A Mixed-Methods Study of Wait Time Perception and Discrepancy in Technology-Mediated Mobility Systems

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Mobility services are becoming increasingly reliant on new technologies and mobile apps to manage and enable rides. In recent years, we have witnessed a rapid growth of technology-mediated mobility services (e.g., ridesharing and carsharing) with the ubiquity of smartphones. As an important technology-mediated mobility service involving interactions between passengers, drivers, and platforms, ridesharing has attracted great interest from the research community. Even though many existing studies have focused on the ridesharing experience of passengers, few of them have conducted a comprehensive study of passenger wait times in ridesharing systems. Prior research has shown that wait time is highly related to user experience. Understanding wait times in technology-mediated mobility systems and identifying factors that may impact them is of great importance for better user experience and the design of next-generation interactive mobility systems. Hence, in this paper, we adopt a mixed-methods approach to comprehensively examine two wait times in one of the largest technology-mediated mobility systems-DiDi, i.e., (i) the *promised wait time* shown on its mobile app after entering the origin and destination and (ii) the *actual wait time*. We first interviewed 102 individuals (including 52 passengers and 50 drivers) to understand people's perceptions of the two wait times in the DiDi ridesharing system. Our findings reveal that wait time discrepancy causes problems and negative emotions for passengers, and there are multiple potential factors that impact the discrepancy. To further verify some of these findings from a quantitative perspective, we performed a data-driven analysis based on large-scale ridesharing log data from over 36.6 million rides. Based on these findings, we share some design implications for ridesharing systems including those on minimizing expectation mismatch, supporting algorithmic transparency & fairness, and contextual factors consideration.

CCS Concepts: • **Human-centered computing** → *User studies*; *Empirical studies in HCI*.

Additional Key Words and Phrases: Mixed-methods Approach; Algorithmic Awareness; Mobility System; Wait Time

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1 Introduction

In recent years, the prevalence of smartphones and mobile apps has enabled many innovative technology-mediated mobility systems, e.g., ridesharing (e.g., Uber, Lyft, DiDi) [17, 34, 43], carsharing (e.g., Zipcar, car2go) [62, 88], and bikesharing (e.g., Capital Bikeshare, Mobike) [87, 91, 99].

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Among all these technology-mediated systems for more convenient mobility, ridesharing may be the most popular one. For example, over 31 million DiDi drivers provided 48.8 billion kilometers of services for 550 million passengers in 2018. Similarly, Uber is available in over 600 cities across 65 countries in the world. As of 2021, there were 118 million Uber passengers, who were served by a total of five million drivers [39].

As a technology-mediated mobility system involving interactions between the passenger, the driver, and the platform [44, 80], ridesharing has attracted great interest from the research community, and multiple efforts have studied it from different perspectives, e.g., labor opportunities [32, 70], norm and regulations [17], trust and privacy [9, 12, 78], values of time [18], economy and pricing [34, 35], vehicle electrification [89], individual and collaborative behaviors of drivers [2], low-resource populations [24, 92], and support for passengers with vision impairments [11, 44] or drivers with hearing impairments [56]. Even though many existing Human-Computer Interaction (i.e., HCI) studies have focused on the ridesharing experience of the passengers, few of them have conducted a comprehensive study of the passenger wait time in ridesharing systems, which is reported as an important aspect of system design in HCI to enhance the user experience when the interaction between the system and its users is temporarily interrupted (e.g., waiting for the arrival of live agents at call centers and waiting for drivers to pick you up) [4]. Some other works also show that wait time directly impacts user experience. For instance, Dillahunt et al. [24] uncovered that accurate wait time estimation was an important benefit to passengers as it allowed them to make better use of their wait time and prepare for the ride. Yu et al. [100] unveiled that passengers' likelihood to abandon the service increases with a long initial wait time. Li et al. [58] also showed that long wait time is generally viewed as the primary negative emotion source from the user interface. *Therefore, understanding wait times in technology-mediated mobility systems and identifying factors that may impact them is significant for the design of next-generation interactive mobility systems.*

In this paper, we consider ridesharing as one of the most important and representative technology-mediated mobility systems and examine DiDi passengers' wait times for ridesharing applications in China from both qualitative and quantitative perspectives. Due to the on-demand and technology-mediated characteristic of ridesharing usage, there are two wait times interacting between passengers and the ridesharing system, i.e., (i) the **promised wait time** shown on the app after entering the origin and destination (i.e., OD) without sending requests and (ii) the **actual wait time** got by passengers. In particular, we study the following two research questions (RQ) in this work based on both qualitative and quantitative data:

- **RQ1:** How do people perceive the promised and actual wait times in one of the largest technology-mediated mobility systems in the world (i.e., Chinese DiDi)?
- **RQ2:** What factors may impact the unequal actual wait time in DiDi's technology-mediated mobility system?

While some existing studies have focused on the actual wait time [30, 49, 106], we focus more on the **discrepancy** between the promised wait time and actual wait time in ridesharing, as well as people's **perception and potential reasons** of the difference, which, to our knowledge, has not been studied before. This wait time discrepancy issue is common across different platforms (e.g., Uber [64, 72], DiDi [92], and Lyft [71, 84]). As a first step toward answering the above two research questions, we adopted a mixed-methods approach by combining semi-structured interviews and data-driven analysis. We interviewed 102 participants (52 passengers and 50 drivers) to understand people's perceptions towards the promised and actual wait times, where both passengers and drivers reported discrepancy between the promised wait time and the actual wait time. We further examine participants' attitudes to the great discrepancy and the unequal actual wait time. Next, we performed a data-driven analysis based on large-scale real-world ridesharing operation data (including over 36.6 million rides) to quantitatively triangulate the finding of the unequal wait time.

Based on our study, we found the two above-mentioned wait times impact the user experience in different ways, e.g., **(i)** *long actual wait time or inaccurate promised wait times on DiDi mobile apps* may lead to poor user experience and potential loss of users to other platforms. **(ii)** *Inaccurate promised wait times to passengers* may disturb passengers' schedules and cause negative emotions for passengers. **(iii)** *Inaccurate promised wait times to passengers* may also cause more payment for passengers if they make their schedules based on the promised wait times, i.e., promised wait times < driver pickup time = passenger actual wait time. Hence, a comprehensive understanding of passengers' perceptions of the two wait times in ridesharing systems is significant, but it has not been fully studied by existing works potentially due to the challenge in accessing large-scale multi-source data. Fortunately, with the wide deployment of ubiquitous sensing and communication devices on machines (e.g., mobile phones and vehicles), massive accurate log data can be collected, which, combined with qualitative interviews, provides us a great opportunity to comprehensively dissect and understand passenger wait times in technology-mediated mobility systems.

In this work, we also identify some design implications to enhance ridesharing systems and user experience. We summarize three highlighted lessons learned here to provide insights for other similar systems and future work. More detailed discussions will be shown in *Section 6.1*.

- **Lesson learned 1: Value of Mixed-methods Approach in Human-centered Mobility Research.** Our work *highlights the value of the mixed-methods approach* in HCI and human-centered technology-mediated mobility research. The qualitative analysis from the interviews could motivate detailed (scale and granularity) quantitative analysis of logged data. The quantitative analysis using logged data can also complement the results from the qualitative interviews. More importantly, both the qualitative and quantitative analysis can help us identify the important factors that impact wait times in ridesharing platforms.
- **Lesson learned 2: Algorithmic Fairness and Misconceptions.** Our work highlights a new dimension across which differential treatment is met out to female users by algorithms in the ridesharing platform DiDi. The lack of algorithmic transparency in technology-mediated ridesharing could lead to frustration for users, which goes against the original intention of ridesharing for providing convenient mobility. Also, *the perception of the wait time is often just as important as the actual wait times*, as the perception in itself could drive the users away from the platforms, but people may experience cognitive dissonance when expressing perceptions based on past experiences.

2 Related Work

In this section, we discuss prior related works about HCI studies on ridesharing (e.g., papers from CHI and CSCW), HCI studies on wait time, passenger wait time, and algorithmic awareness.

2.1 HCI Studies on Ridesharing

The emerging technology-mediated ridesharing systems (e.g., Uber, Lyft, DiDi) play a more and more important role in our daily traveling. Past HCI studies on ridesharing systems have examined and understood different aspects of them, e.g., dynamic pricing [34, 35], labor opportunity [32], and trip plan for ridesharing [85]. Guo et al. [34] studied passengers' reactions to dynamic prices in ridesharing services from a user-behavior perspective based on both systematic data analysis and theoretical modeling. Kameswaran et al. [44] tried to understand independence through a case study of ridesharing use by people with visual impairments in metropolitan India. Brewer et al. [11] did similar work to examine how drivers support people with vision impairments during rides.

In addition to passengers with disabilities, some works also focused on disabled drivers, e.g., Lee et al. [56] identified and discussed design and product opportunities to improve the hard-of-hearing driver experience on Uber. Glöss ey al. [32] investigated how the design of new technology can create new labor opportunities in services like ridesharing. Almoqbel et al. [2] conducted interviews with drivers in the U.S. to understand how they, individually and collaboratively, address safety-related issues they face conducting their job. Svangren et al. [85] investigated how passengers use ridesharing systems to plan their trips through a qualitative study.

Even though many of these papers [24, 85, 92] mentioned passenger wait time directly impacts user experience, they did not perform an in-depth investigation to understand passenger wait times in ridesharing systems, especially in a combination of a qualitative and quantitative analysis way. In addition, most of the literature on ridesharing systems is focused on Uber, Lyft, or Ola, but our research on a ridesharing system is in a different context, i.e., Chinese DiDi, which has the potential to advance the knowledge of ridesharing in different countries or cultures.

2.2 HCI Studies on Wait Time

There is also a long history of the HCI community studying wait time for better user experience in different services [4, 15, 38, 47, 53], and different techniques have been developed to estimate wait times, e.g., light barrier sensors [7], smartphone WiFi [94], crowdsensing [13], and crowdsourcing [33]. Asthana et al. [4] reported that wait time in HCI is an important aspect of system design to enhance the user experience when the interaction between the system and its user is temporarily interrupted (e.g., file download, waiting for the arrival of live agents at call centers, and waiting for drivers to pick you up). Wang et al. [92] reported that passengers developed their own strategies to shorten the wait time, e.g., sending requests in advance, but it is challenging for passengers to decide when they should do so since both requesting too early and too late may cause unsatisfactory results (e.g., order cancellation or long wait time). Lallemand et al. [53] indicated that wait times were often sources of anxiety and irritation, and they reported that understanding wait time perception may provide valuable information for user interface design. Li et al. [58] showed that long wait time is generally viewed as the primary negative emotion source from the user interface. Kim et al. [47] also uncovered that users' satisfaction is related to their perception of wait time. All these works show that wait time directly impacts user experience [47, 51, 58], and understanding wait time in services has the potential to enhance user experience and interactive systems, but the wait time in ridesharing is still rarely studied.

2.3 Passenger Wait Time

Some existing works studied passenger wait time in public transportation systems (e.g., bus, taxi, or subways) [20, 26, 30, 49, 57, 63, 69, 75, 95, 106]. Kjaerup et al. [49] reported that passengers may encounter a long wait time for public transportation in a rural context with interviews. Fang et al. [30] intuitively inferred the actual wait time of taxi and bus passengers by the time duration of two successive available taxis or buses, which is decided by the number of passengers in the waiting queue. Collins et al. [20] concentrated on delivering wait time information to transit bus passengers for reducing uncertainty about wait times and improving user experience. Zhou et al. [106] estimated the actual wait time of bus passengers by predicting bus arrival time via bus passengers' participatory sensing. However, for public transportation, it is challenging to track passengers' spatiotemporal information (i.e., location and time) when they have travel demand, so it is often hard to analyze the precise actual wait time of passengers on a large scale.

