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Master's Thesis

Reasons and factors behind the gender gap of online ride-hailing: a case study in Wuhan, China

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Disclaimer

I confirm that this master's thesis is my own work and I have documented all sources and material used.

Munich, 15.12.2021 Qingyang Lyu

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Abstract

Benefit from the exponential development of ICT, many ideas have been realized to enrich our lives. Ride-sharing or ride-hailing services like Uber (U.S.) and DiDi (China) offer an alternative to traditional taxi services. With the integration of emerging ICT technologies, ride-hailing services allow people to summon and pay for car rides through an app downloaded on their phones. In response to new technologies and urbanization, the needs of urban dwellers for transportation modes have changed. The travel method of using the app to call a ride through the online platform (E-hailing) has long been in most households and has become a very popular way of travel. However, while E-hailing has brought the advantages of convenience and expeditious to our daily lives, many malicious incidents against the vulnerable gender groups are also quietly breeding in the E-hailing industry.

In this thesis, Wuhan, one of the largest cities in central China with intricate traffic conditions, is chosen for the study. The group differences in the E-hailing market in Wuhan are explored through 2 Binary Logit Models, 3 Ordered Logit Models and 2 Multinomial Logit Models. More attention is paid to the phenomenon of gender differences. Whether these differences affect users' choice of E-hailing as a travel mode and whether there are key factors that influence the use of E-hailing services by gender disadvantaged groups. How these factors should be improved, etc.

The final results show that for the E-hailing market in the surveyed cities, Wuhan, group differences exist, as do gender differences. The reasons for the gender differences in E-hailing are not only socio-demographic, but also attitudinal, i.e. the perceived risk during the use of E-hailing services. On the other hand, there is the residual effect of the malicious incidents against the vulnerable gender groups that have occurred in recent years.

Contents

1 Introduction

This chapter starts with an introduction to the historical origin of E-hailing, followed by, what was the motivation for conducting this research, the research questions and objectives of this thesis. Finally, there is the overall structure of the whole thesis.

1.1 Introduction

The "car-sharing clubs" that sprang up during World War II (N. D. Chan and S. A. Shaheen 2012) can be traced as the origin of ride-sharing behavior, which has been subdivided into many categories, one of which is the online ride-hailing business, based on the traditional taxi industry. Since the term sharing economy was officially defined in 2008 (Thomas and Rainer 2016), to this day, the sharing economy has been divided into many branches. Benefitting from the exponential development of Information and Communication Technologies (ICT), many ideas have been realized to enrich our lives. Shared mobility, which cannot be denied, is an essential aspect in the sharing economy, or, to quote Time magazine in 2011, collaborative consumption will change the world (Time 2011).

Shared mobility, broadly speaking, is reflected in three main categories, car-sharing, ride-sharing, and the sharing of some micro-mobility alternatives. There are two different models to study; the first is centralized car-sharing, which can be subdivided into fleet-owned station-based car-sharing, fleet-owned one-way floating car-sharing, and P2P car-sharing. The other one is decentralized car-sharing, which means private car-sharing. About the sharing micro-mobility alternatives, namely, bike-sharing, scooter-sharing are more concentrated on solving problems in different specific scenarios. Firstly, in urban areas, short-distance bike-sharing or scooter-sharing are used to meet users' daily needs. The bike-sharing or scooter-sharing, which solves the last-mile problem, are generally combined with public transportation. The last one is the long-distance use scenarios or more personalized bike leasing of different lengths of time. The last category of shared mobility is ride-hailing. In comparison with car-sharing, ride-sharing means that each car is equipped with a driver. The journeys, which are brought up as shared, could be planned or dynamic; both are relieving the irritability of parking, the prerequisite requirements for motor vehicle ownership, or the possession of a driver's license.

Ride-sharing or ride-hailing services like Uber and Lyft offer an alternative to traditional taxi services. Ride-hailing services allow people to summon and pay for car rides through an app downloaded on their phones. It is a new, on-demand option for getting from origin to destination with the convenience of a push-of-a-button (Liyanage et al. 2019). The development of ride-hailing has primarily resulted from two separate forces: new technology and urbanization.

In the past few years, ride-hailing has been a microcosm of the broader trend of technological innovation. Whether it is cars for hire, delivery services, or the use of GPS and smartphones to measure distance and calculate speed, technology has been a significant driver in pushing forward our ability to go from origin to destination.

The transportation industry has also been profoundly affected by urbanization since the 1970s. Worldwide view, Uber and Lyft were founded in 2008 and 2011, respectively, as humans began embracing overly convenient forms of mass transport such as mass transit systems. According to data from The World Bank, human beings now spend more than half their time commuting between residential areas and workplaces (Rubiano Matulevich and Viollaz 2019).

Research conducted by KPMG, a professional services company, suggests that ride-hailing could become a trillion-dollar market in the next decade (McManus et al. 2019). As urbanization continues to occur worldwide, with densely populated urban areas encroaching on rural landscapes, the need for easy and efficient forms of transport will only grow. Ride-hailing could provide the most significant part of every car company's profit within the next generation or two.

1.2 Motivation

It is no secret that there has been a big divide when it comes to taxi drivers and ride-hailing services. The latter has grown in popularity in recent years, and now companies like Uber and Lyft dominate the market. Furthermore, while this may seem like a good thing for consumers, there is a dark side: Many drivers have reported being sexually assaulted by riders while driving for Uber or Lyft. Also, the same gloomy scenario is playing out in China, a far cry from where Uber originated. According to Weibo, the largest social media site in China, from 2017.5.18 to 2021.7.13, online ride-hailing (Later abbreviated as E-hailing) has been on the hot search list for 244 times, and 44 of those cases were linked with safety concerns (sexual harassment, inappropriate physical contact, rape, murder, and some other forms of inappropriate behavior). Both crimes committed by passengers against female drivers and crimes committed by male drivers against female passengers have gained widespread attention on social media platforms and have created a large wave of impact on the E-hailing market at the beginning of 2018.

Since 2018, or even earlier, many companies providing E-hailing services have been concerned about gender disparity, gender inequality in the E-hailing market. Three years on, the gender gap in the E-hailing market still exists. If the factors that produce gender differences in the E-hailing environment can be identified, this one problem can be solved in an asymptomatic way. On the other hand, developed countries have paid more attention to these humanistic aspects, or rather, they have acted earlier on this phenomenon. As a substantial E-hailing market, China still has a lot of vicious incidents of rape and murder of female passengers by E-hailing drivers.

1.3 Research objectives and questions

The primary purpose of this research is to investigate the user characteristics, especially gender characteristics, of the E-hailing market in developing countries, to explore the differences in user gender characteristics and the reasons for these differences, to examine the impact of these factors on users' choice of E-hailing services, and what measures can be taken to improve the situation.

After going through this series of research studies, there are two aspects of significance, practical and academic. For practical social applications, at a trim level, it can give suggestions to individual users, provide practical protection measures for both individuals and drivers, or regulate drivers' words and actions. At the intermediate level, companies providing E-hailing services can obtain more valuable and unbiased information to find ways to provide more robust and safer services. At a more significant level, colonial government regulators and agencies can use this research to refine ways to regulate the market so that E-hailing, a young and immature market, can be more constrained and regulated at the legal and regulatory level. From the academic side, because of the current booming E-hailing market in China, this study could provide a large amount of valid and accurate data for research on E-hailing in developing countries, especially in gender inequality. This thesis will focus on the following research questions in the later chapters:

RQ1: Is there group differentiation in the E-hailing market in Wuhan, especially the gender differentiation?

RQ2: What factors affect female users to adopt E-hailing?

RQ3: What regulations/measures will help to fix this gender gap in the E-hailing market?

1.4 Research structure

This thesis is divided into five chapters, and the first one is about the historical development of E-hailing and the background introduction, as well as the elaboration of the gender inequality existing in the E-hailing market. The second chapter is a literature review, which will mainly start with the classification of shared mobility, the existence of gender disparities in the E-hailing market, and then transition to a summary presentation of the research methods of other scholars on similar research topics. The third chapter is the methodology, which describes the generation of the survey questionnaire, the selection of the survey method, the filtering and refinement of the data, and the selection of the model. The fourth chapter presents a detailed analysis of the gender differences in the E-hailing market in Wuhan, the largest city in central China, as a research site, the specific processing of the data obtained, and the creation of the model. The last section is a discussion and summary of the results obtained.

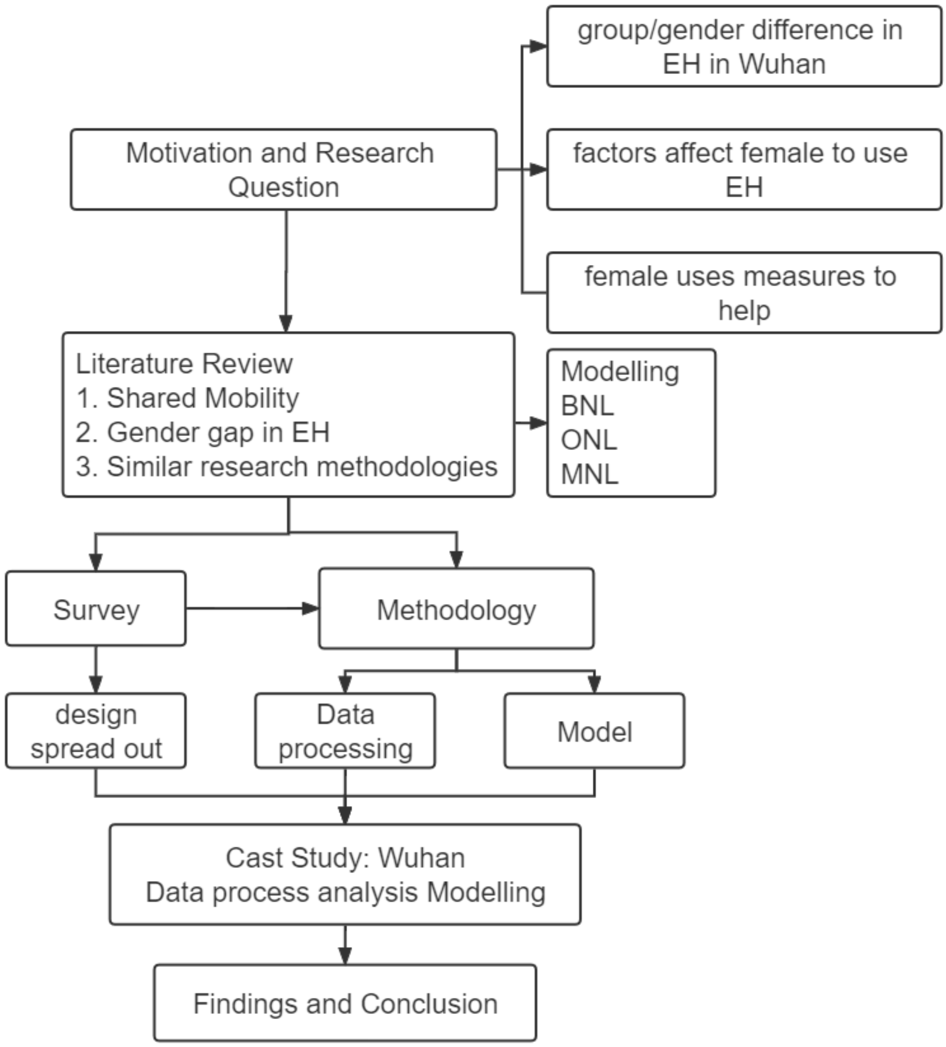


Figure 1.1: Research structure

2 Literature review

This chapter focuses on the categorization of shared mobility, gender inequality in the EH market, and for the impact that gender inequality issues have on the EH sector. Other scholars' research approaches to these issues.

