Very uncomfortable

    Ø Uncomfortable

    Ø Slightly uncomfortable

    Ø Slightly comfortable

    Ø Comfortable

    Ø Very comfortable

29. I would like to share rides with others if it saves money.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

30. My family/friends would feel ( ) to chat with strangers in a shared ride.

    Ø Very uncomfortable

    Ø Uncomfortable

    Ø Slightly uncomfortable

    Ø Slightly comfortable

    Ø Comfortable

    Ø Very comfortable

31. I would trust other ridesharing participants to behave themselves when there is no staff in the driverless vehicle.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

32. I would trust other ridesharing participants to avoid physical contact with me when there is no driver/staff in the driverless vehicle.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

Ø Agree

Ø Strongly agree

33. Sharing a ride with a stranger when there is no driver/staff in the driverless vehicle is ( ).

    Ø Much more dangerous

    Ø More dangerous

    Ø A little more dangerous

    Ø A little safer

    Ø Safer

    Ø Much safer

34. Sharing a ride with a stranger when there is no driver/staff in the driverless vehicle would seem like a ( ) risk choice.

    Ø Very high

    Ø High

    Ø Slightly high

    Ø Slightly low

    Ø Low

    Ø Very low

35. I am ( ) about riding in a vehicle with no driver controls available.

    Ø Very worried

    Ø Worried

    Ø Slightly worried

    Ø Slightly excited

    Ø Excited

    Ø Very excited

36. I would feel ( ) when no one is talking during a shared ride where there is no driver/staff in the driverless vehicle.Ø Very uncomfortable

Ø Uncomfortable

Ø Slightly uncomfortable

Ø Slightly comfortable

Ø Comfortable

Ø Very comfortable

37. Most people chat with strangers in a shared ride.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

38. I don't have enough personal space in a pooled ride hailing vehicle.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

39. I ( ) trust self-driving car technology to keep me safe when I am riding in one.

    Ø Definitely would

    Ø Probably would

    Ø Maybe would

    Ø Maybe would not

    Ø Probably would not

    Ø Definitely would not

40. I don't mind traveling on a crowded bus.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

41. Talking and being with strangers during a shared driverless vehicle where there is no driver/staff would be ( ).Ø Very uncomfortable

    Ø Uncomfortable

    Ø Slightly uncomfortable

    Ø Slightly comfortable

    Ø Comfortable

    Ø Very comfortable

42. The current situation about COVID-19 worries me.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

43. COVID-19 is just a new form of flu.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

44. I think there is a lot of fear mongering around COVID-19.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

45. I believe that the media is exaggerating the severity of COVID-19.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

46. Ride hailing riders will be massively infected by COVID-19.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

    Ø Agree

    Ø Strongly agree

47. During the pandemic, staying in a car with a stranger for a long time (more than 15 minutes) is safe.

    Ø Strongly disagree

    Ø Disagree

    Ø Slightly disagree

    Ø Slightly agree

Ø Agree

Ø Strongly agree

48. During the pandemic, staying in a car with a stranger for a short time (less than 15 minutes) is safe.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

49. Ride hailing riders are at a high risk of being infected during the pandemic.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

50. Ride hailing companies should stop their pooled services during the pandemic.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

51. During the pandemic, it is irresponsible to travel by ride hailing services shared with strangers in the car.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

52. During the pandemic, it is irresponsible to travel by ride hailing services, even without strangers in the car (not including the driver).

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

53. Currently, I would feel comfortable using ride hailing if equipped with disinfectant sprays to sanitize the vehicle after each ride.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

54. Practically speaking, ride hailing vehicles cannot be sanitized adequately.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

55. I would feel more comfortable using ride hailing if the vehicles provide disposable gloves and masks.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

56. I would feel comfortable using ride hailing if equipped with disinfectant sprays to sanitize the vehicle after each ride.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

57. I would feel comfortable sharing a ride with strangers only if "social-distancing" in car design, such as physical dividers between seats, were available.

Ø Strongly disagree

Ø Disagree

Ø Slightly disagree

Ø Slightly agree

Ø Agree

Ø Strongly agree

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