Different from these conventional public transportation systems, technology-mediated ridesharing provides us with a good opportunity to log the actual wait time of each passenger for analysis. Furthermore, there are different wait times when passengers interact with ridesharing systems, which makes it challenging to comprehensively understand them in a single qualitative way or a quantitative way. Hence, we combine both interview data and large-scale operation data to obtain an in-depth understanding of passenger wait times in ridesharing services, which extends existing HCI work on ridesharing services and provides new findings for future studies.

2.4 Algorithmic Awareness

A growing body of research in HCI is exploring how users make sense of the algorithm features (e.g., algorithmic fairness and algorithmic transparency) and how the awareness of these algorithms affects users themselves [27, 29, 37]. They provide a rich understanding of how users react to algorithms on technology-mediated systems and again highlight the potential for uncertainty and frustration. Lee et al. [55] explored the impact of this algorithmic, data-driven management on human workers and work practices in the context of Uber and Lyft. Eslami et al. [27] measured algorithmic awareness with a mixed-methods study and they found users' awareness of the algorithm led to more active engagement with the system.

However, little research has focused on the impact of algorithmic awareness on wait times in technology-mediated ridesharing systems. In this work, we build on existing work by exploring algorithmic awareness and understanding its impact on the wait times of ridesharing passengers. Our choice of mixed methods provides an in-depth perspective into how passengers' perceptions and actions to the algorithm of the DiDi, and the sensemaking also forms the core of our findings.

3 Methodology

In this section, we introduce the methodology of our paper for further analysis. Fig. 1 describes the overall structure of our work, where orange parts represent data, blue squares correspond to methodology, and green squares demonstrate the analysis results and findings. Our research context is described in Sec. 3.1. We first recruited and interviewed 102 participants (52 passengers and 50 drivers) to gain an in-depth understanding of their perceptions towards promised and actual wait times in ridesharing systems, as shown in Sec. 3.2. We then conducted a comprehensive data-driven analysis to quantitatively triangulate the findings of unequal wait time based on large-scale logged data (Sec. 3.3). The results of interviews and logged data analysis are shown in Sec. 4 and Sec. 5, respectively. The final findings and implications of this study are summarized in Sec. 6.

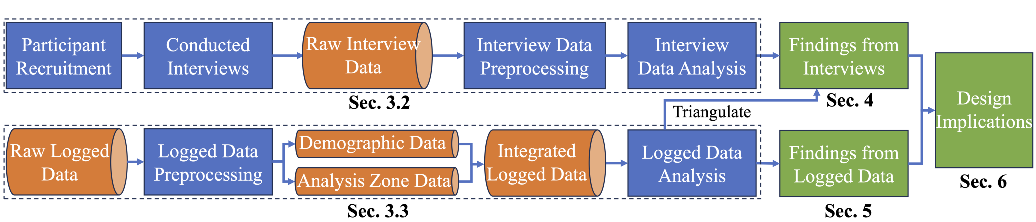


Fig. 1. An overview of the methods and processes.

3.1 Research Context: Wait Times in Ridesharing

In this work, we focus on the Chinese DiDi, which is one of the largest ridesharing companies in the world. Founded in 2012, DiDi operates in over 400 cities with over 550 million users and tens of millions of drivers. In China, DiDi has 377 million annual active users and 13 million drivers providing 25 million rides each day [14], so understanding its operation is very important for large-scale users, and can also potentially provide guidelines for other ridesharing operators. We utilize Fig. 2 to illustrate the wait times on the DiDi app from three parallel dimensions, i.e., *time*, *action*, and *app display*.

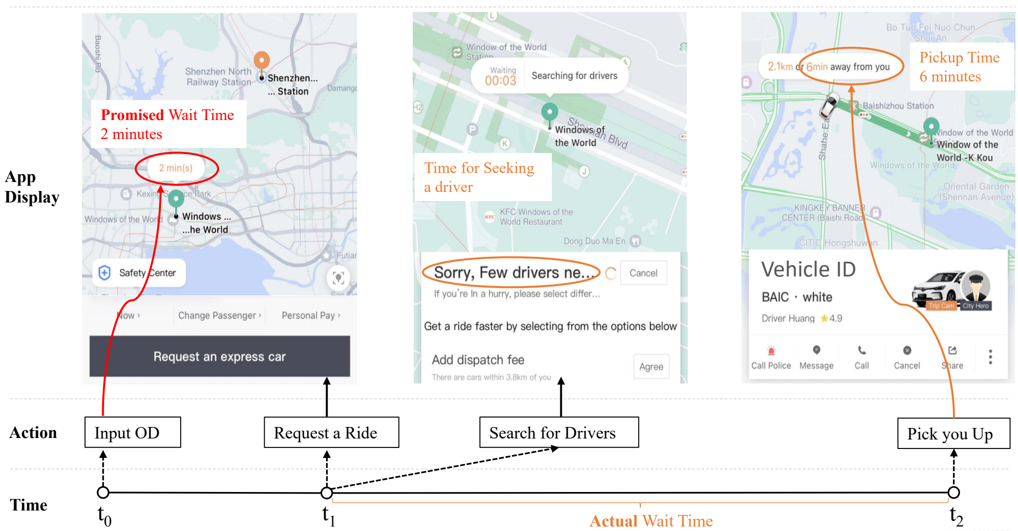


Fig. 2. An illustration of the wait times in ridesharing.

① At the time t_0, passengers input their origin and destination on the DiDi app, (suppose they plan to go to the Shenzhen North Railway Station by taking a DiDi ride after a visit at the Windows of The World), there will be a **promised wait time** shown on the app ***before they send the request*** (e.g., the 2 minutes in Fig. 2).

② At the time t_1, they press the confirm button and send the ride request. The platform will then search for drivers for the passengers and the app will count the *seeking time* until it matches a driver. In some cases, e.g., in rush hours or remote rural areas, there are few drivers around the passengers, so the app will show "Sorry, Few drivers near you", which means the potential *seeking time* will be longer. After matching a driver for the passengers, the driver will go to pick the passengers up.

③ At the time t_2, the driver meets the passengers and picks them up. Here, $t_2 - t_1$ (i.e., the time spent waiting for the ride once it is requested) is defined as the **actual wait time** of the passengers, so it consists of two components, i.e., (i) the time spent by the platform for searching for a driver (i.e., *seeking time*) and (ii) the time for the assigned driver pick the passengers up (i.e., *pickup time*, the 6 minutes in Fig. 2). It should be noted that during the waiting process, both passengers and drivers may cancel the requests for some reasons (e.g., passengers change their minds or drivers cannot arrive at the pickup locations due to heavy traffic congestion). Hence, the period from t_0 to t_2 is defined as a *successful* and *complete* ride request process. Each successful ride will be recorded by the DiDi ridesharing platform when the driver picks the passengers up.

It should be noted that sometimes people only want to check how long it will take for them to wait for a ridesharing vehicle, so they can decide whether they need to request a ride in advance or not. In this case, they will open an app, and then input their origin and destination information for checking the promised wait time without sending requests, so the promised wait time is what they care about. However, few existing works pay enough attention to the promised wait time shown on an app, which may have a large difference from the actual wait time. Hence, in this paper, we consider *promised wait time* as an important component of user-system interaction in ridesharing systems and comprehensively examine the wait times, and show their significance to user experience.

3.2 Interviews

To understand users' perceptions towards the promised and actual wait times in DiDi's ridesharing systems, we first conducted interviews with 52 passenger participants in a semi-structured format for around 40 minutes. We then further recruited 50 driver participants, who were interviewed to supplement the findings obtained from the interviews with passenger participants. The format of interviews with drivers is the same as the passenger participants. All interviews were conducted in Chinese, and our native co-authors translated the interview recordings into English for analysis.

3.2.1 Participant Recruitment and Interview Process. We looked for passenger participants who had previous or ongoing experience in using the ridesharing service operated by the DiDi. We did not specify how much experience one should have for ridesharing services. We provided the participants with a detailed explanation of the purpose and procedure of the interview, which they should understand before starting the interview. The recruitment process started in June 2019 by posting digital flyers on the most visited ride-sharing discussion forums in China. We also advertised our study on our social networks, and some other people also advertised the study for us via their social media. To make the sample more representative, we recruited participants from diverse demographic backgrounds, including various age groups, genders, occupations, and geographic locations. In particular, we also tried to make the age distribution of participants similar to the overall age distribution of DiDi users [65]. After careful selection of our participants, we finally recruited 52 passenger participants (26 males and 26 females). Their average age was 30, and the standard deviation value was 5.3. The age distributions of our samples and all DiDi passengers are shown in Fig. 3, and we found they are similar. Our participants have different job occupations, including financial analysts (5.8%), software engineers (9.6%), professors (3.8%), graduate students (11.5%), doctors (3.8%), unemployment(11.5%), etc. Participants are from 18 cities covering all city tiers (i.e., tier 1 to tier 4). We posted digital flyers on two ridesharing discussion forums in China to recruit driver participants, and we also went to different ridesharing driver lounges to recruit driver participants. All driver participants were also informed about our interview purposes in the same manner. There were 38 male drivers and 12 female drivers recruited. Their average age was 37, and the standard deviation value was 3.2.

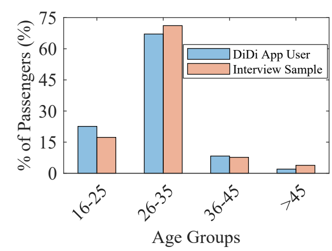


Fig. 3. Age distributions of passengers and interview samples.

Interviews with passengers were conducted through in-person (25%), video chat (10%), or phone call (65%), depending on the interviewee's location and preference. The passenger interviewer began with questions about the participant's demographic information, last ride, frequency of ridesharing use, and motivation for using ridesharing. Followup questions probed participants' perceptions of the promised wait time and actual wait time in ridesharing and how their understanding influenced their feelings and ride request strategies. Passenger participants were also asked about their perceptions of the factors that may impact their wait times. We did a similar interview procedure with drivers with different questions. The percentages of interviews with driver participants through in-person, video chat, or phone call are 22%, 2%, and 76%, respectively. The detailed questions made at interviews are shown in Appendix A.

3.2.2 Interview Data Analysis. To analyze the interview data, we transcribed the interview recordings and conducted a thematic analysis [10], which includes the following four phases: (i) read transcripts while making notes; (ii) go over the notes to generate initial codes and collate; (iii) sort different codes into potential themes; (iv) revise themes and then finalize themes. We use a qualitative data coding software tool called AXQDA [77] to analyze and preprocess the interview data, which can help us find initial codes and potential themes behind the notes.

We created a coding system that includes codes agreed by coders such as satisfaction, disappointment, and anger. Coders received thorough training on the coding framework and the specific criteria for each code, and they also practiced coding on a subset of interviews and provided feedback to improve consistency before coding the whole dataset. Coders assessed the initial Kappa coefficient and identified areas of disagreement based on the practice, and they used the results from the practice to refine the codebook and improve the training. Coders then apply the codes to label the data, e.g., highlight sections of the text in interview transcripts that correspond to codes. After coding interviews, they review the coded segments to ensure consistency and accuracy. The final coding scheme had good reliability across two coders with a Kappa value of 0.93. Conflicts between coders were resolved through discussion. In total, there were 525 codes finalized by the end of the coding phase. They captured passenger participants' motivations and purposes for using ridesharing, all participants' perceptions towards wait times in ridesharing, emotions toward ridesharing and wait time, explanations for inaccurate and unequal wait time, etc.

We then started to analyze the initial codes and consider how different codes may combine to form an overarching theme. Finally, all data and codes gradually converged on 18 interrelated themes. We focused on three themes relevant to our research questions around passenger perception of wait times: (i) inconsistency between the promised wait time and actual wait time, (ii) attitudes of participants to the inconsistency, and (iii) unequal actual wait time for different participants.

3.3 Logged Data: Real-world Ride Records

From our interview results, we found accurate promised wait time is very important for user experience, and many factors may impact the unequal wait times of passengers. To further delve and have a better understanding of the impact factors for the ridesharing passengers' unequal wait times, during this project, we also conduct a quantitative analysis based on large-scale real-world data. Our dataset used in this work includes over 36.6 million ridesharing rides in the Chinese city Shenzhen, which was collected in 2019. In order to verify more factors that might impact passenger wait time, we utilize the official urban analysis zone data in this work, which can help to capture more fine-grained spatial features. The details of the two datasets are shown below.