2.1 Taxonomy of shared mobility

In the past few decades, many types of shared mobility have been developed and implemented worldwide. Shared mobility is a broad term that can encompass different types of public transit offered by passengers without making individual trips themselves. Examples include riding bikes with others, taking public transportation to meet up with friends at a specific time and place, or participating in carpooling programs. Many people enjoy shared mobility options because they reduce their carbon footprint by not always having to take their cars out on the road each day, so they are better for the environment and personal health issues related to air pollution. Shared mobility also has multiple positive benefits for the community, the environment, and the economy. Benefits for individuals including helping to reduce road congestion by adding more vehicles on the road, which could eventually reduce car ownership in some areas. On a larger scale, shared mobility could potentially reduce regional pollution levels, suitable for everyone's health.

The broad category of shared mobility encompasses a wide range of modes and services. Roukouni and Correia (Roukouni and Homem de Almeida Correia 2020) divided shared mobility into seven major types according to different modes: car sharing, bike sharing, ride sharing, on-demand transportation services, (shared) micro-mobility, alternative transit systems, and courier network services see Figure(2.1).

Car sharing is a modern approach to vehicle access for those who cannot afford their car or who need only occasional transport. It was invented as a response to the decline of mass transit and the rise in fuel cost, leading to an increase in necessary daily departures from urban areas. If we continue to refine the classification of car-sharing operation models in chronological order, the earliest is the station-based round-trip, which has a single fixed pick-up and drop-off point, and the two-way trips are completed by the person who is renting the car. Compared with the earliest station-based round-trip, the one-way car sharing, or at that time, more specifically, car rental, although still need to go to a fixed point to pick up and drop off the car, the pick-up point and drop-off point can

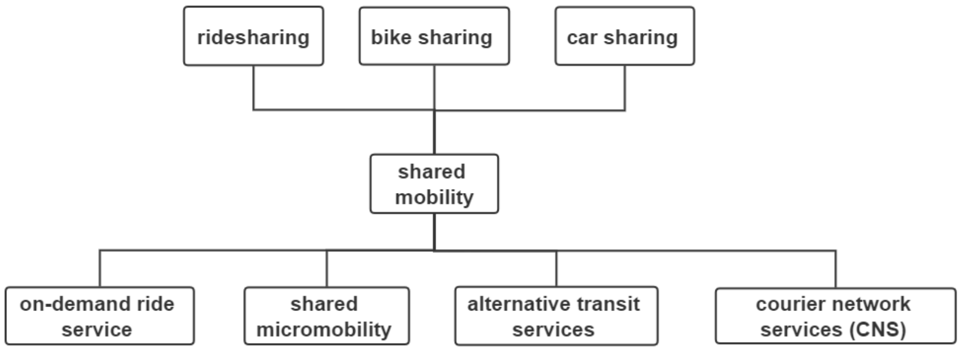


Figure 2.1: Shared mobility modes and services

not be the same point, which also increases the possibility of using the car-sharing services in the context of different cities (Shibayama and Emberger 2020). As time drew closer to the present, free-floating car-sharing and personal vehicle sharing models gradually emerged.

Bike-sharing programs are now widely regarded as a new non-motorized method of transportation that can mitigate traffic problems like congestion, air pollution, etc (X. Ma et al. 2020). If we trace the bike-sharing projects from the chronological order, the earliest bike-sharing models are station-based (Z. Chen, Lierop, and Ettema 2020) and slightly later bike-leasing. The former is an innovative move for municipal public transportation mode that emerged in 1965 in Amsterdam, while the latter is more suitable for short trip travel, recreation, and leisure purposes. Since 2016, a new, more convenient bike-sharing system – dockless system has seen a rapid increase in popularity in China, spreading to the United Kingdom, Singapore, the United States of America, and the Netherlands (Shen, Zhang, and Zhao 2018). During this period, two dockless bike-sharing systems with a different scope of application existed simultaneously. The first is a bike-sharing system used on campus or in a defined, relatively closed area, and the other is a bike-sharing system used on a large scale, for example, throughout a city or between multiple cities, such as the famous Chinese companies OFO and Mobike. Admittedly, the latter has had many problems, with broken capital chains, theft of vehicles, and excessive vehicle scrapping, which this paper will leave aside for now (Shead 2019).

E-scooters, E-bikes, and E-mopeds represent three different types of micro-mobility products. They can range from electric wheeled devices of 5 miles to 10 miles to wheeled machines powered by human power. What is shared among all these options is that they are straightforward on the environment because they radically reduce CO2 emissions and fuel consumption (with some exceptions) (Moller 2020). The trend for micro-mobility has grown exponentially in recent years. The European Union has led more than 80 million scooter journeys across Europe each day(Spotlight News 2019), while China has seen 28% growth year on year in its global market share for these products. The strength of micro-mobility lies in its role in the overall transportation network and its synergy with other modes of transportation. In some ways, micro-mobility and bike-sharing are similar in that they both meet the last mile of the daily commute and are environmentally friendly.

In today's world, the use of courier services is growing exponentially. Whether for a package or other essential item to be delivered or a passenger ride, online couriers are an affordable and efficient way to get it where it needs to go. On-demand service matching people with couriers is another business that has seen growth in recent years. These businesses have been paired with on-demand services for riders and delivery companies, providing a niche market perfect for entrepreneurs looking to get their start in this competitive field without the capital necessary to buy competitors out. Courier Network Services (CNS) (also known as 'flexible goods delivery') are defined by (S. Shaheen, N. Chan, et al. 2015) as "for-hire delivery services for monetary compensation using an online application or platform (such as a website or smartphone app) to connect couriers with freight using their vehicles, bicycles, or scooters." The introduction of CNS demonstrates how the lines between freight and passenger transportation are blurring.

In addition to established public transportation networks, several other modes of mobility are available. Shaheen et al. (S. Shaheen, Cohen, et al. 2020) named them all as micro-transit, Roukouni, and Correia (Roukouni and Homem de Almeida Correia 2020) addressed them as alternative transit services and believed it encompassed two different forms of services like shuttles and micro-transit. The minibus service in the Netherlands (Weckström et al. 2018), the light tricycles or four-wheelers that pick up and drop off passengers from railway stations in India (Mahadevia and Advani 2016), and the Colectivos or combis in Mexico (Expat 2020), a kind of passenger vans that are particularly famous in scenic places, are examples of alternative transit services both in developed and developing countries.

The last two categories of shared mobility systems classified by Roukouni and Correia (Roukouni and Homem de Almeida Correia 2020) are ride-sharing and on-demand ride services. The most significant difference between these two is the driver's destination or the nature of the driver's purpose for traveling. In ride-sharing mode, the driver's and passenger's destinations may be the same, or the driver's and passenger's destinations go by way of each other. In the on-demand services mode, the driver's duties are more similar to those of a traditional taxi driver, except that they are dispatched by the demand responding companies instead of looking for passengers on the roadside themselves. Ridesharing is generally divided into two categories: carpooling and vanpooling, with the former focuses on serving a relatively small number of passengers and the latter on serving a more significant number of passengers. Carpooling allows individuals to share rides with friends or family members to make their commute more environmentally friendly. Vanpooling is a relatively new form of carpooling that provides commuters with a ride in a vehicle that's dedicated for their use, like an electric bus or shuttle. The first ride-sharing service was launched as a competition on the Internet as part of Carnegie Mellon University's project "CarPool" in 1999 (Ferguson 1997). Since then, many startups have attempted to create innovative ride-sharing solutions for cars and beyond.

Talking about on-demand ride services, the concept has been around since a long time ago, such as the old telephone cab-hailing. However, the development of ICT in recent years has given the concept a whole new dimension and a real sense of growth. Ride-hailing or E-hailing has become the most popular service for traveling throughout the world, based on the concept of on-demand services. The E-hailing industry is expected to have annual revenue of $206 billion by 2025 (Guske n.d.), which would create thousands of new jobs in the field. Uber, a ride-hailing platform that delivers door-to-door for-hire vehicle services, was valued at $41.2 billion by the end of December 2014(Picchi 2015). The most prominent players in the E-haling business include Uber, Lyft, Didi Kuadi Dache, GrabTaxi, and Ola Cabs (Ride-hailing market value worldwide as of May 2018, by the key operator, 2018). Ride-hailing apps are available for almost every region around the world. Uber drivers are estimated to be more than 2 million worldwide. Uber has gained traction in many markets, including China, India, the United States, Mexico, and Japan.

2.2 Gender gap in E-hailing market

Women make up half of the world's population. Their unique travel patterns deserve our study. The study of women's travel patterns can generally begin with their travel behavior and transportation mode choice. Unlike men, who make up the majority of daily commuting needs, women travel for much more purposes and have more diverse needs when traveling—women are associated with fewer work-related trips when compared to males. Women's takes the form of multi-chain travel. They need to juggle more of their daily needs, such as picking up and dropping off children to or from school, shopping for groceries, social need fulfillment, sending and picking up deliveries, and more. These daily trips are not necessarily long-distance and much time-consuming, but they are undoubtedly trivial and complex, and it is more difficult to find a fixed pattern of travel than men's travel patterns.

According to Fan's research (Fan 2017), while the feminist and affirmative action around the world has led to an increase in female employment and a shift in domestic activities in favor of men, more and more men are involved in a variety of domestic and child-rearing activities. However, by focusing on both work travel and family support travel, her study found gender differences in both trips. The main difference exists in the option of having children, with slightly more minor differences in work-related trips for men and women in childless households relative to those in households with children. Couple households with children have significantly more significant gender differences in work travel time than single households with children. This suggests that the exacerbation effects of spouse/partner presence on the gender difference in work travel are contingent upon children's presence. This also explains why women's trips are more family-related compared to males.

Fan's research is based on the U.S. market (ibid.), but a decade ago, the Canadian market also received research on the differences in travel mode choice between men and women (Patterson, Ewing, and Haider 2005). Their research found that women are more likely to take public transportation than men. Within the group of women, low-income women use public transportation more often than high-income and middle-income women because their household income does not support the purchase and cost of a vehicle for commuting. Also, they found that male respondents were more time-sensitive than female respondents. Therefore, improving travel time using public transportation would attract more male users.

On the other side of the ocean in India, Mahadevia and Advani's paper explores the travel pressures and difficulties faced by women in Rajkot (Mahadevia and Advani 2016), a medium-sized city in a developing country. Women are not only responsible for reproduction, childbearing and parenting, and general household maintenance but may also be required to perform the duties of workers and community organizers. This makes their travel patterns more diverse and multi-chain. At the same time, as a medium-sized city in a developing country, Rajkot still has a part of its population that is poor in composition. Travel options are not as diverse as in developed countries, with nearly one-third of the population either walking or biking, meaning that one-third of the population chooses to travel by non-motorized means, and they do not have public transportation options. Consequently, women in every economic bracket in the city travel at a lower rate and shorter periods than their male counterparts. Both the rate of travel and the duration of the trip increase as income rises, although men's rates rise faster than women. Women in this city have limited mobility, with low-income women having the lowest mobility of any women category.

In 2013, Peters noted that women have more complex travel needs (Peters 2013). A significant portion of these needs stems from the activities and roles women are expected to play in a patriarchal society. These studies suggest that this pull from a patriarchal society may not be as pronounced for developed countries. However, according to Gustafson's research (Gustafson 2006), even in the most developed and egalitarian societies, differences in social roles between men and women still exist. The presence of children reduces women's travel activities, while there is no significant effect for men. Currently, the field of shared transportation has grown and progressed considerably, where the primary research objectives exist in the study of car-sharing and, to a lesser extent, bicycle sharing. In Singh's study (Singh 2020), he notes that little attention is paid to how shared mobility affects women's mobility, safety, convenience, and comfort. Because women's travel needs are significantly different from men's, they face more barriers and have more difficulty accessing more cost- and time-efficient modes of travel.