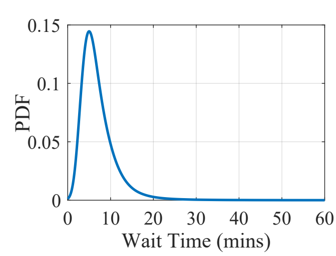


Fig. 4. PDF of passenger wait time.

(i) **Ridesharing Logged Data.** After successfully completing a ride, an order record will be generated, which consists of over 20 key fields describing the order (related to both passenger & driver), e.g., the order ID, order time, passenger ID, passenger gender, pick-up time, pick-up location, drop-off time, drop-off location, ride distance, pick-up distance, vehicle ID, etc. The actual wait time can be obtained by (pick-up time - order time). Note that gender information was limited to male and female, which we consider a limitation of this work. Fig. 4 shows the passenger actual wait time distribution based on our logged data, which indicates 678,300 (12.5%), 266,600 (4.91%), and 98,200 (1.81%) rides have wait times longer than 10 minutes, 15 minutes, and 20 minutes per week in Shenzhen, respectively. Some passengers' wait time is even longer than 60 minutes. More details of the logged data will be shown in Appendix B.

(ii) **Urban Analysis Zone Data.** It describes the urban partition for the population census of the studied city (i.e., the Chinese city Shenzhen). In this data, Shenzhen city is divided into 491 regions, and each region has a region ID and longitudes & latitudes of its boundary. In particular, we recognize nine representative areas (e.g., residential area, central business districts (CBD), industrial area, and airport) using the method in [101] to investigate the area-based wait time.

4 Qualitative Results from Interviews

In this section, we present the details of our key findings from our interview data analysis.

4.1 What You See Is Not What You Get: Discrepancy Between The Promised Wait Time and The Actual Wait Time

4.1.1 Wait time and (in)convenience. From our interviews, we found most passenger participants use ridesharing in a hurry **for time-saving purposes.** For example, a 35-year-old male participant said, *"I usually use ridesharing in a hurry [...]"*(P03, M, 35) [1]. Another 28-year-old female participant also noted *"Sometimes I used it when there was an emergency"*(P11, F, 28). Many passenger participants perceived short wait time as a reason to prefer ridesharing to taxi, but still, the discrepancy between the promised wait time to passengers after inputting origin-destination and the actual wait time creates problems for them.

"I use ridesharing because it is convenient for me to order a ride via mobile apps. The promised wait time declared by the DiDi app was always very short. However, after I sent my request, it sometimes changed into a very long wait time estimation and I finally waited much longer than the promised wait time. [...] "(P08, M, 31).

Another female passenger participant also expressed a similar perception.*"I used to check if there are vehicles available around me and how long I will wait when I need to use ridesharing. However, I found the promised wait time is really inaccurate. [...]"* (P49, F, 29).

Some participants also reported that they would not use the ridesharing service if the promised wait time before sending a request is longer than 10 minutes, so it may be a business strategy of ridesharing platforms to show a short promised wait time on the app to attract people to use it, which may potentially impair user experience of ridesharing passengers when they encounter the discrepancy.

4.1.2 Wait time and (dis)satisfaction. Passengers also expressed dissatisfaction about the inaccurate promised wait time shown on apps, and many participants reported encountering a discrepancy between the promised wait time and the actual wait time. One 33-year-old female participant remarked that her experience of the inaccurate promised wait time and long actual wait time in the interview, *"[...] I inputted my origin-destination and tried to request a ride. It showed I needed to wait 5 minutes. However, after I submitted the request, I waited 25 minutes to have the vehicle pick me up. [...] It is a really terrible experience."* (P21, F, 33). This participant also mentioned she had several ridesharing experiences with a wait time longer than 10 minutes, mostly on bad weather days and late nights, although the app always indicated a relatively short wait time before I sent requests.

The discrepancy between the promised wait time and the actual wait time not only disturbed participants' plans but also caused extra costs for some of them when the promised wait time was longer than the actual wait time. One participant noted, *"When I opened the DiDi app and inputted my origin and destination, it showed the wait time was 11 minutes [...] However after I sent the request, a vehicle was assigned to me immediately instead of waiting 11 minutes. Even though I hurried up to the pickup location, I still received an extra charge due to my lateness."* (P44, F, 35).

[1](P03, M, 35) means the passenger participant number 3, Male, 35 years old.

4.2 Mood Change of Passenger Participants When They Encounter Great Discrepancy Between Promised Wait Time and Actual Wait Time

4.2.1 Wait time and passenger churn. Almost all participants perceived wait times are highly related to the user experience of ridesharing passengers. There are interactions between ridesharing services and passenger ride experience, and an intuitive reflection is the wait time. Poor ridesharing services or unreasonable dispatching will lead to long wait times or inaccurate wait time estimations, which potentially cause an unsatisfactory user experience, resulting in passengers switching to other ridesharing platforms. For example, one female passenger noted in the interview, *"I will switch to take a taxi or another ridesharing platform if the wait time of DiDi is too long. Usually, after waiting for 15 minutes, I will cancel the request and try other alternatives."* (P11, F, 28).

Participants always wished vehicles could pick them up as fast as possible, although they understood that the wait time is inevitable. They also mentioned that **the wait time should be expectedly short or predicted accurately**, so they can decide when to request their rides. For example, one female participant said,

"The promised wait time by the platform should be accurate, so I can know when I should send the request and schedule my time better.[...] Although the promised wait time is usually accurate during non-rush hours, there may be a huge gap between the promised wait time and actual wait time during rush hours, especially in the CBD areas and residential areas." (P06, F, 29)

4.2.2 Attitudes and strategies to the discrepancy of wait times. Most participants expressed **negative attitudes** towards a great discrepancy (over 10 minutes) between the promised wait time and the actual wait time, even though a few participants indicated that they did not mind it. We found that there were typically four moods of participants when they encountered a large discrepancy from our interview based on our thematic analysis: (i) Anxious, (ii) Mistrust and Disappointment, (iii) Boring, and (vi) Do not care. We also leverage the Circumplex Model of Emotions [73, 74] to systematically code and interpret emotions in a structured way that takes into account both the intensity and the pleasantness of the emotional experience, which makes the process of identifying and categorizing moods more rigorous. It indicates that (i) Anxious is High Arousal and Negative Valence, (ii) Mistrust and Disappointment is Medium to Low Arousal and Negative Valence, (iii) Boring is Low Arousal and Slightly Negative Valence, and (iv) Do not care is Very Low Arousal and Neutral Valence. Some participants who used ridesharing for commuting or meetings indicated that they worried about being late, which may potentially disturb their schedules, and some of them also developed strategies to deal with the discrepancy. For example, a male passenger said, *"I work at an IT company. [...] I usually use ridesharing for commuting. There are many times that I found the promised wait times had great discrepancy with the actual wait times in the morning rush hours. I felt anxious as I was worried about being late for work, so I usually left and sent requests 10 minutes earlier in the morning rush hour to avoid being late."* (P05, M, 32).

Another female passenger said, *"Normally, I sent ride requests several minutes in advance before I went out of my house since I found the actual wait time was usually longer than the promised wait time. I do not want to waste my time waiting outside, especially on rainy and snowy days."* (P36, F, 29).

Strategies: Some passengers also stated they usually send requests in advance at some specific locations, e.g., railway stations. For example, one 46-year-old passenger said, *"Ridesharing is more convenient when I need a ride at a railway station since I can send a request in advance. Every time I take a train, I will send a ride request several minutes before arriving at my destination."* (P45, M, 46).

However, even though some strategies are adopted by passengers to deal with this discrepancy issue (e.g., in-advance-request), some of them also reported they have been charged a wait time fee since they cannot arrive at the pickup locations in time when the promised time is much longer than the actual wait time. For these participants, they complained about the extra charge and they were eager to have the precise promised wait time shown on the ridesharing app. For example, a male passenger noted,

"In the university where I work, all ridesharing vehicles are not allowed into our campus and they normally stop outside the gates. When I opened the DiDi app and inputted my OD, it showed the wait time was eight minutes. However, after I sent the request, a vehicle was assigned to me immediately instead of waiting eight minutes. Even though I hurried up to the gate, I was unable to arrive at the pickup location on time. [...] I think the promised wait time on the app is unreliable and should be more precise." (P35, M, 46).

In addition to the statements from the passenger participants, some driver participants also expressed similar situations. For example, a male driver indicated, *"Some passengers sent requests too early, so I waited for more than 10 minutes. Even though there are some compensations for me, it is much less than the normal operating earnings."* (D01, M, 38) [2].

Mistrust and Disappointment: Many passenger participants also expressed their mistrust and disappointment towards this discrepancy, especially for people who trusted the platform. One 29-year-old female passenger noted, *"On a cold winter night, I planned to ride a DiDi home from my office. When I opened the app and inputted my destination, it showed the wait time would be 2 minutes, so I requested a ride when I arrived at a pickup location. However, when the platform assigned a driver for me, the wait time turned out to be 10 minutes, so I was freezing in the cold wind for a long time. I felt very disappointed with the DiDi app, and I had an extremely bad ridesharing experience since there was a large gap between the promised time and the actual wait time."* (P20, F, 29).

This discrepancy not only damages user experience but also causes loss of passengers since passengers may switch to other ridesharing platforms if they feel disappointed. For example, a 37-year-old female passenger said, *"I unloaded the app after encountering the discrepancy several times. I did not trust it anymore."* (P22, F, 37).

Interestingly, several participants specifically pointed out that they did not have large mood swings and they did not mind it if the actual wait time was less than half an hour. They reported that they would utilize this time to check their emails, and listen to music (e.g., *"I check my emails or listen to music while waiting and I don't care about it."* (P12, M, 33)), or make phone calls (e.g., a male passenger said *"I can listen to music or chat with my girlfriend when I wait for the driver. [...]"* (P43, M, 26)). However, even for these wait time nonsensitive passengers, they also reported that they could not tolerate a very long wait time, e.g., they mentioned that they would also have a negative emotion if the actual wait time largely exceeded the promised wait time. Most people do not like waiting, so they will feel more dissatisfied and disappointed when they spend money to access those convenient services but get a long wait time.

4.3 Unequal Actual Wait Time of Passengers

4.3.1 Wait Time and Order Time & Location. Even though most passenger participants perceived different actual wait times when using ridesharing services, participants expressed diverse perceptions of the potential factors for the unequal wait time. Based on our interview results, we found, among all factors, the order time and location are considered the most significant two factors that impact the wait time by passengers. For example, similar statements are mentioned by two passengers: *"The actual wait time is different when I order ridesharing services at different locations. It is also different in the morning and afternoon, weekdays and weekends, and especially it is long in holidays."* (P03, M, 35) (P51, F, 29).

4.3.2 Wait Time and Weather Condition. Weather condition is also highly involved in the interview, and over half of the participants reported the wait time is largely prolonged on bad weather days

[2](D01, M, 38) indicates the driver participant number 1, Male, 38 years old

(e.g., heavy rainy days) compared to good weather days. However, people expressed different ideas about the impact of temperature on the unequal wait time. One passenger noted, *"The wait time would be much longer and uncertain on rainy days, but I did not see large differences between Summer and Winter."* (P10, M, 46)

4.3.3 Wait Time and Passenger Gender. One of the most ***surprising findings*** is that some participants perceived it is unequal for male and female passengers regarding the actual wait times even though most participants did not mention it. For example, a 29-year-old female passenger said,

"I have tried to request a ride with my boyfriend at the same time and at the same location, but it showed 25 minutes waiting for me and 3 minutes waiting for my boyfriend." (P15, F, 29).

Another 32-year-old female passenger also expressed similar experiences of her colleagues and gave a possible explanation, *"My female colleagues always complained they needed to wait a longer time compared to the male colleagues when they requested rides at the same locations at late night time."* (P39, F, 32).

This may be an unexpected byproduct of the AI-based scheduler adopted by the ridesharing platform, where safety is the prerequisite for providing services. Platforms treat female users as a more vulnerable group, so they have higher standards to match drivers to female users compared to male users, e.g., male drivers with low ratings or complaints from female passengers in the past will not be assigned to female passengers. Interviews with some drivers also validated this finding. For example, one male driver noted, *"After getting a poor rating from a female passenger, the platform has not dispatched female passengers to me anymore."* (D03, M, 33). Another male driver also said he has no female passengers for a long time, *"I did not receive ride requests from female users for over three months."* (D07, M, 35).

Some drivers also mentioned that their income has also been impacted since no orders from female passengers are assigned to them. *"It is very strange that I did not receive orders from female passengers for two months. [...] My income also decreased since I had no orders from female passengers although I had the same operating time. [...]"* (D25, M, 38).

Different from the statements from male drivers, no female drivers indicated that they lost female passengers. One female driver said, *"I did see a decrease of female passengers, and I always have female passengers during nights. [...]"* (D43, F, 35). This finding implies that the dispatching mechanism of ridesharing platforms may yield unequal treatment to female users, and an explicit perception of a long wait time compared to male users.

4.3.4 Wait Time and Trip Distance. Drivers' preferences make the actual wait time of passengers more uncertain. Many participants reported that they waited a long time when their destinations were near to their origins. For example, one passenger noted, *"Sometimes I waited a long time when my destination was near to my origin location."* (P17, M, 38). Some passengers thought drivers prefer to serve long trips. *"[...] I think drivers normally prefer longer trips compared to short trips, especially at some locations with heavy traffic jams."* (P23, M, 29).

Some drivers also expressed a similar view in terms of the trip distances. One 32-year-old driver said, *"I will reject the request if the ride distance is short and traffic is heavy."* (D04, M, 32).

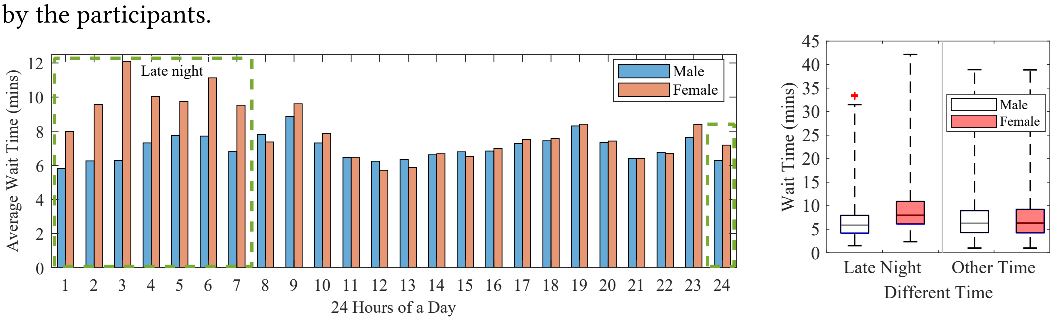
4.3.5 Wait Time and Trip Origin & Destination Locations. This may be because long rides could bring higher income for drivers since they do not need to spend extra time waiting for an order from the platform. In addition, we found rides that originate from rural areas usually have a long wait time, and some participants also mentioned that they waited over half an hour from rural areas to downtown CBD areas sometimes. For instance, a 28-year-old female passenger noted, *"[...] I found it really hard to get a ridesharing service in rural areas. I waited for over 20 minutes. One* *reason is that there is a low ridesharing vehicle supply in rural areas, so drivers need to be dispatched from long distances. [...]"* (P11, F, 28).

Furthermore, some areas with heavy traffic congestion were also hard to have access to ridesharing services, as indicated by both passengers and drivers. One passenger participant noted, *"[...] It would be faster to take a taxi or other transportation modes in the CBD areas during rush hour or on weekends compared to ridesharing since drivers may cancel the order if the traffic is very heavy at that time.[...]"* (P13, M, 37) The same situations are expressed by some drivers, e.g., *"[...] Sometimes when I am stuck in heavy traffic, I will cancel the order in case I cannot pick the passenger up in time."* (D02, M, 43).

Summary: (i) Some participants perceived it is unequal for male and female passengers regarding the actual wait times, i.e., female passengers have longer wait times than male passengers during the night, which may be caused by the system design due to safety considerations.
(ii) People use ridesharing in a hurry for time-saving purposes, and perceived short wait time and convenience are two important reasons to prefer ridesharing to taxi.
(iii) The discrepancy between the promised wait time to passengers before sending a request (what they saw) and the actual wait time (what they got) potentially causes "broken expectations".
(iv) Some strategies (e.g., in-advance-request) were adopted to deal with this discrepancy.

5 Triangulating Interview Results with Large-Scale Logged Data

Even though participants expressed their perceptions of possible factors that impact actual wait time, findings from a sample of population may not be able to represent the public opinion or the fact due to possible cognitive dissonance. Hence, we further conducted a quantitatively statistical analysis based on large-scale logged data of over 36.6 million rides to study the factors mentioned by the participants.



(a) Average wait time of male and female passengers in different hours (b) Wait time of each trip

Fig. 5. Relationship between ride distance and wait time of each trip during different hours.

5.1 Actual Wait Time of Passengers of Different Genders

Our most surprising finding regarding the unequal actual wait time from interviews is the perceived gender differences in wait times (reported in Sec. 4.3), so we first compare the actual wait time of female passengers and male passengers based on our large-scale logged data. As shown in Fig. 5a, we found the average wait time of female passengers during the late night (23:00-7:00) is noticeably longer than that of male passengers. Especially in 2:00-3:00, the average wait time of female passengers is 4-6 minutes longer than that of male passengers on average. But from 8:00-22:00, the average wait time difference between the female passengers and the male passengers is very small. To have a better understanding of the wait time of each ride from female and male passengers, we compare the wait time distributions of female and male passengers at late night and at other times in Fig. 5b. We found there is a huge difference in wait time between female and male passengers during late night (i.e., 23:00-7:00). Particularly, more than 31.6% and 18.6% of rides from female passengers have wait times longer than 10 and 12 minutes, and some females also wait for over 40 minutes.

We then utilize the Wilcoxon Rank-Sum test [3] [96, 103] to perform a statistical test in order to verify the differences between male and female passengers. This test can be used to determine whether two independent samples were selected from populations having the same distribution. The Wilcoxon test results are shown in Table 1. We found there is a significant difference ($h = 1, p = 2.9 * 10^{-6}$), which indicates female passengers have statistically different wait times from male passengers in general. More specifically, the difference is very significant during the late-night hours ($h = 1, p = 3.4 * 10^{-22}$), but there is no statistical difference during other daytime hours ($h = 0, p = 0.8798$). This result suggests that there actually exist unequal wait times for female and male passengers during the night, which uncovers the differential treatment of the DiDi ridesharing platform (or its algorithm) to female passengers.

Table 1. Wilcoxon Rank-Sum test for wait time of females and males

Time	h-value	p-value
Overall	1	2.9^*10^{-6}
Late night	1	3.4^*10^{-22}
Other Time	0	0.8798

One possible reason behind this gender disparity in wait times would be that DiDi orders of female passengers have to be served by female drivers at night for safety considerations, but there are fewer female drivers at night, which results in longer wait time of female passengers at nights. This explanation is also reflected in our interviewers. *"[...] My husband and I talked to a male driver during a night trip, and he mentioned that orders from female passengers were typically served by female drivers instead of him, so he suggested my husband send requests if we traveled at night. [...] The driver also complained it was unreasonable since few female drivers were operating during the night"*(P12, F, 30), a 30-year-old female passenger said. Some other participants also expressed similar situations, e.g., excerpts of interviews with P29 and P39 in Section 4.3. Even though it might be for safety considerations, the long wait time will still damage the user experience of female passengers.

5.2 Actual Wait Time of Passengers with Different Ride Features

As we reported in our interview results, some participants mentioned ride features (e.g., ride distance, ride origin, and destination) also related to the unequal wait time. Hence, we examine the passenger wait time with different ride features with large-scale logged data. We report some interesting/broken expectation results below.

5.2.1 Origin Location & Order Request Time of Rides. We first examine the correlation between passenger wait time and the ride origin location & order request time. We utilize the official urban analysis zone data described in Sec. 3.3 to divide the city into a set of regions. Fig. 6 visualizes the average wait time of passenger rides in the 491 analysis zones at different hours, including the late-night hour (0:00-1:00), morning rush hour (8:00-9:00), and evening rush hour (18:00-19:00). The darker red part means a longer average wait time in this region during this time slot, and the lighter yellow part means a shorter average wait time in this region during this time slot.

As shown in Fig. 6, we found that the average wait time in most zones is shorter than 7.1 minutes on both weekdays and weekends. In particular, the average wait time in the airport area is longer at the late-night hour. During the morning rush hour on weekdays, the average wait time in the CBD area and commercial business area is long. However, the wait time in these areas on weekends

[3] h = 1 indicates a rejection of the null hypothesis, and h = 0 indicates a failure to reject the null hypothesis. The null hypothesis is the two groups have the same distribution. If the p-value is lower than the significance level (e.g., 0.05), then we can say that we have statistically significant evidence to reject the null hypothesis.

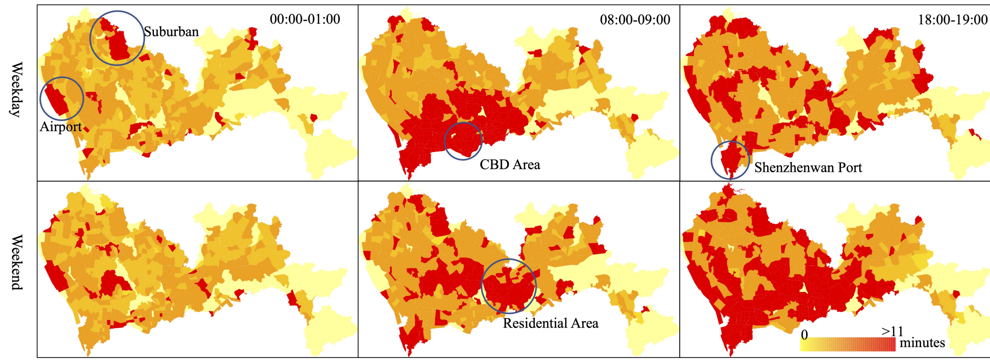


Fig. 6. Average wait time in each region at different hours.

becomes shorter, but the average wait time in residential areas is long. A possible reason would be that the traffic in the CBD area and commercial business areas in the morning rush hour of weekdays is heavy, which potentially prolongs the wait time in these areas. However, on weekends, the traffic in the CBD area and commercial business areas are light since many people do not need to work, but more people may use ridesharing services to hang out on weekends, so the high passenger demand and heavy traffic may have a strong correlation with long wait time in residential areas on weekends. Furthermore, there is a large difference in wait time between the evening rush hour of weekdays and the evening rush hour of weekends. Specifically, the long wait time regions are in ports and some suburban areas on weekdays, but the wait time is long in most areas on weekends, including the CBD area, commercial area, airport areas, residential areas, etc.

Although participants of interviews perceived the time and location of sending ride requests can impact wait time, they hardly reported the in-depth relationships between them, so such a comprehensive statistical analysis may supplement participants' perceptions.

5.2.2 Origin-Destination Pair Location of Rides. We further studied the passenger wait time from different origin areas to different destination areas since some participants indicated that they waited a long time from rural areas to downtown CBD areas sometimes. We utilize nine representative areas as mentioned in Sec. 3.3 to perform this examination, including *airport, rail station, high-speed rail station, CBD, scenic, residential, industrial, commercial, and port areas.* Fig. 7 shows the average wait time of rides from one type of area to another type of area, e.g., the average wait time of rides from the airport area to the rail station area is 15.104 minutes.