A large-scale global survey of customers' satisfaction with public transportation systems was used to quantify satisfaction with public transportation systems and thus obtain gender-specific differences in perceptions of safety in public transportation (Ouali et al. 2020). The nature of the subway itself has a significant impact on the perception of safety, and the emptier carriages in the subway can make female users feel more dangerous or less secure in their personal safety. Moreover, the presence of staff in subway stations does not very obviously enhance the perception of the safety of female passengers. Even with the same treatment measures, for female users, the increase in the sense of security brought always magnified.

According to an International Finance Corporation (IFC) report some exploration and investigation of the gender differences behind the E-hailing market (IFC 2018). The report reveals that social norms limit the extent to which women participate as drivers in ride-hailing services. Furthermore, recruiting more female drivers to E-hailing services can attract more female passengers to use E-hailing services, thus traveling a virtuous cycle. The potential female drivers who are discouraged from becoming part of the E-hailing service are mainly discouraged by their family members or friends. Attitudes towards female drivers vary significantly from market to market due to different religious beliefs and social cultures. Male drivers surveyed in Egypt and Indonesia said they would be miserable if a female family member wanted to sign up as an E-hailing driver, while in contrast, male drivers in Mexico and the UK said they would strongly support it. According to the report, E-hailing has increased the mobility of female passengers. Therefore, to attract more women to the E-hailing industry, whether they are female drivers or passengers, the E-hailing industry must continue to enhance its security, reduce perceived threats, and add more security measures considered from the perspective of vulnerable groups.

The gender gap or gender differential is not an immeasurable quantity but rather a multidimensional value or indicator that can obtain a corresponding result. As a stylish way to travel nowadays, the gender gap in the E-hailing market needs some more attention. The gender imbalance in E-hailing services is manifested in many ways, on the one hand by the driver population in the E-hailing market and the other hand by the gender differences among users and passengers. As for the gender composition of R&D and design managers employed in companies providing E-hailing services, the gender difference phenomenon is not very different from other similar companies, such as Internet companies. Therefore, this paper focuses on the gender gap in the driver group and passenger group.

Again, this same 2018 report from the IFC (ibid.) mentioned the percentage of female drivers in the E-hailing industry from their research in six different countries. These countries have different characteristics, such as different religious backgrounds, geographical features, and climatic conditions, some are developed countries, and some are developing countries. Nevertheless, the same thing is that the percentage of female drivers did not exceed 10%, the highest was only 5.2%, while the lowest was only 0.2%. This is shown in the table(2.2) below. The data source is Uber.

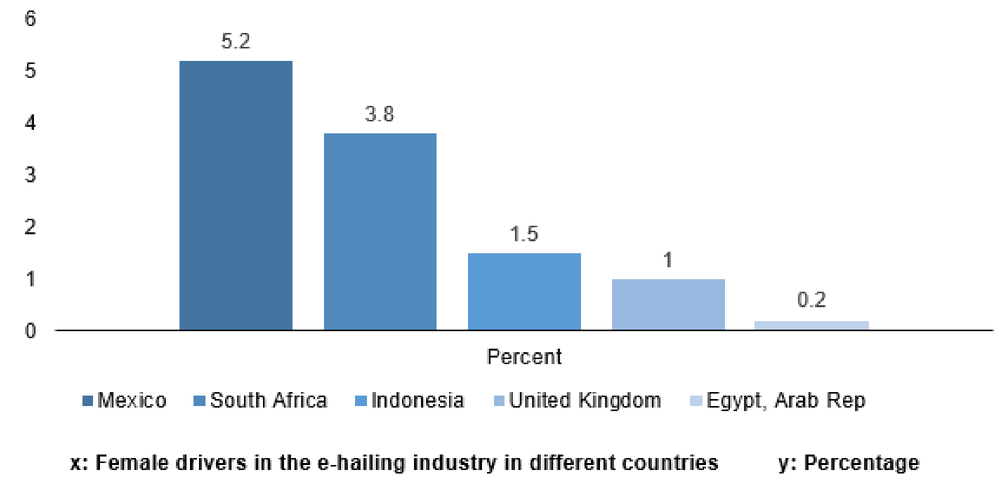


Figure 2.2: Percentage of female drivers in the E-hailing industry in different countries

One of the reasons for this situation, or rather a large part of it, is security. Safety is a significant concern for female drivers and a critical barrier to recruiting and retaining them. 64% of female drivers surveyed cited safety as a reason why most women are reluctant to become E-hailing drivers (ibid.).

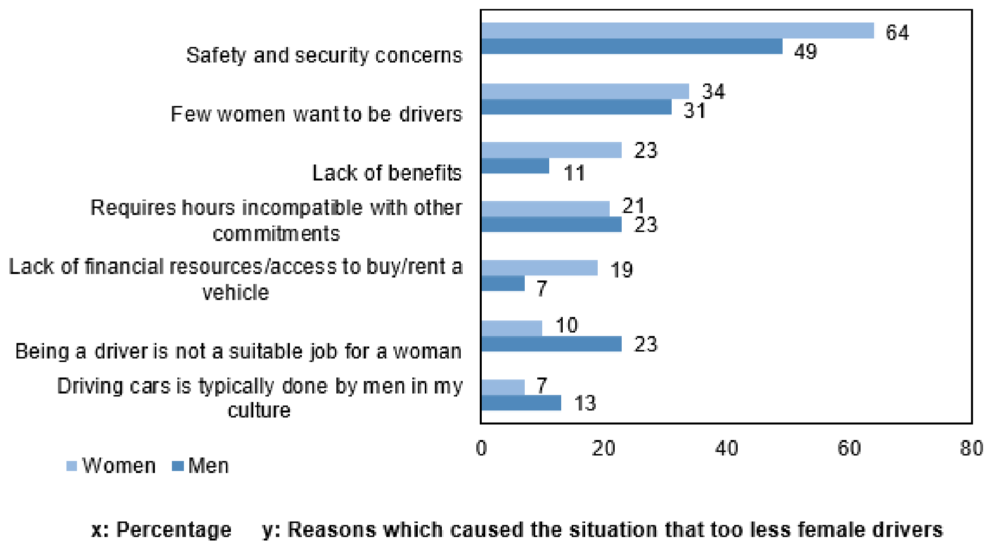


Figure 2.3: Survey Responses by Women and Men Drivers to the Following Question

Does the same dilemma exist for female passengers? The answer is positive, and the same gender gap exists for passenger groups. The situation will not be the same in different countries. A study of the travel patterns of these female passengers revealed that their trips were short primarily but with a somewhat higher frequency count.

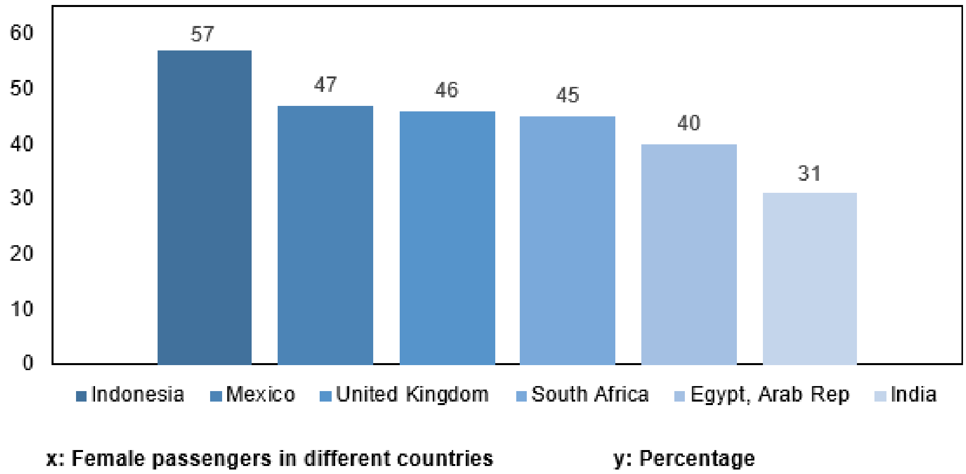


Figure 2.4: Percentage of female drivers in the E-hailing industry in different countries

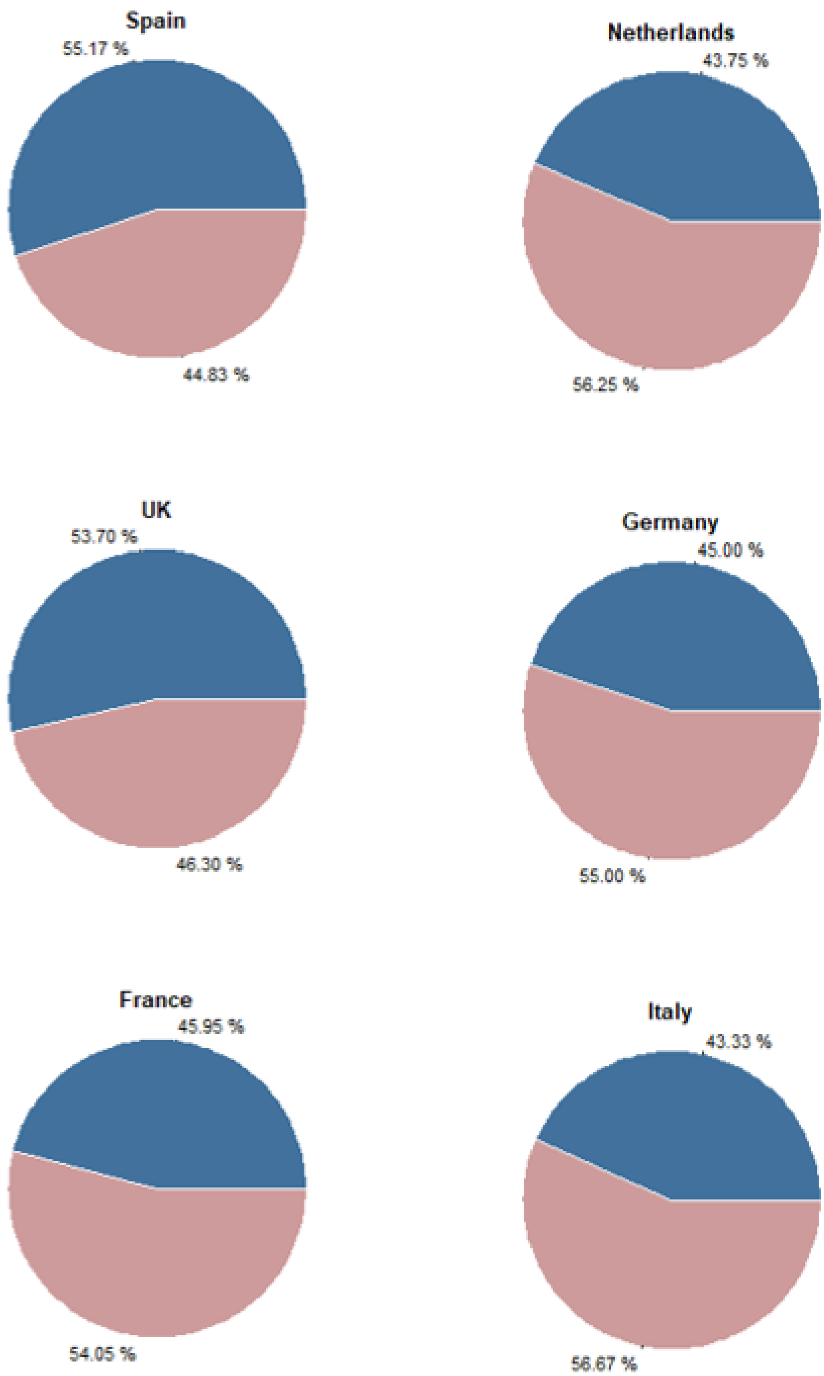


Figure 2.5: Percentage of male and female users in ride-hailing market in 6 European countries

The graph(2.5) above shows the percentage of male and female users in the ride-hailing market in six European countries in 2019. These six countries are Spain, Netherlands, UK, Germany, France, and Italy. All data are from Statista (Statista 2019). Unlike the survey data given by IFC, the number of female users compared to male users in the six countries given on Statista when using ride-hailing services is not less and even more than male users compared to the six countries surveyed by IFC. The authors believe that this has something to do with the average affluence of the residents of these six countries, as the number of private cars leads to the fact that the number of people who use E-hailing services is small, while men choose to use private cars more often.

2.3 Similar research methodology

2.3.1 Correlation tests

Correlation analysis is the quantitative depiction of strong, direct, or indirect correlations between variables. Pearson correlation coefficient (product-moment correlation coefficient, PPMCC), Spearman's rank correlation coefficient, and Kendall's Tau correlation coefficient are often used correlation metrics.

Pearson correlation coefficient

The Pearson correlation coefficient(Benesty et al. 2009) between two variables is defined as the quotient of the covariance and standard deviation between the two variables, as the following equation:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{2.1}$$

The covariance between two random variables measures their degree of correlation. If one variable follows the other and grows or shrinks concurrently, the covariance between the two variables is positive, and vice versa. Although the covariance can reflect the correlation between two random variables (a covariance greater than 0 indicates a positive correlation and a covariance less than 0 indicates negative correlation), the size of the covariance is not a good measure of the correlation between two random variables, as its value is proportional to the magnitude of the two variables, which makes comparison difficult. The Pearson correlation coefficient is calculated by dividing the covariance of two random variables by their standard deviation. The correlation coefficient is comparable to "normalizing" the covariance, removing the magnitude impact.

The above equation establishes the correlation coefficient at the aggregate level, often denoted by the lowercase Greek letter ρ(rho). The sample correlation coefficient (sample Pearson coefficient) is calculated by calculating the sample covariance and standard deviation, which is often denoted by the lowercase letter r.

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{2.2}$$

$\overline{X}$:sample mean for X_i sample
σ_X:sample standard deviation for X_i sample

A significant mathematical characteristic of the Pearson correlation coefficient is that it is unaffected by changes in the location and scale of the two variables, i.e., it is invariant of the change (determined by the sign). That is if we change X to $a + bX$ and Y to $c + dY$, where a, b, c, and d are constants, the correlation coefficient between the two variables remains unchanged (this conclusion holds in both the overall and sample Pearson correlation coefficients).

Due to $\mu X = E(X)$, $\sigma X_2 = E[(X - E(X))^2] = E(X_2) - E_2(X)$, so as Y, and with the following equation

$$E[(X - E(X))(Y - E(Y))] = E(XY) - E(X)E(Y) \tag{2.3}$$

Therefore, the correlation coefficient can also be expressed as follows.

$$\rho_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - (E(X))^2}\sqrt{E(Y^2) - (E(Y))^2}} \tag{2.4}$$

Kendall's Tau correlation coefficient

The Kendall correlation coefficient (Bolboaca and Jäntschi 2006) is named after Maurice Kendall in statistics and is often denoted by the Greek letter τ(tau). Kendall's correlation coefficient is a statistical measure of the correlation between two randomly chosen variables. A Kendall test is a nonparametric hypothesis test that evaluates the statistical dependency of two random variables by using the estimated correlation coefficient. Kendall's correlation coefficient is between -1 and 1. When τ is equal to 1, two random variables have a consistent rank correlation; when τ is equal to -1, the two random variables have an identical opposite rank correlation; and when τ is equal to 0, the two random variables are completely independent of one another.

Assume that the two random variables X and Y (which may alternatively be thought of as two sets) have a total element count of N. The two random variables i $(1 \leq i \leq N)$ values are indicated by Xi and Yi, respectively. When two items (Xi, Yi) in the set XY have the same ranking as (Xj, Yj) (that is, when either case 1 or 2 happens; case 1: $Xi > Xj$ and $Yi > Yj$, case 2: $Xi < Xj$ and $Yi < Yj$), these two elements are regarded identical. When either instance three or case 4 happens (case 3: $Xi > Xj$ and $Yi < Yj$, case 4: $Xi < Xj$ and $Yi > Yj$), these two components are deemed incompatible. When either instance 5 or 6 happens (case 5: $Xi = Xj$, case 6: $Yi = Yj$), these two components exhibit neither consistency nor inconsistency.

The following formula was used to calculate the value of the Kendall correlation coefficient(Kendall 1938):

$$T_{au-a} = \frac{C - D}{\frac{1}{2}N(N-1)} \tag{2.5}$$

Where C denotes the number of pairs of elements in XY that have consistency (two elements are a pair), D denotes the number of pairs of elements in XY that have inconsistency.

Spearman rank correlation coefficient

Pearson's linear correlation coefficient has two limitations: first, the data must be acquired in pairs from a normal distribution, and second, the data must be at least equidistant within the logistic range. Moment correlation coefficients cannot characterize correlations when the data does not follow a normal distribution. In this scenario, rank correlation, alternatively referred to as rank correlation, may be used to explain the strength and direction of the relationship between two variables. One of them is Spearman's rank correlation coefficient (Lehman 2005).

Spearman's rank correlation coefficient is a statistician's term often indicated by the Greek letter ρ(rho). The Spearman rank correlation coefficient is used to evaluate the correlation between two variables X, Y, where a monotonic function gives the connection. If none of the two sets from which the two variables get their values has the same two members, then the relationship between the two variables may reach $+1$ or -1 if one of the variables can be written as a decent monotonic function of the other (i.e., the two variables have the same tendency to change).

The Spearman's rank correlation coefficient does not imply any less stringent data criteria than Pearson's correlation coefficient. As long as the two variables' observations contain paired rank-rated information or rank information derived by converting continuous variable data, Spearman's rank correlation coefficient may be employed regardless of the general distribution pattern of the two variables or the sample size.

As with the most fundamental correlation coefficient, the Spearman Rank correlation coefficient indicates if two sets of data are trending in the same direction. Not to be confused with the correlation coefficient, the Spearman Rank correlation coefficient examines the link between data ranks rather than the relationship between the data itself. This is more resistant to outliers and large data sets.

Now there are two data sets X and Y, each of length n. The $i-th(1 \leq i \leq n)$ values taken by the two attendant variables are denoted by Xi, Yi, respectively. Sorting X and Y (in ascending or descending order at the same time) yields two sets of elemental rows x and y, where elements xi and yi are the rows of Xi in X and the rows of Yi in Y, respectively. The elements in the set x and y are correspondingly subtracted to obtain a ranking difference set d, where $di = xi - yi$, $1 \leq i \leq N$. The Spearman rank correlation coefficient between the random variables X and Y can be calculated from x, y, or d, shown below (Myers, Well and Lorch Jr, 2013).

$$r_s = 1 - \frac{6\sum_{i=i}^{n} d_i^2}{n(n^2-1)} \tag{2.6}$$

2.3.2 Modelling

Discrete choice models' fundamental goal is to provide a model for selecting from a collection of mutually exclusive and jointly exhaustive possibilities. In general, the utility maximization concept is the guiding principle in discrete choice models. Rational decision-makers prefer to pick the option with the most utility among accessible possibilities. For many years, academics in various academic disciplines have been fascinated by the topic of discrete choice. The probabilistic decision model has its origins in mathematical psychology (Orr and Thurston 1927). Both of these models are discrete and have been used in biostatistics for many years (Berkson 1944). Discrete choice models have been used in econometric research by McFadden (McFadden 1981), Hensher and Johnson (Hensher and Johnson 1981), and Judge et al. (Judge, Richmond, and Chu 1980).

There are many standard DCM models, including Binary Logit Model, Multinominal Logit Model, Generalized Logit Model, Conditional Logit Model, Nested Logit Model, Ordered Logit Model, Mixed Logit Model, Logit/Probit (Ordered Logit/Probit) Model, and Mixed Logit Model.

Based on the 2017 NHTS data, Mitra, Bae and Ritchie analyzed the factors affecting the use of E-hailing services by older adults using a variant of the regression model, the ZINB model (zero-inflated negative binomial model) (Mitra, Bae, and Ritchie 2019). The results found that urban dwellers, those living alone, those with higher education levels, and more affluent male users were more likely to use Uber and Lyft. Another significant result was that the most critical factor preventing these seniors from using Uber and Lyft was whether they were disconnected from the digital revolution, i.e., whether they could access the Internet.

Recent researchers also like to compare traditional logistic regression models with machine learning models (Assi et al. 2018). The mode choice behavior of high school students in Khobar, Saudi Arabia, was modeled using traditional logistic regression models and Multilayer Perceptron Neural Networks (MLP). The results of the Logistic Regression Model showed that travel time, household income, and parental education level were significant variables influencing mode choice behavior in public high schools in the study area. This implies that passenger cars are more popular for students who require longer travel time and whose parents have a higher income level and a college degree.

In 2020, two Binomial logit models (BNL) models were constructed to study the mode choice of metro-taxi and mobile-taxi by including socioeconomic and demographic variables, urban form and land-use variables, and travel schedule-related variables as influencing factors (F. Chen et al. 2020). The results show that travel distance, fare, and time differences are the most significant compared to other attributes. During peak hours, the proportion of residential land and the number of office buildings near the origin and destination promotes the use of the subway, strengthening its position as the primary commuting mode.

A study of Nanjing, China, used a random forest approach to analyze model selection (Cheng et al. 2019). In contrast to other machine learning methods that operate in a "black box," RF approaches can assess the relative relevance of explanatory factors, which is vital for establishing a successful and suitable transportation policy. The built environment often contributes more than household and personal characteristics among the explanatory factors. Among built environment factors, household attributes, and personal attributes, the most influential variables are land use mix, automobile ownership, and age, in that order. When evaluating the consequences of a proposed transportation policy, particular attention should be given to the answers of families with and without automobiles and the responses of various age groups.

A survey with Brazil as the study site analyzed the Brazilian ride-hailing market by using a logistic regression model (Souza Silva, Andrade, and Maia 2018). The survey found that leisure was the primary motive for automobile travel, followed by homecoming. Ride-hailing use was infrequent rather than every day for both of these travel objectives (leisure and homecoming). This use pattern may indicate a high degree of customer satisfaction with the service. The more knowledgeable service is, the more likely it is that the public would discover its shortcomings and assign it a lower grade. The logistic regression model indicates that safety is the most critical element in sharing. This indicates that this factor has a more considerable effect on women, implying that women are more fearful about carpooling with strangers.

Fu's research used an Ordered Logit Model to elicit information on the causes and incentives for ride-hailing software adoption in the Chinese setting (X. m. Fu 2020). Respondents were classified as heavy or light ICT users, with the former group being more reliant on ICT, more likely to possess more ICT devices, use ICT for more extended periods, and perceive that ICT usage had a significant impact on their lives. Females, those under the age of 40, those with a higher degree, and those with at least one kid under 18 are more likely to be heavy ICT users.

Several studies have inferred trip intent from passively acquired riding trajectory data using MNL, NL, and MMNL models (Hossain and Habib 2021). The findings imply that riders arriving at the same area in the E-hailing market in the city of Toronto may be doing so for various reasons, which may change based on the trip start time and departure location. The primary objective of journeys made through E-hailing is to engage in leisure activities (e.g., shopping and errands, eating out, entertainment, and social visits) and to return home. Around a quarter of daily automobile, travel is for business and educational purposes.

A prominent national dataset was also utilized to find a variety of factors associated with the usage of a vehicle or ride-hailing journeys rather than walking or vice versa

(Khattak, Miller, and Ohlms 2021). Several significant characteristics that boost a person's inclination to use ride-hailing and taxi services include having a smartphone with Internet connectivity, being male, having a medical problem, being interested in technology, and making longer journeys—being youthful, being worried about fuel expenses, and having a non-work travel objective contribute to an individual's desire to walk.