From Fig. 7, we found the average wait time for rides from the airport area is much longer than the rides from other areas. The average wait time for rides originating at transportation hubs (e.g., airport, rail station, high rail station, and port) is longer. One possible reason would be that passengers in these areas usually take subways or taxis since it is convenient for them to find taxis or subway lines there (there are fixed taxi pickup spots in these transportation hubs but ridesharing vehicles are not allowed to park there). Hence, ridesharing will lose its advantage of convenience in transportation hubs, which potentially lead to low demand & supply and long wait time. However, the wait time for rides from the CBD area is usually short as the average wait time to different areas is shorter than 6 minutes. The reason may be that there is a high and dense vehicle supply in the CBD area. Even though some participants perceived long wait times in the CBD area during rush hours, we found most rides have a relatively short wait time, which lowers the average wait time.

In general, the average wait time of passengers that originate at the transportation hubs (e.g., airport, rail stations, and port) is longer, while the wait time of passengers originating at the CBD

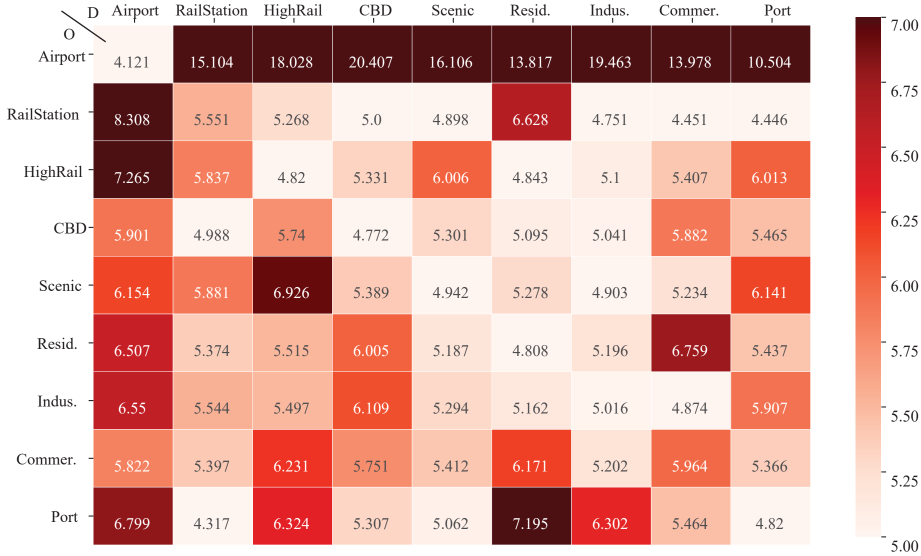


Fig. 7. The average wait time of passengers from different origin areas to different destination areas.

area is usually short. Although some participants in interviews (e.g., P13 in Sec. 4.3) also indicated that different origin-destination pair locations impact their wait time, they only expressed subjective cognition based on their experiences. However, an in-depth finding was covered by the statistical analysis based on large-scale system operation data, which showed that the large-scale operation data can be leveraged to reveal more in-depth and comprehensive findings.

Table 2. Correlation of wait time and ride distance.

Wait Time (mins) vs. Ride Distance (km)	Time Duration	Pearson correla. coeff.	p-value
The correlation of wait time and ride distance	0:00-3:00	0.210	$<10^{-15}$
	4:00-7:00	0.184	$< 10^{-15}$
	8:00-11:00	0.038	$6.9*10^{-15}$
	12:00-15:00	0.191	$< 10^{-15}$
	16:00-19:00	0.193	$< 10^{-15}$
	20:00-22:00	0.165	$< 10^{-15}$
	23:00-0:00	0.112	$< 10^{-15}$

5.2.3 Ride Distance. Surprisingly, we found the Pearson correlation of passenger wait time and ride distance is always positive during different hours of a day with an overall value of 0.1617, and the results are significant ($p < 0.001$), as shown in Table 2. The results indicate that passengers for longer rides may need to wait a longer time. This is consistent with the findings from Sec. 5.2.1 and Sec. 5.2.2, e.g., the wait time for rides from the airport area to other areas is long because the airport is very far away from other areas as shown in Fig. 6. Also, since the Shenzhenwan Port is far away from residential areas and other transportation hubs, the average wait time for rides originating at the port is also long. However, our interview results show that some passengers reported long wait times when their rides were short, and drivers also preferred to serve long-distance rides and possibly rejected short-distance rides, which potentially indicates that passengers with long-distance rides may have a short wait time. One possible explanation for this disparity may be the memory lapses and biases that humans have [41, 81]. People may have **cognitive dissonance** when they express their perceptions based on past experiences, and they are also easily suffering from cognitive limitations when conducting interviews. This *interesting and unexpected* finding underscores the value of complementary layers of data. Further interpretation and analysis of such dissonance could be a direction of interesting future work. Another possible reason would be that these passengers' short rides originate in the CBD area or residential areas in the morning rush hour of weekdays, where traffic congestion is heavy at these places, which potentially prolongs their wait time in these areas, as shown in Fig. 6, so they perceived a long wait time for those short trips in these areas at that time.

5.2.4 Weather Conditions. We compare the passenger wait time in three typical weather conditions, i.e., sunny, rainy, and typhoon. Even though typhoons are always accompanied by rain, they are more adverse than normal rain. To avoid the interference of other factors (e.g., temperature and day of the week), we choose the types of days carefully. All the datasets for the weather condition comparison are from workdays (i.e., Thursday), during which have similar temperatures (i.e., about 23-27 °C). From Fig. 8, we found that there is a large difference in wait time distributions between days of different weather conditions. More trips have longer wait times on typhoon days and rainy days compared to sunny days. Quantitatively, the average wait time on typhoon days is 2.7 minutes longer than on sunny days, and the standard deviation is also larger on typhoon days.

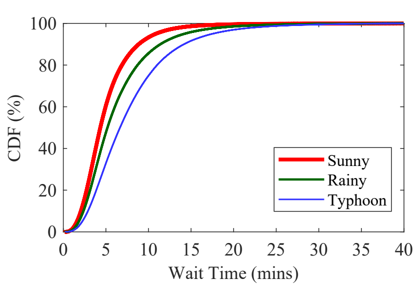


Fig. 8. Impact of weather conditions.

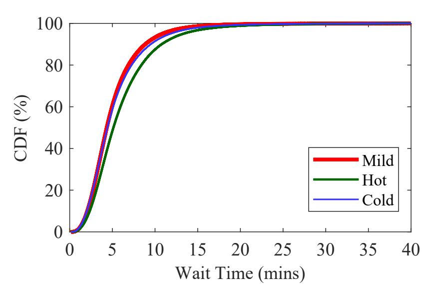


Fig. 9. Impact of temperature.

5.2.5 Temperature. We divide the temperature into three levels to investigate the passenger wait time in different temperatures, i.e., high (27 - 35 °C), mild (24 - 27 °C), low (11 - 15 °C). Similarly, to prevent the interference of other factors, we also choose the there types of days carefully. All three kinds of days for the temperature comparison are workday (i.e., Thursday), and they have the same weather conditions (i.e., sunny). From Fig. 9, we found there is no obvious difference between the wait time distribution on mild days and cold days, even though the hot weather may cause a little longer wait time compared to them. In general, the average wait time in mild sunny days is 5.1 minutes with a standard deviation of 3.2. The average wait time in hot days is 1 minute longer than in mild days.

Summary: (i) Our large-scale data analysis indicates the differential treatment of the DiDi ridesharing platform (or its algorithm) to female passengers, which may be related to the safety considerations of ridesharing services. This matches with the findings in Sec. 4.3.
(ii) Different factors that impact passenger wait time are identified from our qualitative study and quantitative study. Some findings are consistent in the two studies, e.g., wait time is highly relevant to order time, origin and destination locations, weather conditions, and passenger gender. However, some conclusions from the two studies are conflicted, e.g., the relationship between wait times and ride distance. Also, the impact of some other factors on wait time (e.g., temperature) is not obvious.

6 Discussions

Understanding wait time is crucial for technology-mediated systems such as on-demand mobility (e.g., ridesharing [42, 100]), instant delivery [93, 104], last-mile delivery [1, 105], and telemedicine [46]. When individuals have a clear understanding of how long they need to wait for a service or response, they can better organize their tasks within the wait time and manage their expectations. For example, if ridesharing passengers can know the accurate wait times when they input their origins and destinations, they can decide when or if they should send a ride request or go to the pickup location. However, these platforms always provide an inaccurate wait time perceived by users. Prior HCI literature has studied the importance of "broken expectations" in the smart home, mobile apps, and digital device scenarios [8, 50, 82]. In this work, we highlight the discrepancy between the promised wait time and the actual wait time in the technology-mediated mobility systems, which potentially leads to poor user experience, mistrust, and abandonment of the systems or seeking alternative solutions [22]. Although ridesharing users actively try to make sense of the algorithm and interpret its actions, they may have cognitive limitations since these algorithms are highly complex and dynamic, which makes it challenging for users to fully comprehend how the algorithms work. Especially when they are in a hurry (a common scenario when users use ridesharing), users may not have the time or mental bandwidth to delve deeply into the workings of a ridesharing algorithm. In addition, people may have cognitive dissonance [6] and cognitive biases [16] when they express their perceptions based on past experiences, and a possible explanation for this dissonance may be the memory lapses and biases that humans have [41, 81], leading to perceptions that may not align with the algorithm's actual behavior. This may be considered a drawback of using small-scale qualitative studies to understand user perceptions or experiences [21]. However, the perception of the wait time is often just as important as the actual wait times, as the perception in itself could drive the users away from the platforms. This is also the reason why we need to conduct in-depth interviews with users with diverse backgrounds and experiences. Although existing work has studied passenger wait times in public transportation systems (e.g., bus [61], taxi [49], or subways [30]) through interviews or surveys, there has been limited exploration into comprehending the wait times in technology-mediated mobility frameworks like ridesharing combining qualitative and quantitative perspectives, which is more important since those relatively young users may be more sensitive to wait time [68]. Also, the work presented here highlights the significance of large-scale logged data in validating qualitative findings from a statistical perspective, which can provide a statistical value of passenger wait time discrepancy and impact levels of different factors on wait times based on millions of trips.

Technology-mediated systems are becoming increasingly reliant on software algorithms to manage the information needs of their users and deal with the increasing amounts of data generated for satisfying user demand [55]. In recent years, algorithmic fairness has gained significant interest in the HCI community [27, 28, 90, 98]. Prior research adopted different methods such as surveys [90], interviews [54, 98], workshops [3], and content analysis [23] for in-depth investigation. Different from them, our work highlights the value of mixed methods in algorithmic fairness and human-centered research. The qualitative analysis from the interviews motivated detailed (scale and granularity) quantitative analysis of logged data. The quantitative analysis using logged data can also complement the results from the qualitative interviews. The initial qualitative analysis space was useful in hypothesis generation, which could be tested at scale (and the nuances explored) using quantitative analysis. Also, this is the first work to study wait time perception and discrepancy in technology-mediated mobility systems with a mixed-methods approach, which can potentially lay a foundation for future research on algorithmic fairness in different areas like Social Media and Online Platforms [52], Healthcare [19], Recruitment [79], and Education [48]. Existing work on understanding user experience usually conducts in-depth qualitative studies such as interviews [66, 67, 97]. This work reveals that large-scale operational logged data analysis is effective in triangulating the findings from qualitative studies for a more comprehensive study. Although ridesharing platforms had female passengers' interests (safety) in their minds when they designed the intervention of selective matching of female passengers and drivers, the design interventions may cause *unintended consequences* such as unequal wait time between male users and female users [86]. This unfair design will not only damage passenger user experience (e.g., increase wait time) but also have a negative impact on driver income and vehicle utilization efficiency.

6.1 Design Implications

Our work provides novel design implications for the HCI community. We demonstrate the importance of actual wait time and perceived wait time discrepancies in user experience when using ridesharing systems. Specifically, to improve the user experience in technology-mediated mobility systems, we delineate the typical features of promising technology-mediated mobility platforms.