Research using the city of Munich as an example demonstrates that the influence of ride-hailing (RH) on mode share can be anticipated using the Nested Logit Model and users' willingness to pay for such services (Shoman and Moreno 2021). Calculate the travel times between RH and metro. RH was expected to have an 8.04 percent mode share in HBO (Home-based others) and a 4.66 percent mode share in HBW (home-based work). In comparison to other trip reasons, HBE (home-based education) travels are more time-sensitive, whereas HBW journeys include essentially no RH excursions (less than 1 percent in the most favorable case).

A Generalized Ordinal Logit Model was used to undertake a descriptive and econometric study of E-hailing services in the city of Santiago, Chile (Tirachini and Ro 2019). The ridership rate (number of passengers per vehicle) drops as the family income grows, although the ridership rate for leisure trips tends to increase. Cabs and public transit are the modalities most replaced by E-hailing services. Each month, younger individuals and households with a higher income level utilize ride-hailing services more often. When family income and age are considered, automobile ownership has no impact on the frequency of E-hailing. Safety and consumer protection and labor and taxes were deemed to need priority control by users.

The research examined the factors that impact people's mode of transportation choice in Johor Bahru city by conducting interviews with residents who have lived there for more than a year (Puan et al. 2019). The study used an attitudinal survey approach, namely the expressed preference survey. Following that, the data were analyzed using the Binary Logit Model. The research discovered that consumers' mode of transportation choice was statistically related to their age, income, vehicle ownership, automobile comfort, transit service dependability, emotional motivation, and instrumental motivation.

Two Logit Regression Models are used to model the E-hailing company's data on passenger preferences (Wu, X. Chen, and J. Ma 2018). The findings indicate that, when all other factors remain constant, the chance of picking a dedicated vehicle drops as the cost of the dedicated vehicle or the distance traveled rises and that more customers choose cabs and E-hailing. When the cost of E-hailing grows, the chance of passengers utilizing it falls, and more passengers choose for a taxi or a specialized vehicle. Additionally, customers are far more inclined to use a taxi when the wait time for a specialized vehicle or E-hailing rises.

For the above literature is summarized according to the models used, as shown in the following table(2.1).

Table 2.1: Summary of the research regarding E-hailing topic using mainly Logit Model

Research	Study area	Model	Key
(Mitra, Bae, and Ritchie 2019)	The United States	Zero−inflated Negative Binomial Model	• Urban dwellers, those living alone, those with higher education levels, and more affluent male users were more likely to use Uber and Lyft. • The most important factor preventing these seniors from using Uber and Lyft was whether they were disconnected from the digital revolution.
(Assi et al. 2018)	Khobar, Saudi Arabia	traditional Logistic Regression Models and Multilayer Perceptron Neural Networks	• Travel time, household income, and parental education level were significant variables influencing mode choice behavior in public high schools.
(F. Chen et al. 2020)	Shanghai, China	Binary Logit Model	• Travel distance, fare and time differences are the most significant compared to other attributes. • During peak hours, the proportion of residential land and the number of office buildings near the origin and destination promote the use of the subway.
(Cheng et al. 2019)	Nanjing, China	Random Forest Method	• Among the explanatory factors, the built environment often contributes more than household and personal characteristics. • Among built environment factors, household attributes, and person attributes, the most influential variables are land use mix, automobile ownership, and age, in that order. • When evaluating the consequences of a proposed transportation policy, particular attention should be given to the answers of families with and without automobiles, as well as to the responses of various age groups.

Research	Study area	Model	Key
(Souza Silva, Andrade, and Maia 2018)	Brazil	Logistic Regression Model	• Leisure was the primary motive for automobile travel, followed by homecoming. • The more familiar a service is, the more likely it is that the public would discover its shortcomings and assign it a lower grade.
(X.-m. Fu 2020)	China	Ordered Logit Model	•The group being more reliant on ICT, more likely to possess more ICT devices, to use ICT for longer periods of time, and to perceive that ICT usage had a significant impact on their life. •Females, those under the age of 40, those with a higher degree, and those with at least one kid under the age of 18 are more likely to be heavy ICT users.
(Hossain and Habib 2021)	Toronto, Canada	Multinomial Logit Model, Nested Logit Model, Mixed Multinomial Logit Model	•Riders arriving at the same area in the E-hailing market in the city of Toronto may be doing so for a variety of reasons, which may change based on the trip start time and departure location. •The primary objective of journeys made through E-hailing is to engage in leisure activities (e.g., shopping and errands, eating out, entertainment, and social visits) and to return home.
(Khattak, Miller, and Ohlms 2021)	The United States	Binary Logit Model	•Several significant characteristics that boost a person's inclination to use ride-hailing and taxi services include having a smartphone with Internet connectivity, being male, having a medical problem, being interested in technology, and doing longer journeys. •Being youthful, being worried about fuel expenses, and having a non-work travel objective all contribute to an individual's desire to walk.
(Shoman and Moreno 2021)	Munich, Germany	Nested Logit Model	• Ride-hailing was expected to have an 8.04% mode share in HBO (Home-based others) trips and a 4.66% mode share in HBW (home-based work) trips.

Research	Study area	Model	Key
(Tirachini and Ro 2019)	Santiago, Chile	Generalised Ordinal Logit Model	•The ridership rate (number of passengers per vehicle) drops as the passengers' family income grows, although the ridership rate for leisure trips tends to increase. • Cabs and public transit are by far the modalities most replaced by E-hailing services.
(Puan et al. 2019)	Johor Bahru City, Malaysia	Binary Logit Model	• Consumers' mode of transportation choice was statistically related to their age, income, vehicle ownership, automobile comfort, transit service dependability, emotional motivation, and instrumental motivation.
(Wu, X. Chen, and J. Ma 2018)		Logistic Regression Model	• When all other factors remain constant, the chance of picking a dedicated vehicle drops as the cost of the dedicated vehicle or the distance traveled rises, and that more customers choose cabs and E-hailing.

3 Methodology

This chapter describes some of the ways and means of conducting the survey, as well as the sources of the survey questions set in this dissertation and the classification of the answers set by other scholars to these questions. How to integrate the estimation of BNL, ONL and MNL models as well as evaluate the models.

3.1 Survey design

Investigation and surveys can be traced back to Victorian Britain. At that time, the primary purpose of a survey was to collect information about the living conditions of the different working-class and social poverty situation (Vernon 1958). Surveys are well suited for descriptive analysis, which deals with general descriptive characteristics, such as income, gender, age, and education level. Similarly, surveys can provide testable data for proposed hypotheses. Twenty years ago, the mainstream survey methods were postal questionnaires, face-to-face interviews, and telephone interviews (Kelley et al. 2003). However, two decades have passed; with the rapid development of Internet technology, many new survey methods have emerged, but most rely on the Internet for dissemination. These years, email questionnaires, online focus groups, website surveys, or social media surveys are non negligible tools. Although online surveys are prevalent these days, face-to-face interviews are still valued; most attention is paid to their reliability of questionable data (Pate 1993). Therefore, considering the convenience of collecting data online and the reliability of data collected offline, both online social media surveys and offline, face-to-face interviews were chosen for this thesis.

To get insight into travel behavior and the reasons that contribute to the gender divide in E-hailing services, the stated preference (SP) survey is being used to collect more accurate data. As such, this part will discuss the survey's overall form, the design of a stated choice experiment for eliciting travel behavior and elucidating the causes for gender differentials, and the survey's finalization after the pilot survey.

3.1.1 Survey composition

In general, the whole questionnaire is divided into four sections: the socio-demographic section, the travel behavior section, the E-hailing section, and the risk perception of the

E-hailing section. The survey structure is shown in the figure(3.1) below.

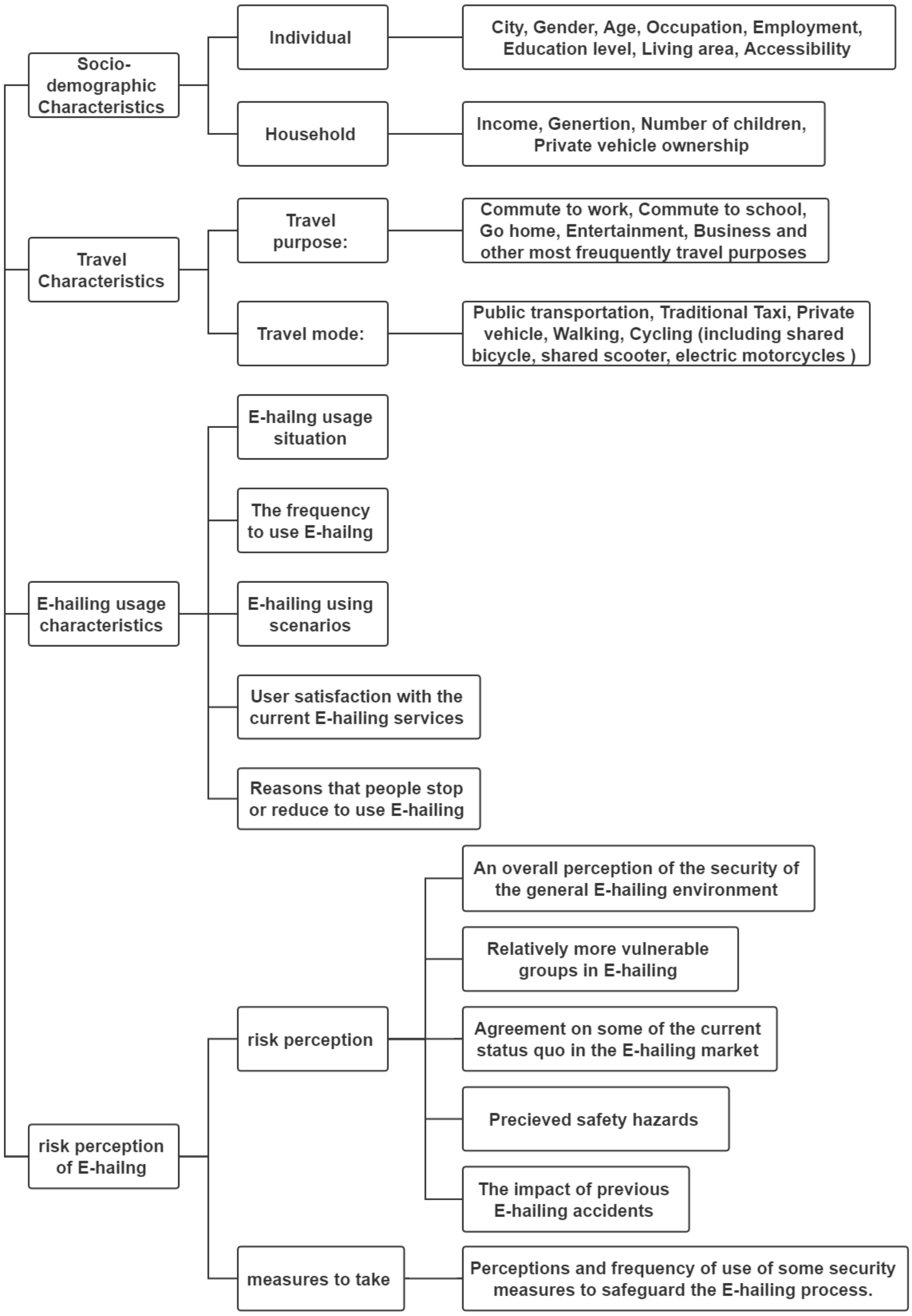


Figure 3.1: Survey Structure

3.1.2 Research question sources

To ensure that each question in the questionnaire was sourced and substantiated, each question in each section and its corresponding response options were screened. For specific questionnaires and options, please see the appendix. In this section, only the source of each question is mentioned.

Age: age grouping, since the age composition of the population varies from country to country. In this thesis, the main target of the survey is Wuhan, Hubei Province, China, so it is necessary to refer to the age groups given by the National Bureau of Statistics of China for grouping (Ning 2021). According to the information given by the National Bureau of Statistics of China, generally speaking, China divides its population into 0 to 14 years old, 15 to 59 years old, and over 60 years old when conducting population statistics. According to the General Principles of Civil Law of China (Yang 1997), a citizen over 18 years old is an adult with total civil capacity. Finally, according to the statistics of the age group of victims in the book "Ten Essays on the Development of Criminal Offenses in China" (Feng 2010), more than 60% of the victims of criminal offenses are between the ages of 18 and 38.

Therefore, the ages in the questionnaire were divided into four groups: 0 to 17 years old, 18 to 37 years old, 38 to 59 years old, and over 60 years old.

Occupation: According to the classification of internationalized occupations provided by ilostat (ILOSTAT, no date), the standard number is ICSE-18-A. ilostat classifies occupations into two broad categories, independent workers and dependent workers. ilostat provides the specific classification in the table(3.2) below.

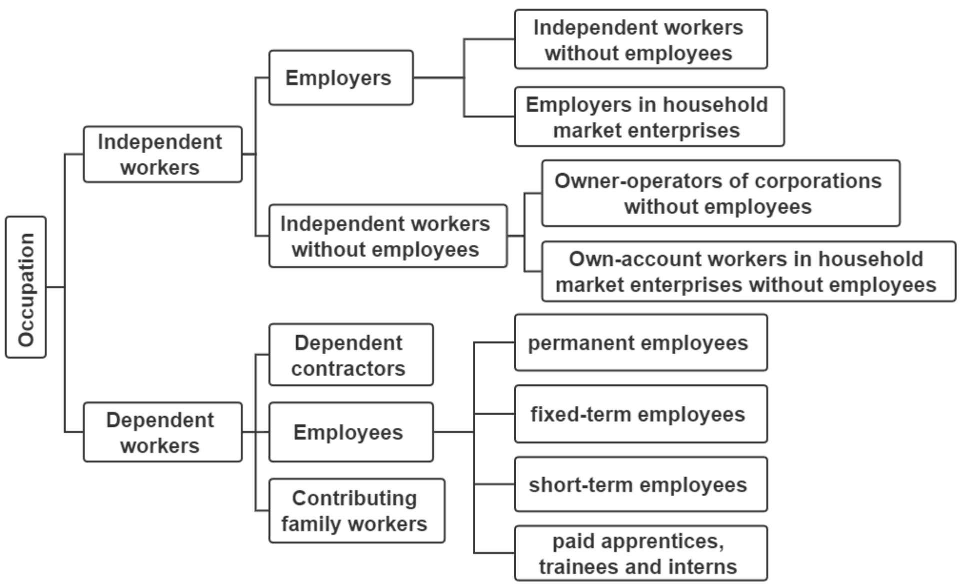


Figure 3.2: Occupation Classification

However, these classifications are not necessarily appropriate for the Chinese context. Therefore, according to the classification given by the CHFS (CHFS 2020), occupations are divided into 13 categories: students ($<$ 18 years old), students ($\geq$ 18 years old), freelance, self-employed, skilled workers, ordinary employees of companies, professional and technical people (teachers, doctors, lawyers, etc.), ordinary civil servants (ordinary employees of government agencies or institutions), senior manager (senior civil servants, senior management of enterprises above the managerial level, etc.), housewives and husbands, unemployed or looking for work, retired and other occupations.

Employment: The difference between the employment methods and the occupations described above is that the employment methods are more concerned with the nature of the work and the hours of work. Because different work periods affect the perception of using E-hailing services thus, the variables Employment and Occupation are listed separately here. Similarly, according to the CHFS report (ibid.), there are five common types of Employment: permanent, fixed-term, short-term or temporary, paid apprentice trainees or interns, and other types of Employment.

Education: According to a questionnaire conducted by Peking University listed under CFPS(Xie, Qiu, and Lv 2012), the educational levels in China are classified into nine categories from low to high: Never attend school, Illiterate, semi-literate, Elementary school, Junior high school, High school/vocational school, Specialty, Undergraduate, Master's degree and Ph.D. In a survey conducted by Peking University, the educational level in China was classified into nine categories from low to high: Never attend school, Illiterate, semi-literate, Elementary school, Junior high school, High school/vocational school, Specialty, Undergraduate, Master's degree and Ph.D.

Household income per capita: According to the 2019 STATS on the per capita monthly income of Chinese households(STATS 2019), the income of Chinese households is divided into ten categories from low to high: 0-500, 500-800, 800-1000, 1000-1500, 1500-2000, 2000-3000, 3000-5000, 5000-10000 10000-20000 and more significant than 20000 RMB. All the categories are displayed in RMB units, which are converted into Euro units: 0-67, 67-107, 107-133, 133-200, 200-267, 267-400, 400-667, 667-1333, 1333-2667 and more significant than 2667 Euros. This concept is also explained in the authors' questionnaire under the household income question for the family concept. The concept of family as identified in the survey is that those who live together for a long time or are related by blood are considered family members, and children who leave home and do not achieve their financial independence or do not move to live alone are still considered family members.

Household generation: The different number of generations in the household, that is, the generations living together in a family, also has an impact on the characteristics of the mode of travel. Because families with children and older people (three-generation households) and couples without children (one-generation households) will generate travel patterns that are never the same and carry out different social activities daily, here, referring to the classification in a paper that investigated app-based ride-hailing in

China (Tang et al. 2020), the number of generations in the household is divided into five categories: live alone, live with a spouse, two-generation family, three-generation family and more than three-generation family.

Household children number: Unlike the standard number of children in foreign families, China introduced a policy in the 1990s called the "one-child policy," which means that a pair of parents can only raise one child left. Although this policy has been abolished in the last decade due to the gradual aging of China, new policies have been introduced to encourage young parents to have children in 2021.July (Agency 2021). However, the lingering effects of the "one-child policy" are still present, and most families still have only one child. Therefore, the number of children in a family is classified into six categories: no children, one child, two children, three children, four children, and more than four children.

Travel purpose and travel mode: After referring to the literature (Acheampong et al. 2020), the questionnaire in this thesis divides the mode of travel and the purpose of travel into six categories each.

Travel modes: public transportation (bus, subway, light rail), traditional taxi, private vehicle, walking, bicycle (shared bicycle, shared electric motorcycles, electric bicycle, motorcycle are included), and E-hailing. ***Travel purpose***: Commute to work, commute to school, go home, entertainment, business, and others.

Household vehicle: For private vehicle ownership in households, the classification is borrowed from the paper(Tang et al. 2020) and is divided into no private vehicle, one private vehicle, two private vehicles, and more than two private vehicles.

Living area: Tang et al. believed that the location of residence affects the likelihood and frequency of respondents choosing to use E-hailing (ibid.). People who live in the city center are likely to use E-hailing services more often because of their location. Therefore, the residential location is divided into downtown and suburban areas.

Accessibility: It is also of great interest to study the Accessibility of the places where the investigators live and work. Accessibility still has a significant impact on whether people E-hailing the service or not, with people closer to public transport stops being less likely to use E-hailing services, especially for those daily sympathetic journeys. The formula for the accessibility measure for individuals is shown below.

$$A_i = D_j \times f(C_{ij}) \tag{3.1}$$

The accessibility measure adopted in the questionnaire was derived from an experiment in London, UK, called PTAL(Authority 2000), which was later used in Ahmedabad, India in 2014 (Shah and Adhvaryu 2016), according to which the walking time from the place of daily residence and work to the nearest public transport station was divided into four categories: less than 8 minutes, 8 to 12 minutes, 12 to 20 minutes, and more than 20 minutes.

Use frequency (E-hailing usage frequency):: A group of Chinese researchers classified the frequency of E-hailing into four categories: Seldom used (several times a year), Occasionally used (several times a month) (several times a month), Often used (several times a week), and Very frequently used (several times a day) (Jing et al. 2021). Here, adds an item, Never, as an option for users who have never used E-hailing. Because the scope of the survey for this thesis includes the elderly population, the never-used condition may exist.

E-hailing using scenarios: To regulate the services of E-hailing, it is necessary to clarify the E-hailing usage scenarios. Most research studies have focused on the following scenarios of E-hailing: work and study-related travel (Acheampong 2021), shopping and dining, visiting friends and relatives, tourism and entertainment, business trips (in the same city or to train stations, airports, etc.), going to hospitals, going home (Jing et al. 2021), night trips (when public transportation is not running), etc.

Obstruction reason (Reasons for not using E-hailing): : To improve service, there is no doubt that one needs to know what is stopping people, or users, from using E-hailing or not using the service anymore. As it happens, a group of researchers has investigated the reasons behind the change in users' willingness to use E-hailing, using the city of Nanchang in Jiangxi Province, China, as the subject of a study. The reasons for not using E-hailing were divided into four categories: feeling unsafe, expensive, long waiting time, and other reasons (He et al. 2020).

The other questions were graded using a seven-point Likert scale on respondents' attitudes, intentions, and perceptions. For example, the answer to the question: satisfaction with the services provided by E-hailing company is divided into Very unsatisfied, Unsatisfied, Relatively unsatisfied, Neither unsatisfied nor satisfied, Relatively satisfied, Satisfied and Very satisfied, totally seven categories.

3.1.3 7-point Likert scale

This paragraph is a description of why the 7-point Likert scale was chosen. Generally speaking, there are 5-, 7-, 9- and 10- points of Likert scale. However, because the range of values and partition intervals for both the 9-point Likert scale and the 10-point Likert scale are relatively close, the 9-point Likert scale is often overlooked.

For the remaining 5-, 7-, and 10-point Likert scales, an experimental study was conducted to examine whether and how these three different scales would affect the analysis of the experimental data (Dawes 2008). Only those using literalized scales are discussed here, not those using numerical scales. The experiment results found that respondents do use more response options if they use scales with more options, i.e., the results obtained with more finely categorized scales do not all focus on only a few of the items.

Meanwhile, a study conducted an experimental analysis using Likert scales that were consistent in content but differed in scale classification levels (Leung 2011). The results found that statistical indicators such as mean, standard deviation, item correlation, item score-total score correlation, reliability, and factor loadings did not show significant differences between the 4-point, 5-point, 6-point, and 11-point scales. However, the 6-point and 11-point scale data followed a normal distribution on the data, while the 4-point and 5-point scale data showed a skewed distribution, which means that the more refined the grade distinction of the scale, the closer it is to a normal distribution, the better the data performance. In particular, the 11-point scale data has the smallest kurtosis and is the scale closest to the normal distribution. Since both the 5-point and 11-point scales have midpoints, which are often considered to have a "convergence effect," the researcher believes that the effect of midpoints may be diluted by adjacent scales in more extended response levels, especially in long response levels such as the 11-point scale, which is another reason why the researcher recommends the multi category scale.

3.2 Data collection

As mentioned in a previous subsection, the survey is conducted online and offline face-to-face interviews. After nearly two months of dissemination of both methods, it was found that the ideal number of experimental data was still far from the ideal.

So, after constant communication and struggle with Wuhan Municipal Government, the link to the survey questionnaire was finally put up on the homepage of the official websites of the three district governments. The link has been taken down now because the agreed condition was to hang it for two weeks. The specific distribution locations for the face-to-face conversation questionnaire will be described in the first subsection of the next chapter.

3.3 Data preparation

The implementation of several functions in this subsection relies on the tidyverse package (Wickham et al. 2019a), psych package(Revelle 2016), janitor package (Firke 2021), caret package(Kuhn et al. 2021) in *R*.