Algorithm Fairness and Transparency. The lack of algorithmic transparency manner in which the matching of passengers and drivers is implemented could lead to frustration for both the passengers and the drivers. The *disparate impact* principle in algorithmic fairness suggests that large differences in outcomes for different demographic groups are considered unacceptable irrespective of the *intent* of the designers [5]. Hence, our results motivate more transparent and more equitable approaches by ridesharing apps in their matching algorithms in the future, e.g., considering the travel demand of female users at late night to reduce their wait time. Ridesharing platforms should ensure that algorithms used for driver allocation are fair and do not discriminate against certain demographics or areas. Platforms should also make wait time prediction algorithms transparent and explainable to build trust with users and allow them to understand how predictions are made and the factors influencing their wait time to manage passenger expectations. This has implications for user experience design and is important from the perspectives of value-sensitive design [28, 31].

Wait Time Prediction-based Vehicle Repositioning. Large-scale logged data allows for the development of predictive models that anticipate demand fluctuations and wait time to optimize resource allocation accordingly. Ridesharing platforms should proactively dispatch more vacant ridesharing vehicles to some regions that will have high demand based on wait time prediction and provide incentives for those drivers to reduce passenger wait time, which will benefit drivers and passengers, as well as the long-term profits of platforms. The vehicle repositioning should also be dynamic and real-time since the passenger wait time is highly related to the order time, order location, weather conditions, trip distance, traffic conditions, and the origin & destination locations.

Feedback Mechanisms. Understanding user experience is important for platforms to improve user experience. Our study emphasizes the importance of mixed-methods approaches. Platforms can maintain a feedback mechanism that allows passengers to provide input on their experience, including punctuality of drivers and wait times, and use this feedback and large-scale logged data to continually improve the platform's performance.

User Experience Design. Future technology-mediated mobility app designers can consider designing a user-friendly interface creating visualizations and sharing information that can provide clear and easily accessible information about wait times, driver details, and trip progress, and help remove user misconceptions such as short-distance rides have longer wait times.

6.2 Advancing The Non-WEIRD HCI Literature

Compared to conventional user study works based on surveys and/or interviews, one advantage of our work is that we collect large-scale real-world technology-mediated system operation data to triangulate findings from our interviews. We believe that such large-scale system operation data is quite meaningful for HCI studies. Further, there is a growing acknowledgment of the need to move the HCI literature beyond the "WEIRD", i.e., western, educated, industrialized, rich, and democratic realm [36, 40, 59, 76, 83]. Hence, we believe our work has the potential to advance the non-WEIRD HCI literature on wait times, ridesharing interactive systems, and algorithmic fairness. *To benefit the research community, we plan to release real-world ridesharing operation data with proper privacy protection mechanisms in the camera-ready version.* This large-scale ridesharing data has the potential to promote other research related to user behavior and ridesharing interactive system design.

6.3 Limitations and Future Work

Like any study, this work has some limitations. This work particularly focuses on a specific cultural context instead of a global setting, so our findings may not generalize to all other countries or technology-mediated platforms, which is also a common limitation of many CSCW studies [2, 11, 25, 45, 60, 92, 102]. Our results are from interviews with passengers and drivers. We could not interview algorithm developers or official representatives of the DiDi companies as it was against company policy. Our findings should be complemented by future research that uses different research methods such as ethnography or surveys. The research findings presented in this study are mainly derived from one ridesharing platform. Therefore, they might be biased due to the platform designs, dispatching algorithms, and the cultural background of the user population, so we are cautious to make any claims about the generalization capabilities of our findings to other countries or platforms. However, the problem identified and the features we considered in this study are based on the settings shared by similar platforms, which potentially improves their generalizability. We are actively seeking research opportunities on other ridesharing platforms like Uber and Lyft and perform a more comprehensive cross-platform analysis in future work. Another limitation is our interviews are conducted in China, but people in different countries may have different perceptions about wait times. Also, different conditions in different countries may also affect the actual result. For example, easiness of finding a taxi may be an important factor that affects how users consider the wait time. We plan to run our interviews in parallel in the U.S. to see how passengers' perceptions of wait times are different between China and the U.S. However, it is challenging and time-consuming to collect similar datasets used in this paper, and this parallel comparative study is also not the focus of this paper, so we will leave it for our future work. Although we conducted interviews with both passengers and drivers, in our work, we focus on passengers' perception of wait times, and future work can also focus on drivers' perceptions. Moreover, while studying wait time in ridesharing helped us understand the real-world impact factors, finding-based applications will be useful for verifying potential benefits. Hence, in the future, we will integrate our findings into later system design to enhance user experiences in ridesharing services. Our interview data contain participants' self-reported memories of past ridesharing experiences and subjective interpretations of their experiences. Some participants might memorize more details of certain kinds of experiences than other people, which could bias our findings. Another possible direction would be follow-up interviews with some participants for long-term perception understanding. Also, the percentage of participants (drivers and passengers) who leave the platform over different times of the year can be interesting to study. Finally, future work will also explore contextual details about why certain discrepancies (e.g., 4-6 minutes longer wait time for female passengers than males at night) were observed. In addition, although we have identified many factors (e.g., ride features, time, and locations) influencing wait time disparity, there may be some other factors that have not been uncovered, so we will further investigate those potential factors with additional contextual information (e.g., other transportation modes and socioeconomic status of users) in the future.

7 Conclusion

In this paper, we comprehensively examined the promised and actual wait times in one of the largest technology-mediated mobility systems with a mixed-methods approach. We first presented a qualitative study with 102 participants (including 52 passengers and 50 drivers) to understand their perceptions towards the two wait times in one of the largest ridesharing systems in the world. We found the wait time discrepancy between the promised wait time and actual wait time led to psychological discomfort and negative emotions for passengers, and there were some unexpected factors for the unequal wait time, e.g., the *gender of passengers* and *ride distance*. We then performed a quantitative analysis based on large-scale real-world ridesharing logged data to triangulate the findings from interviews. Finally, we shared some lessons learned (e.g., people may have cognitive dissonance when they express their perceptions based on past experiences) and design implications (e.g., minimizing expectation mismatch, supporting algorithmic transparency and fairness), which may potentially guide designers to improve their systems for better user experience and pave the way for the next generation interactive mobility systems.

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References

[1] Julian Allen, Maja Piecyk, Marzena Piotrowska, Fraser McLeod, Thomas Cherrett, Karen Ghali, Thuba Nguyen, Tolga Bektas, Oliver Bates, Adrian Friday, et al. 2018. Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: The case of London. *Transportation Research Part D: Transport and Environment* 61 (2018), 325–338.

[2] Mashael Yousef Almoqbel and Donghee Yvette Wohn. 2019. Individual and collaborative behaviors of rideshare drivers in protecting their safety. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–21.

[3] Oscar Alvarado and Annika Waern. 2018. Towards algorithmic experience: Initial efforts for social media contexts. In *Proceedings of the 2018 chi conference on human factors in computing systems*. 1–12.

[4] Siddhartha Asthana, Pushpendra Singh, and Parul Gupta. 2015. Survival analysis: Objective assessment of wait time in hci. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 367–376.

[5] Solon Barocas and Andrew D Selbst. 2016. Big data's disparate impact. *Calif. L. Rev.* 104 (2016), 671.

[6] Sergio Barta, Raquel Gurrea, and Carlos Flavián. 2023. Using augmented reality to reduce cognitive dissonance and increase purchase intention. *Computers in Human Behavior* 140 (2023), 107564.

[7] Dietmar Bauer, Markus Ray, and Stefan Seer. 2011. Simple sensors used for measuring service times and counting pedestrians: strengths and weaknesses. *Transportation research record* 2214, 1 (2011), 77–84.

[8] Sara Bly, Bill Schilit, David W McDonald, Barbara Rosario, and Ylian Saint-Hilaire. 2006. Broken expectations in the digital home. In *CHI'06 extended abstracts on Human factors in computing systems*. 568–573.

[9] Paul Bossauer, Thomas Neifer, Gunnar Stevens, and Christina Pakusch. 2020. Trust versus Privacy: Using Connected Car Data in Peer-to-Peer Carsharing. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.

[10] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.

[11] Robin N Brewer, Amy M Austin, and Nicole B Ellison. 2019. Stories from the Front Seat: Supporting Accessible Transportation in the Sharing Economy. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–17.

[12] Robin N Brewer and Vaishnav Kameswaran. 2019. Understanding trust, transportation, and accessibility through ridesharing. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–11.

[13] Muhammed Fatih Bulut, Yavuz Selim Yilmaz, Murat Demirbas, Nilgun Ferhatosmanoglu, and Hakan Ferhatosmanoglu. 2012. Lineking: Crowdsourced line wait-time estimation using smartphones. In *International Conference on Mobile Computing, Applications, and Services*. Springer, 205–224.

[14] Bloomberg Businessweek. 2021. Didi Crackdown Shakes Foundations of Chinese Ride-Share Industry. https://www.bloomberg.com/news/articles/2021-07-14/china-s-didi-crackdown-threatens-to-upend-country-s-ride-hailing-industry.
[15] Carrie J Cai, Philip J Guo, James R Glass, and Robert C Miller. 2015. Wait-learning: Leveraging wait time for second language education. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 3701–3710.
[16] Ana Caraban, Evangelos Karapanos, Daniel Gonçalves, and Pedro Campos. 2019. 23 ways to nudge: A review of technology-mediated nudging in human-computer interaction. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–15.
[17] Anita Chen, Chien-Wen Yuan, Ning F Ma, Chi-Yang Hsu, and Benjamin V Hanrahan. 2019. Navigating Ride-Sharing Regulations: How Regulations Changed the'Gig'of Ride-Sharing for Drivers in Taiwan. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.
[18] Jamie M Chen, Jesper de Groote, James F Petrick, Tracy Lu, and Peter Nijkamp. 2020. Travellers' willingness to pay and perceived value of time in ride-sharing: An experiment on China. *Current Issues in Tourism* 23, 23 (2020), 2972–2985.
[19] Richard J Chen, Judy J Wang, Drew FK Williamson, Tiffany Y Chen, Jana Lipkova, Ming Y Lu, Sharifa Sahai, and Faisal Mahmood. 2023. Algorithmic fairness in artificial intelligence for medicine and healthcare. *Nature Biomedical Engineering* 7, 6 (2023), 719–742.
[20] Carl Collins, Amy Grude, Matthew Scholl, and Robert Thompson. 2007. txt bus: wait time information on demand. In *CHI'07 Extended Abstracts on Human Factors in Computing Systems*. 2049–2054.
[21] John W Creswell and J David Creswell. 2017. *Research design: Qualitative, quantitative, and mixed methods approaches.* Sage publications.
[22] Peter R Darke, Laurence Ashworth, and Kelley J Main. 2010. Great expectations and broken promises: Misleading claims, product failure, expectancy disconfirmation and consumer distrust. *Journal of the Academy of Marketing Science* 38, 3 (2010), 347–362.
[23] Michael A DeVito, Darren Gergle, and Jeremy Birnholtz. 2017. "Algorithms ruin everything" # RIPTwitter, Folk Theories, and Resistance to Algorithmic Change in Social Media. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 3163–3174.
[24] Tawanna R Dillahunt, Vaishnav Kameswaran, Linfeng Li, and Tanya Rosenblat. 2017. Uncovering the values and constraints of real-time ridesharing for low-resource populations. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 2757–2769.
[25] Xianghua Ding, Yunan Chen, Zhaofei Ding, and Yiwen Xu. 2019. Boundary negotiation for patient-provider communication via wechat in china. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–24.
[26] Mohammad Ansari Esfeh, Saeid Saidi, SC Wirasinghe, and Lina Kattan. 2022. Waiting time and headway modeling considering unreliability in transit service. *Transportation Research Part A: Policy and Practice* 155 (2022), 219–233.
[27] Motahhare Eslami, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. 2015. " I always assumed that I wasn't really that close to [her]" Reasoning about Invisible Algorithms in News Feeds. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. 153–162.
[28] Motahhare Eslami, Kristen Vaccaro, Karrie Karahalios, and Kevin Hamilton. 2017. " Be Careful; Things Can Be Worse than They Appear": Understanding Biased Algorithms and Users' Behavior Around Them in Rating Platforms.. In *ICWSM*. 62–71.
[29] Motahhare Eslami, Kristen Vaccaro, Min Kyung Lee, Amit Elazari Bar On, Eric Gilbert, and Karrie Karahalios. 2019. User attitudes towards algorithmic opacity and transparency in online reviewing platforms. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.
[30] Zhihan Fang, Yu Yang, Shuai Wang, Boyang Fu, Zixing Song, Fan Zhang, and Desheng Zhang. 2019. MAC: Measuring the Impacts of Anomalies on Travel Time of Multiple Transportation Systems. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (2019), 1–24.
[31] Batya Friedman. 1996. Value-sensitive design. *interactions* 3, 6 (1996), 16–23.
[32] Mareike Glöss, Moira McGregor, and Barry Brown. 2016. Designing for labour: uber and the on-demand mobile workforce. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. ACM, 1632–1643.
[33] Jorge Goncalves, Hannu Kukka, Iván Sánchez, and Vassilis Kostakos. 2016. Crowdsourcing queue estimations in situ. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. 1040–1051.
[34] Suiming Guo, Chao Chen, Yaxiao Liu, Ke Xu, and Dah Ming Chiu. 2018. Modelling Passengers' Reaction to Dynamic Prices in Ride-on-demand Services: A Search for the Best Fare. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 4 (2018), 1–23.