Summary statistics

Generally speaking, the data obtained are dirty, cluttered, and need to be organized and cleaned. In order to get a general impression of the acquired data, we need to generate summary statistics about the data. And the psych package in *R* provides an efficient function, $describe()$ (Revelle 2016), or the function $skim()$ in package skimr. Both functions can provide beneficial information about obtained data, for example, the standard deviation, mean, median, median (standard or interpolated, mad: median absolute deviation (from the median), minimum, maximum, skew, kurtosis and standard error, etc.

Data cleaning

After getting a general impression of the acquired data, it is time to start cleaning the dirty raw data. Variables have a variety of names. In order to read the data more clearly and use it later, it is necessary to extract the variable names from the data file and replace the original variable names as character vectors. This way, the variable names can be extracted and referred to in the following global variables easily and quickly. Using the $clean\_names()$ function in the janitor package in R, all variable names can be transferred into lowercase without spaces, but with an underscore instead, a procedure that is particularly meaningful for data sets with a large number of variables. This process makes the subsequent process much more manageable.

Creating dummy variables

In constructing a regression model, if the independent variable is continuous, the regression coefficient can be interpreted as the average amount of change in the dependent variable caused by each unit change in one of the independent variables, with other independent variables held constant. However, when the independent variables are multi-category, it is less desirable to use only one regression coefficient to explain the relationship between the changes in these multi-category variables and their effects on the dependent variable.

Therefore, these original multi-category variables were transformed into dummy variables. With the regression model, an estimated regression coefficient is obtained for each dummy variable, thus making the regression results more easily interpretable and practically meaningful. For independent variables with n categorical attributes, selecting one classification as the reference is usually necessary so that $n - 1$ dummy variables can be generated. The introduction of dummy variables into the regression model is more complex, and however, it can reflect the influence of different attributes of this independent variable on the dependent variable more intuitively, improving the model's precision and accuracy.

Dummy variables below full-rank pasteurization can be easily created using the $dummyVar()$ function under the caret package in R(Kuhn et al. 2021). It is worth noting that such an approach allows having a dummy variable for each factor for each level.

Mistakes and missing data

In the statistical summary stage, we can see some obvious errors or values not filled in. For these values, the first step is first to rewrite them all to missing observations (NA) by using the $mutate()$ function in the tidyverse package (Wickham et al. 2019a).

After converting the wrong values to missing values, the missing values can be identified by the is for these missing $values.na()$ function. If the amount is small for these missing values, it is not meaningful; the missing values can be removed simply by using the $drop\_na()$ function. If indeed the values are meaningful, the $mutate()$ function can replace them with a specific value, such as 0 or -99, etc. If necessary, the missing values can also be interpolated utilizing mean imputation or multiple imputations.

Spot outliers

Finding outliers is an integral part of the data cleaning process. For numerical data, the steps to find outliers are simple; a scatter plot can be drawn to find outliers in it. Drawing a scatter plot also allows for examining numerical outliers in a category based on another variable.

The $standardized()$ function in the effectsize package makes it easy to check for outliers (Makowski, Ben-Shachar, and Lüdecke 2020). Outliers can be removed, set to missing values (NA), or replaced using the Winsorizing method (William Revelle 2011). Because a reasonable range of responses was set in this thesis when setting up the questionnaire, very few outliers were generated, less than 1% in number, so the outliers were deleted directly.

Zero- and Near Zero-Variance predictors

In some cases, the data generation mechanism creates only feature variables with a single value (e.g., zero variance feature variables). This can cause model corruption or unstable data fits. Similarly, the eigenvariables may have unique values that occur very infrequently. These eigenvariables may become zero variance eigenvariables when such data are sampled using cross-validation or bootstrap methods or when some samples may excessively affect the model. It can be identified, removed or merged by using the $nearZeroVar()$ function in the caret package (Kuhn et al. 2021).

Multicollinearity

Collinearity is a phenomenon that may exist between independent variables and could have existed objectively. Collinearity introduces a great deal of uncertainty in parameter estimation when collinearity exists. Multicollinearity is generally diagnosed by the variance inflation factor (VIF) and tolerance, which are reciprocals of each other.

Each independent variable has its VIF and tolerance. For the independent variable X_i, a linear regression model is established with X_i as the dependent variable and the respective variables other than X_i as the independent variables, and the coefficient of determination of the regression model is noted as R_i^2. Then the tolerance of the independent variable X_i is $tolerance = 1 - R_i^2$. The variance inflation factor (VIF)$VIF = \frac{1}{1-R_i^2}$. The larger the VIF value, the more severe the multicollinearity. The VIF and tolerance are calculated only on the independent variables so that even if a logistic regression is performed, a multi-factor linear regression can be forced. The larger the VIF, the more severe the multicollinearity. If there is an exact correlation between the independent variables, the tolerance is zero, and the VIF is infinite. The methods to solve the multicollinearity are the elimination of variables, LASSO regression, ridge regression, etc (Daoud 2017).

3.4 Model estimation

After the data have been processed and cleaned, correlation tests are performed between the variables, and after the correlation tests have been passed, the screened variables are used to model the research questions that need to be answered.

3.4.1 Correlation tests

Correlation analysis is the description of strong, direct, or indirect associations between variables through quantitative indicators. The common correlation indicators are: Pearson correlation coefficient (product-moment correlation coefficient, PPMCC), Spearman's rank correlation coefficient and Kendall's Tau correlation coefficient (*An overview of correlation measures between categorical and continuous variables* 2018) (Benesty et al. 2009) (Winter, Gosling, and Potter 2016) (Bolboaca and Jäntschi 2006).

The Pearson correlation coefficient is the most common indicator used to indicate the magnitude of the correlation, with values ranging from -1 to 1. The closer to 0, the lower the correlation, and the closer to -1 or 1, the higher the correlation. Spearman's rank correlation coefficient, also known as the rank correlation coefficient, is a nonparametric statistical method that uses the rank order of two variables to conduct analysis. Kendall's Tau correlation coefficient is also a nonparametric test.

The applicability of these three methods used to analyze data correlation is different. The Pearson correlation coefficient is only applicable to two customarily distributed continuous variables. The Spearman rank correlation system applied to correlation measures between continuous variables and ordered categorical variables that do not meet the requirements of the normal distribution of the Pearson correlation coefficient. The Kendall's Tau correlation coefficient, on the other hand, can only be applied between two ordered categorical variables.

Because continuous variable data were not collected in the questionnaire in this thesis, the method used to test the correlation of the data was the Spearman correlation coefficient.

3.4.2 Discrete choice model

As described in subsection(2.3.2), the target of the Discrete Choice Model is to provide a method to choose from a collection of mutually exclusive and jointly exhaustive possibilities. This process of making a choice will usually involve the below four elements: decision-maker, alternatives, attributes of alternatives, and decision rules (McFadden 1981).

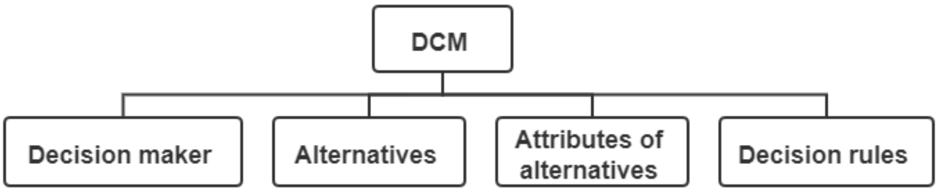


Figure 3.3: Elements of DCM

Decision maker

The choice behavior (decision maker) can be an individual, a household, a business, a government agency, etc. It is important to note that the decision maker's attributes also impact the outcome of the choice. In other words, even when faced with the same set of alternatives, different decision-makers will make different choices. This is why it is necessary to collect information on the individual socioeconomic status of respondents when investigating and studying the choice behavior of users/consumers. Common individual economic attributes include the respondent's age, gender, income, employment status, etc.

Alternatives

An alternative is a set of options for decision-makers to choose from. For example, the travel options available to people are conventional bus, BRT, subway, private vehicle, taxi, ride-hailing, bicycle, e-bike, walking, etc. Generally speaking, the actual choice domain faced by different individuals may not be the same. Therefore, there are three different classifications of choice sets as follows, Universal Choice Set, Feasible Choice Set and Consideration Choice Set.

Attributes of alternatives

In addition to the personal attributes of the decision-maker, each choice has its attributes that affect the outcome of the choice. Different option attributes describe each option's utility to people in different dimensions. "Utility" is one of the most commonly used concepts in economics, and "Utility" describes a measure of how well consumers satisfy their needs, wants, etc., by consuming or enjoying leisure. When people make choices, they consider the sum of all attributes of each option - "utility maximization" is also the most common decision criterion.

The abstract expression equation of DCM is as followed.

$$P_{ij} = f(D_i,\ A_j) \tag{3.2}$$

$P_i j$: the probability of decision maker i chooses alternative j.
D_i: decision maker i.
A_j: alternative j.

Decision rules

The expected Rational Choice Behavior is Dominance Rule, Satisfactory Rule, the Lexicographic Rule, and Utility Maximization Rule. The other three decision rules will not be discussed here except for the Utility Maximization Rule.

Maximizing utility, in common parlance, means maximizing satisfaction. For a particular travel mode, the lower the cost, the shorter the travel time, the better the safety, and the higher the reliability, the higher the utility of that model. The utility can be expressed as a function of different attributes. Suppose that there exist two different alternatives, i and j, for which there are many different properties. Then for alternative i, choosing i means accepting the utility provided by alternative i. The equation is as follows. For alternative j, the same applies. Finally, according to the utility of these different alternatives, choose the one with the greatest utility(Train 2009).

$$U_i = \beta_{k_1} X_{i,k_1} + \beta_{k_2} X_{i,k_2} + \cdots + \beta_{k_n} X_{i,k_n} \tag{3.3}$$

U: Utility.
β_{k_n}: Weight for property. k_n
k_n: different property for alternative

For DCM, the dependent variable does not satisfy the conditions for using a linear regression model and, therefore, does not allow least squares to estimate the coefficients. It would be better and easier to calculate using the logistic regression model.

3.4.3 Logistic Regression Model

In statistics, both Probability and Odds are used to describe the likelihood of something happening. Probability describes the ratio of the number of occurrences of a specific event to the number of occurrences of all outcomes. Probability is an actual number between 0 and 1; $P = 0$ means that it must not happen, while $P = 1$ means that it will happen. The formula is expressed as.

$$P = \frac{Number\ of\ a\ specific\ event}{Total\ Number\ of\ Outcomes} \tag{3.4}$$

Odds refers to the ratio of the probability of an event occurring to the probability of it not occurring.

$$Odds = \frac{Probability\ of\ event}{Probability\ of\ no\ event} = \frac{P}{1-P} \tag{3.5}$$

Alternatively, the derivation of Odds using the formula for probability above. The Odds of a particular event is equal to the ratio of the number of occurrences of the particular event to the number of occurrences of other events.

$$Odds = \frac{P}{1-P} = \frac{\frac{Number\ of\ specific\ event}{Total\ Number\ of\ outcomes}}{\frac{Number\ of\ other\ event}{Total\ Number\ of\ outcomes}} = \frac{Number\ of\ specific\ event}{Number\ of\ specific\ event} \tag{3.6}$$

The probability P varies in the range of $[0, 1]$, while Odds varies in the range of $[0, +\infty)$. If the natural logarithm (i.e., Log) is taken for Odds, it is possible to map the probability P from the range $[0, 1]$ to $(-\infty, +\infty)$. Therefore, the logarithm of Odds is called Logit. In the Logit model, the left side of the equation is the logarithm of the occurrence of an event over its non-occurrence, and the right side is a linear combination of the independent variables.

$$log(Odds) = ln\left(\frac{p_1}{p_0}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{3.7}$$