[35] Suiming Guo, Chao Chen, Jingyuan Wang, Yaxiao Liu, Ke Xu, Daqing Zhang, and Dah Ming Chiu. 2018. A simple but quantifiable approach to dynamic price prediction in ride-on-demand services leveraging multi-source urban data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 3 (2018), 1–24.

[36] Julia Himmelsbach, Stephanie Schwarz, Cornelia Gerdenitsch, Beatrix Wais-Zechmann, Jan Bobeth, and Manfred Tscheligi. 2019. Do we care about diversity in human computer interaction: a comprehensive content analysis on diversity dimensions in research. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–16.

[37] Victoria Hollis, Alon Pekurovsky, Eunika Wu, and Steve Whittaker. 2018. On being told how we feel: how algorithmic sensor feedback influences emotion perception. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 3 (2018), 1–31.

[38] Christophe Hurter, Audrey Girouard, Nathalie Riche, and Catherine Plaisant. 2011. Active progress bars: facilitating the switch to temporary activities. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems*. 1963–1968.

[39] Mansoor Iqbal. 2022. Uber Revenue and Usage Statistics. https://www.businessofapps.com/data/uber-statistics/.

[40] Jack Jamieson, Naomi Yamashita, Daniel A Epstein, and Yunan Chen. 2021. Deciding if and how to use a COVID-19 Contact Tracing App: Influences of social factors on individual use in Japan. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–30.

[41] Samantha Jaroszewski, Danielle Lottridge, Oliver L Haimson, and Katie Quehl. 2018. "Genderfluid" or "Attack Helicopter" Responsible HCI Research Practice with Non-binary Gender Variation in Online Communities. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–15.

[42] Shan Jiang, Le Chen, Alan Mislove, and Christo Wilson. 2018. On ridesharing competition and accessibility: Evidence from uber, lyft, and taxi. In *Proceedings of the 2018 World Wide Web Conference (WWW)*. International World Wide Web Conferences Steering Committee, 863–872.

[43] Vaishnav Kameswaran, Lindsey Cameron, and Tawanna R Dillahunt. 2018. Support for social and cultural capital development in real-time ridesharing services. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.

[44] Vaishnav Kameswaran, Jatin Gupta, Joyojeet Pal, Sile O'Modhrain, Tiffany C Veinot, Robin Brewer, Aakanksha Parameshwar, and Jacki O'Neill. 2018. 'We can go anywhere' Understanding Independence through a Case Study of Ride-hailing Use by People with Visual Impairments in metropolitan India. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–24.

[45] Vaishnav Kameswaran, Jatin Gupta, Joyojeet Pal, Sile O'Modhrain, Tiffany C Veinot, Robin Brewer, Aakanksha Parameshwar, and Jacki O'Neill. 2018. 'We can go anywhere' Understanding Independence through a Case Study of Ride-hailing Use by People with Visual Impairments in metropolitan India. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–24.

[46] Yi-Chin Kato-Lin and Shawn T Thelen. 2021. Telemedicine for acute conditions during COVID-19: a nationwide survey using crowdsourcing. *Telemedicine and e-Health* 27, 7 (2021), 714–723.

[47] Woojoo Kim, Shuping Xiong, and Zhuoqian Liang. 2017. Effect of loading symbol of online video on perception of waiting time. *International Journal of Human–Computer Interaction* 33, 12 (2017), 1001–1009.

[48] René F Kizilcec and Hansol Lee. 2020. Algorithmic fairness in education. *arXiv preprint arXiv:2007.05443* (2020).

[49] Maria Kjærup, Mikael B Skov, and Niels Agerholm. 2020. Digital-Enabled Last Mile: A Study of Passenger Trips in Rural, Low-density Populated Areas. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–12.

[50] Aylin Koca, Evangelos Karapanos, and Aarnout Brombacher. 2009. 'Broken Expectations' from a global business perspective. In *CHI'09 Extended Abstracts on Human Factors in Computing Systems*. 4267–4272.

[51] Piyush Kumar, Manohar U Kalwani, and Maqbool Dada. 1997. The impact of waiting time guarantees on customers' waiting experiences. *Marketing science* 16, 4 (1997), 295–314.

[52] Kyriakos Kyriakou, Pınar Barlas, Styliani Kleanthous, and Jahna Otterbacher. 2019. Fairness in proprietary image tagging algorithms: A cross-platform audit on people images. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 313–322.

[53] Carine Lallemand and Guillaume Gronier. 2012. Enhancing User eXperience during waiting time in HCI: contributions of cognitive psychology. In *Proceedings of the Designing Interactive Systems Conference*. 751–760.

[54] Min Kyung Lee, Anuraag Jain, Hea Jin Cha, Shashank Ojha, and Daniel Kusbit. 2019. Procedural justice in algorithmic fairness: Leveraging transparency and outcome control for fair algorithmic mediation. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–26.

[55] Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish. 2015. Working with machines: The impact of algorithmic and data-driven management on human workers. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. 1603–1612.

[56] Sooyeon Lee, Bjorn Hubert-Wallander, Molly Stevens, and John M Carroll. 2019. Understanding and Designing for Deaf or Hard of Hearing Drivers on Uber. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.

[57] Wang-Chien Lee, Weiping Si, Ling-Jyh Chen, and Meng Chang Chen. 2012. HTTP: A new framework for bus travel time prediction based on historical trajectories. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems*. 279–288.

[58] Shasha Li and Chien-Hsiung Chen. 2019. The effects of visual feedback designs on long wait time of mobile application user interface. *Interacting with Computers* 31, 1 (2019), 1–12.

[59] Sebastian Linxen, Christian Sturm, Florian Brühlmann, Vincent Cassau, Klaus Opwis, and Katharina Reinecke. 2021. How weird is CHI?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.

[60] Alex Jiahong Lu and Xuecong Xu. 2020. "Learning for the Rise of China": Exploring Uses and Gratifications of State-Owned Online Platform. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (2020), 1–25.

[61] Hui Lu, Peter Burge, Chris Heywood, Rob Sheldon, Peter Lee, Kate Barber, and Alex Phillips. 2018. The impact of real-time information on passengers' value of bus waiting time. *Transportation Research Procedia* 31 (2018), 18–34.

[62] Man Luo, Bowen Du, Konstantin Klemmer, Hongming Zhu, Hakan Ferhatosmanoglu, and Hongkai Wen. 2020. D3P: Data-driven Demand Prediction for Fast Expanding Electric Vehicle Sharing Systems. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 1 (2020), 1–21.

[63] Ratna Mandal, Prasenjit Karmakar, Soumyajit Chatterjee, Debaleen Das Spandan, Shouvit Pradhan, Sujoy Saha, Sandip Chakraborty, and Subrata Nandi. 2023. Exploiting multi-modal contextual sensing for city-bus's stay location characterization: Towards sub-60 seconds accurate arrival time prediction. *ACM Transactions on Internet of Things* 4, 1 (2023), 1–24.

[64] Joe McGauley. 2016. Yes, Your Uber Wait Times Are Almost Always Wrong. Here's Why. https://www.thrillist.com/tech/nation/why-uber-wait-times-are-always-wrong.

[65] Aurora Mobile. 2019. Ridesharing Market Research Report in 2019.

[66] Jimmy Moore, Pascal Goffin, Jason Wiese, and Miriah Meyer. 2021. An interview method for engaging personal data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 4 (2021), 1–28.

[67] Ingrid Pettersson, Florian Lachner, Anna-Katharina Frison, Andreas Riener, and Andreas Butz. 2018. A Bermuda triangle? A Review of method application and triangulation in user experience evaluation. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–16.

[68] Ioannis Psarros, Konstantinos Kepaptsoglou, and Matthew G Karlaftis. 2011. An empirical investigation of passenger wait time perceptions using hazard-based duration models. *Journal of Public Transportation* 14, 3 (2011), 109–122.

[69] Jayanth Raghothama, Vinutha Magal Shreenath, and Sebastiaan Meijer. 2016. Analytics on public transport delays with spatial big data. In *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Analytics for Big Geospatial Data*. 28–33.

[70] Noopur Raval and Paul Dourish. 2016. Standing out from the crowd: Emotional labor, body labor, and temporal labor in ridesharing. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. 97–107.

[71] Reddit. 2024. Can we do anything over wait time discrepancies? https://www.reddit.com/r/Lyft/comments/1ax8rt2/can_we_do_anything_over_wait_time_discrepancies/.

[72] Reddit. 2024. Uber problems - false wait time. https://www.reddit.com/r/washingtondc/comments/1bnt9f4/uber_problems_false_wait_time/.

[73] James A Russell. 1980. A circumplex model of affect. *Journal of personality and social psychology* 39, 6 (1980), 1161.

[74] James A Russell, Maria Lewicka, and Toomas Niit. 1989. A cross-cultural study of a circumplex model of affect. *Journal of personality and social psychology* 57, 5 (1989), 848.

[75] Mohammad Sadrani, Alejandro Tirachini, and Constantinos Antoniou. 2022. Vehicle dispatching plan for minimizing passenger waiting time in a corridor with buses of different sizes: Model formulation and solution approaches. *European Journal of Operational Research* 299, 1 (2022), 263–282.

[76] Manika Saha, Delvin Varghese, Tom Bartindale, Shakuntala Haraksingh Thilsted, Syed Ishtiaque Ahmed, and Patrick Olivier. 2022. Towards Sustainable ICTD in Bangladesh: Understanding the Program and Policy Landscape and Its Implications for CSCW and HCI. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW1 (2022), 1–31.

[77] Elif Kuş Saillard. 2011. Systematic versus interpretive analysis with two CAQDAS packages: NVivo and MAXQDA. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research*, Vol. 12.

[78] Shruti Sannon, Billie Sun, and Dan Cosley. 2022. Privacy, Surveillance, and Power in the Gig Economy. In *CHI Conference on Human Factors in Computing Systems*. 1–15.

[79] Candice Schumann, Jeffrey Foster, Nicholas Mattei, and John Dickerson. 2020. We need fairness and explainability in algorithmic hiring. In *International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS)*.

[80] Dilruba Showkat and Najeefa Nikhat Choudhury. 2019. Pathao Ride-sharing App Design: What Do The Users Have To Say?. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing*. 372–376.

[81] Vivek K Singh and Arushi Jain. 2017. Toward harmonizing self-reported and logged social data for understanding human behavior. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 2233–2238.

[82] Vivek K Singh, Marie L Radford, Qianjia Huang, and Susan Furrer. 2017. " They basically like destroyed the school one day" On Newer App Features and Cyberbullying in Schools. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. 1210–1216.

[83] Christian Sturm, Alice Oh, Sebastian Linxen, Jose Abdelnour Nocera, Susan Dray, and Katharina Reinecke. 2015. How WEIRD is HCI? Extending HCI principles to other countries and cultures. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*. 2425–2428.

[84] SueGarvz. 2023. Inaccurate information when selecting a ride. https://www.reddit.com/r/Lyft/comments/15lgxb4/inaccurate_information_when_selecting_a_ride/.

[85] Michael K Svangren, Mikael B Skov, and Jesper Kjeldskov. 2018. Passenger trip planning using ride-sharing services. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.

[86] Edward Tenner. 1997. *Why things bite back: Technology and the revenge of unintended consequences*. Vintage.

[87] John Wamburu, Stephen Lee, Mohammad H Hajiesmaili, David Irwin, and Prashant Shenoy. 2021. Ride Substitution Using Electric Bike Sharing: Feasibility, Cost, and Carbon Analysis. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 1 (2021), 1–28.

[88] Guang Wang, Harsh Rajkumar Vaish, Huijun Sun, Jianjun Wu, Shuai Wang, and Desheng Zhang. 2020. Understanding User Behavior in Car Sharing Services Through The Lens of Mobility: Mixing Qualitative and Quantitative Studies. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (2020), 1–30.

[89] Guang Wang, Fan Zhang, and Desheng Zhang. 2023. When mobility on demand meets vehicle electrification: a longitudinal study on evolution of city-scale ridesharing. *CCF Transactions on Pervasive Computing and Interaction* 5, 2 (2023), 226–240.

[90] Ruotong Wang, F Maxwell Harper, and Haiyi Zhu. 2020. Factors Influencing Perceived Fairness in Algorithmic Decision-Making: Algorithm Outcomes, Development Procedures, and Individual Differences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–14.

[91] Shuai Wang, Tian He, Desheng Zhang, Yuanchao Shu, Yunhuai Liu, Yu Gu, Cong Liu, Haengju Lee, and Sang H Son. 2018. BRAVO: Improving the rebalancing operation in bike sharing with rebalancing range prediction. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–22.

[92] Yi Wang. 2019. When DiDi Is Not Really A Choice in Small Chinese Cities, Taxi Drivers Build Their Own. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–30.

[93] Yuting Wang, Hongli Wang, and Honggang Xu. 2021. Understanding the experience and meaning of app-based food delivery from a mobility perspective. *International Journal of Hospitality Management* 99 (2021), 103070.

[94] Yan Wang, Jie Yang, Yingying Chen, Hongbo Liu, Marco Gruteser, and Richard P Martin. 2014. Tracking human queues using single-point signal monitoring. In *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*. 42–54.

[95] Alexander Webb, Pramesh Kumar, and Alireza Khani. 2020. Estimation of passenger waiting time using automatically collected transit data. *Public Transport* 12 (2020), 299–311.

[96] Wikipedia. 2021. Mann–Whitney U test. https://en.wikipedia.org/wiki/Mann%E2%80%93Whitney_U_test.

[97] Richmond Y Wong. 2021. Tactics of Soft Resistance in User Experience Professionals' Values Work. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–28.

[98] Allison Woodruff, Sarah E Fox, Steven Rousso-Schindler, and Jeffrey Warshaw. 2018. A qualitative exploration of perceptions of algorithmic fairness. In *Proceedings of the 2018 chi conference on human factors in computing systems*. 1–14.

[99] Di Wu, Tao Xiao, Xuewen Liao, Jie Luo, Chao Wu, Shigeng Zhang, Yong Li, and Yike Guo. 2020. When Sharing Economy Meets IoT: Towards Fine-grained Urban Air Quality Monitoring through Mobile Crowdsensing on Bike-share System. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 2 (2020), 1–26.

[100] Qiuping Yu, Yiming Zhang, and Yong-Pin Zhou. 2022. Delay Information in Virtual Queues: A Large-Scale Field Experiment on a Major Ride-Sharing Platform. *Management Science* (2022).

[101] Jing Yuan, Yu Zheng, and Xing Xie. 2012. Discovering regions of different functions in a city using human mobility and POIs. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. 186–194.

[102] Renwen Zhang, Jordan Eschler, and Madhu Reddy. 2018. Online support groups for depression in China: Culturally shaped interactions and motivations. *Computer Supported Cooperative Work (CSCW)* 27, 3 (2018), 327–354.

[103] Shuo Zhang, Khaled Alanezi, Mike Gartrell, Richard Han, Qin Lv, and Shivakant Mishra. 2018. Understanding group event scheduling via the outwithfriendz mobile application. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 4 (2018), 1–19.

[104] Yan Zhang, Yunhuai Liu, Genjian Li, Yi Ding, Ning Chen, Hao Zhang, Tian He, and Desheng Zhang. 2019. Route prediction for instant delivery. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 3 (2019), 1–25.

[105] Shuya Zhong, Carl Lomas, and Tracey Worth. 2022. Understanding customers' adoption of express delivery service for last-mile delivery in the UK. *International Journal of Logistics Research and Applications* 25, 12 (2022), 1491–1508.

[106] Pengfei Zhou, Yuanqing Zheng, and Mo Li. 2012. How long to wait? Predicting bus arrival time with mobile phone based participatory sensing. In *Proceedings of the 10th international conference on Mobile systems, applications, and services*. 379–392.

A Details of Interviews

A.1 Questions for Passenger Participants

(1) Do you mind telling me about your gender, age, job occupation?
(2) Did you use the DiDi ridesharing app for trips before?
(3) How often do you use the DiDi ridesharing app for trips?
(4) Why do you usually use ridesharing? What purposes do you use ridesharing for, e.g., for commuting, shopping, or emergency?
(5) In your opinion, what are the advantages of ridesharing compared to traditional taxis?
(6) Did you encounter a situation like this: when you open the ridesharing app, you saw a lot of ridesharing vehicles around you, but you still waited a long time after you sent a request?
(7) Do you think the promised wait time on the app when you input your origin and destination (note that you did not send the request right now) is consistent with your actual wait time?
(8) Will you still stay on this platform if the promised wait time is too long?
(9) How did you feel if the difference between the promised wait time and the actual wait time is too large?
(10) What is the longest wait time you had for a ridesharing ride?
(11) How long can you tolerate before switching to other platforms or vehicle types?
(12) In your view, what may be the factors that influence your wait time when requesting a ridesharing ride?
(13) What is your expected wait time? Will it change for different ridesharing trips, at different times, or in different areas?
(14) Did you have some strategies to deal with the inaccurate wait time promised by the DiDi app?
(15) What did you usually do when you waited for the ridesharing vehicle?
(16) Have you ever been charged the wait time fee for your ridesharing trips? Why did it happen?
(17) Do you think the accurate promised wait time estimation is important?
(18) Do you think the DiDi platform treats all passengers equally?
(19) Did you have any unforgettable experiences related to the wait time when using ridesharing services? Could you please tell me about it?
(20) Which parts do you think the ridesharing company should improve?

A.2 Questions for Driver Participants

(1) Could you please tell me your gender and age?
(2) How many hours do you usually operate your ridesharing vehicle per day?
(3) In your opinion, what are the advantages of ridesharing compared to traditional taxis?
(4) Did you have experiences in waiting for passengers for over 10 minutes?
(5) Do you think the promised wait time by the platform is accurate?
(6) Do you think an accurate promised wait time by the platform is important?
(7) Do you think the passenger wait time impacts your income?
(8) Did you get complaints from passengers due to late arrival to the pickup location?
(9) What would be the reasons that passengers send ride requests before they arrive at the pickup location?
(10) Do you think the DiDi platform treats all passengers equally?
(11) Do you think the DiDi platform treats all drivers equally?
(12) Do you think there is a difference between male and female passengers at different hours of a day?
(13) In your view, what may be the factors that impact the wait time of passengers?

(14) Did you reject some trips? Why?
(15) Which parts do you think the ridesharing company should improve?

B More Details of the Logged Data

We show more details of our logged data here.

As shown in Fig. 10, we show the demographic information of all ridesharing drivers in Shenzhen. We found the age range of drivers is between 20 to 64 years old, and about 80% of drivers are 30-49 years old. Among all drivers, male drivers account for 98.86% and only 1.14% of them are female. The extremely unbalanced ratio between male and female drivers provides good evidence to the finding of unequal wait time between male and female passengers.

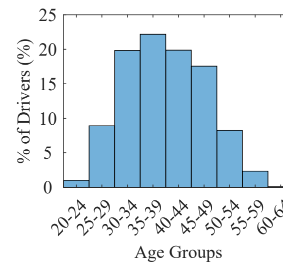
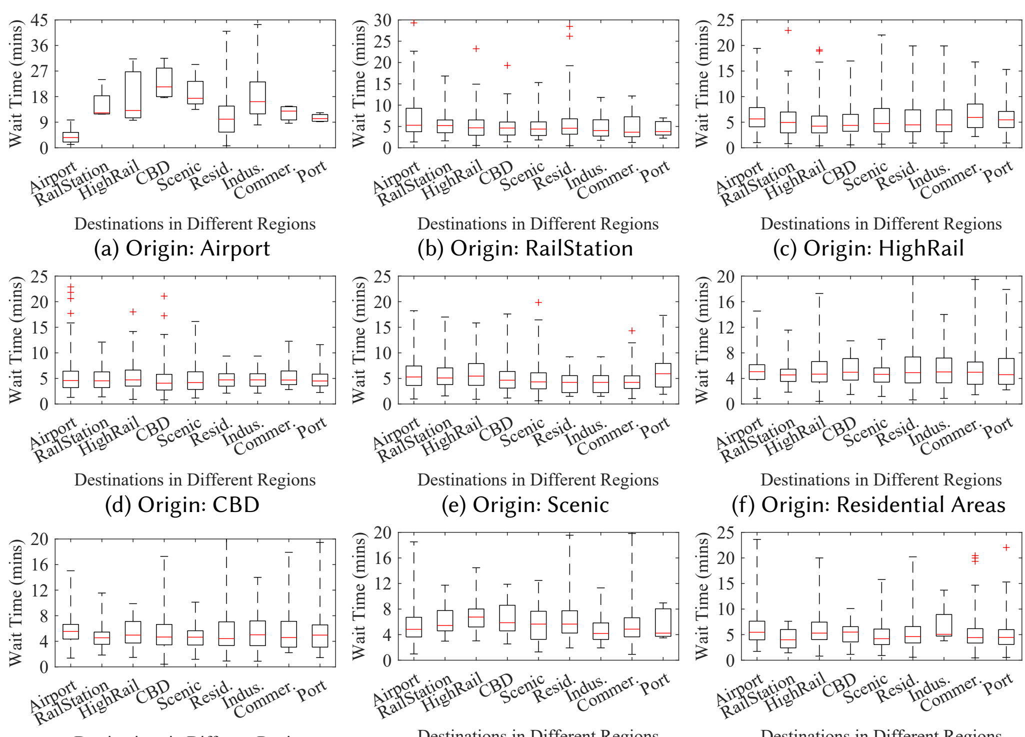


Fig. 10. Age distribution of drivers.

In Fig. 7, we only show the average wait time of passengers from different origin areas to different destination areas, which may miss some detailed information. Hence, we also show the wait time distributions of passengers from different origin areas to different destination areas, as shown in Fig. 11.



(a) Origin: Airport (b) Origin: RailStation (c) Origin: HighRail
(d) Origin: CBD (e) Origin: Scenic (f) Origin: Residential Areas
(g) Origin: Industrial Areas (h) Origin: Commercial Areas (i) Origin: Port

Fig. 11. Wait time of passengers from different origin areas to different destination areas.

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