Applying the utility maximization criterion discussed in the previous subsection. For decision maker n, if the utility U_{in} of alternative i is higher than the utility U_{jn} of alternative j, then decision maker n chooses alternative i. That is, the probability that alternative i is selected by decision maker n is equivalent to the probability that $U_{in} > U_{jn}$ occurs. If $U_{in} > U_{jn}$, then n choose i, $P_n(i) = P(U_{in} > U_{jn})$. The modeling treats utility as a random variable; it consists of a deterministic component that can be observed and a random component.

$$U_{in} = V_{in} + \epsilon_{in} \tag{3.8a}$$

$$U_{jn} = V_{jn} + \epsilon_{jn} \tag{3.8b}$$

V_{in}, V_{jn}: deterministic component
$\epsilon_{in}, \epsilon_{jn}$: random component

The deterministic components of utility can generally be expressed as a linear combination of multiple independent variables.

$$V_{in} = \beta_1 X_{in1} + \beta_2 X_{in2} + \cdots + \beta_K X_{inK} = \beta' X_{in} \tag{3.9a}$$

$$V_{jn} = \beta_1 X_{jn1} + \beta_2 X_{jn2} + \cdots + \beta_K X_{jnK} = \beta' X_{jn} \tag{3.9b}$$

The relative difference between the utility of alternative i and the utility of alternative J affects the decision, not the absolute magnitude of the utility of each option. Therefore, the probability of alternative i being selected by decision-maker n is:

$$P_n(i) = P(U_{in} > U_{jn}) = P(V_{in} + \epsilon_{in} > V_{jn} + \epsilon_{jn}) = P(\epsilon_{jn} - \epsilon_{in} < V_{in} - V_{jn}) \tag{3.10}$$

The random variable x follows a logistic distribution means that it has the following distribution function and density function.

$$F(x) = P(X \leq x) = \frac{1}{1 + e^{-(x-\mu)/\gamma}} \tag{3.11a}$$

$$f(x) = F'(x) = \frac{e^{-(x-\mu)/\gamma}}{\gamma(1 + e^{-(x-\mu)/\gamma})^2} \tag{3.11b}$$

Maximum Likelihood Estimate

The core idea of maximum likelihood estimation (MLE) is for random variables X, if event $X = x_1, X = x_2, \ldots, X = x_n$ has observed the probability distribution of X should be such that the probability of these events occurring is maximized. θ is some unknown parameter, $L(\theta)$ is the likelihood of the event occurred, $f(x_i, \theta)$ is the density function of X_i. Thus the main goal is to find the parameter θ, which can make the value of $L(\theta)$ maximum(Small 1987).

$$L(\theta) = P(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = f(x_1, \theta) \times f(x_2, \theta) \ldots f(x_n, \theta) = \prod_{i=1}^{n} f(x_i, \theta) \tag{3.12}$$

Binary Logit Model

Gumbel distribution

The Gumbel distribution is an extreme value type distribution that is often used to estimate and predict extreme events. Its probability density function (PDF) can be expressed as:

$$f(x,\ \mu,\ \beta) = \frac{1}{\beta} e^(-z - e^{-z}),\ z = \frac{x - \mu}{\beta} \tag{3.13}$$

If the random variables ϵ_{in} and ϵ_{jn} both obey the Gumbel distribution and ϵ_{in}, ϵ_{jn} are independent of each other, then $\epsilon_{in} - \epsilon_{jn}$ obeys the Logistic distribution. According to euqation:

$$P_n(i) = P(U_{in} > U_{jn}) = P(V_{in} + \epsilon_{in} > V_{jn} + \epsilon_{jn}) = P(\epsilon_{jn} - \epsilon_{in} < V_{in} - V_{jn}) \tag{3.14}$$

$(\epsilon_{in}) - (\epsilon_{jn})$ then obeys a logistic distribution with parameters 0 and 1. The distribution function and density function corresponding to the standard logistic distribution are(Marschak et al. 1959):

$$F(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{1 + e^x} \tag{3.15a}$$

$$f(x) = \frac{e^x}{(1 + e^(-x))^2} \tag{3.15b}$$

By fusing the two equations, the essential expression for BNL is obtained as follows.

$$P_n(i) = P(\epsilon jn - \epsilon in < V_{in} - V_{jn}) = F(V_{in} - V_{jn}) = \frac{1}{1 + e^{-(V_{in} - V_{jn})}} \tag{3.16}$$

Furthermore, the probability that decision-maker n chooses alternative i is:

$$P_n(i) = \frac{e^{V_{in}}}{e^{V_{in}} + e^{V_{jn}}} = \frac{e^{\beta X_{in}}}{e^{\beta X_{in}} + e^{\beta X_{jn}}} \tag{3.17}$$

Validity

The validity of BNL is generally tested by the likelihood ratio statistic Ω , which compares the relative magnitude of the likelihood value of a model containing only constant terms ($L0$) with the likelihood value of a model containing all explanatory variables and constant terms (L). The test formula is as follows.

$$\Omega = -2(lnL0 - lnL)\tilde{}X^2(K - 1) \tag{3.18}$$

The Ω statistic follows an X^2 distribution, and its degree of freedom $(K-1)$ is the difference between the number of parameters of the current model and the number of parameters in the model containing only constant terms.

Goodness of fit

$pseudo - R^2$

The most common goodness-of-fit metric used to determine the logit model is $McFadden'sR^2$, or $pseudo - R^2$.
The formula for calculating this indicator is as follows.

$$McFadden'sR^2 = 1 - (lnL/lnL0) \tag{3.19}$$

In comparing the relative magnitude of the likelihood value of the model with only constant terms ($L0$) and the likelihood value of the model with all explanatory variables and constant terms (L).

In general, the index of $McFadden'sR^2$ generally reaches 0.2 or above to indicate a good fit, but if the practical application is focused on the analysis of impact factors, it is not necessary to pay too much attention to this index.

AIC and BIC

The smaller the AIC and BIC, the better the fit of the model, and these indicators are often used in comparing different models.

Ordered Logit Model

The Ordered Logit Model is a derivative of MNL. The alternatives in the Ordered Logit Model are not 0 or 1 like BNL, nor are they completely unrelated like MNL. Rather, they are ordered. See the next subsection on MNL for the detailed derivation process(Small 1987).

When these dependent variables with ordinal order are analyzed by unordered logit models (polynomial logit models, stochastic parametric logit models, latent category logit models, etc.), the ordinal order of the dependent variables cannot be taken into account, which will result in a part of information loss, and therefore an ordinal discrete choice model should be used for such problems.

First construct a latent variable of continuous type y_i^*:

$$y_i^* = x_i'\beta + \varepsilon_i \ with \ i = 1, 2, \ldots, n \tag{3.20}$$

Similarly, the relationship with the dependent variable y_i is constructed through a segmentation function:

$$y_i = \begin{cases} 1 & y_i^* \le r_1 \\ 2 & r_1 < y_i^* \le r_2 \\ \cdots\cdots & \\ j & r_{j-1} < y_i^* \le r_j \\ J & y_i^* \ge r_J \end{cases} \tag{3.21}$$

j: The value of the dependent variable

J: Max dependent variable value

$r_1 \le r_2 \le r_j \le r_J$: intercepts

Parallel test

Ordinal logistic regression, which needs to satisfy the proportional odds assumption (i.e., the parallel test score test for the proportional odds assumption). Some argue that the cumulative ratio model is not sensitive to this condition, i.e., the parameter estimates remain stable when the condition does not hold. Some argue that the proportional odds assumption is not satisfied, suggesting that the data are not suitable for the cumulative ratio logit model and may yield biased estimates, and should be replaced by other models such as the biased proportional odds model for analytical validation. Some argue that the classification of the dependent variable is appropriately combined and the number of values of the dependent variable is reduced. Some argue that the parallel test is not met, and the correct fitting function is chosen; it is treated according to the unordered logistic regression(Long and Freese 2006)(Agresti 2003)(T. F. F. Liao and T. F. Liao 1994).

Multinomial Logit Model

In BNL, decision-maker n will have two alternatives to choose from, either selected or unselected. In MNL, decision-maker n will have K alternatives to choose from $(K \ge 3)$. Then the probability of decision-maker n choosing alternative i can be expressed as the following equation.

$$P_n(i) = P(U_{in} > U_{kn}), \forall k \ne i \tag{3.22}$$

Because the random component ϵ are independent of each other, which is the IIA characteristic of MNL. The above equation can be converted as follows:

$$P_n(i) = \prod_{k \ne i} P(\epsilon_{kn} < \epsilon_{in} + V_{in} - V_{kn}) \tag{3.23}$$

Bringing this into the Gumbel distribution, the following equation can be obtained.

$$P_n(i) = \int \left(\prod_{k \neq i} e^{-e^{\epsilon_{in} + V_{in} - V_{kn}}} \right) \times e^{-e^{\epsilon_{in} + V_{in} - V_{in}}} \times e^{-\epsilon_{in}} d\epsilon_{in} = \frac{e^{V_{in}}}{\sum_k e^{V_{in}}} \tag{3.24}$$

The deterministic component is represented as a linear combination of a series of variables.

$$V_{in} = \beta_0 + \beta_1 x_{1n} + \cdots + \beta_n x_{pn} \tag{3.25}$$

The final common form of MNL is obtained.

$$P_{ni} = \frac{e^{\beta_i X_{in}}}{\sum_{j=1}^{J} e^{\beta_j X_{jn}}} \tag{3.26}$$

4 Case Study

This chapter begins with an introduction to the survey method, the survey site, and a brief description of Wuhan City, and then introduces the Chinese and foreign data on gender differences in EH. The chapter then introduces the Chinese and foreign data on gender differences in EH, as well as the data obtained from our own survey. By using the methods from the previous chapter, the final modeling analysis study is conducted and the model is evaluated.

4.1 E-hailing market in Wuhan

Wuhan, one of China's mega-cities and the largest city in central China, is the political, economic, financial, commercial, logistical, scientific, cultural, and educational center of the central region and a transportation and communication hub. Wuhan covers an area of 8,569.15 square kilometers, nearly 10% of which is covered by water systems. Two of China's major rivers divide the entire city of Wuhan into three, which creates a complex traffic situation in the city. As the city with the most extensive rail, air, and road hub in China, Wuhan has always been the most critical place for transportation in China. All the data sources used in this section are from the 2019 Wuhan Transport Development Annual Report from Wuhan Bureau of Natural Resources and Planning and Wuhan Institute of Transportation Development Strategy(Wuhan Bureau of Natural Resources and Planning and Wuhan Institute of Transportation Development Strategy 2019).

4.1.1 Transportation in Wuhan

According to the 2019 Wuhan Transport Development Annual Report from the Wuhan Bureau of Natural Resources and Planning and Wuhan Institute of Transportation Development Strategy, compared to 2018, the land for transportation facilities increased by 14.7% across Wuhan. As of 2017, the road area per capita in Wuhan reached 12.3 square meters.

In 2018, Wuhan's number of motor vehicles had reached 3.126 million. Among them, the motor vehicle ownership in the main urban area alone has taken up 70% of the total. Wuhan has not yet achieved its goal of being a polycentric city. According to 2018 data, the total road mileage in Wuhan reached 16,400 km, including 720.3 km of expressways, and the road network density reached 195 km per 100 square kilometers. Due to Wuhan's particular geographical shape of two rivers and three districts, river crossing traffic remains essential. Wuhan administrative district is divided into 13 administrative regions as shown in the figure(4.1) below, and the whole city is divided into three large sections by the two rivers. As of 2018, Wuhan has 18 bridges and two river-crossing tunnels. In 2018, Wuhan completed about 2.83 billion passenger trips on public transportation for the year. Indicators such as the number of public transportation modes and their corresponding lines are 550 bus lines (one of which is a BRT line), three tram lines, 14 customized bus lines (customized bus city a new mode of bus service, according to the time and station predetermined by passengers, regular pick-up and drop-off, belonging to the mode of Vanpooling), with nine rail lines, 15 Rail lines are still under construction.

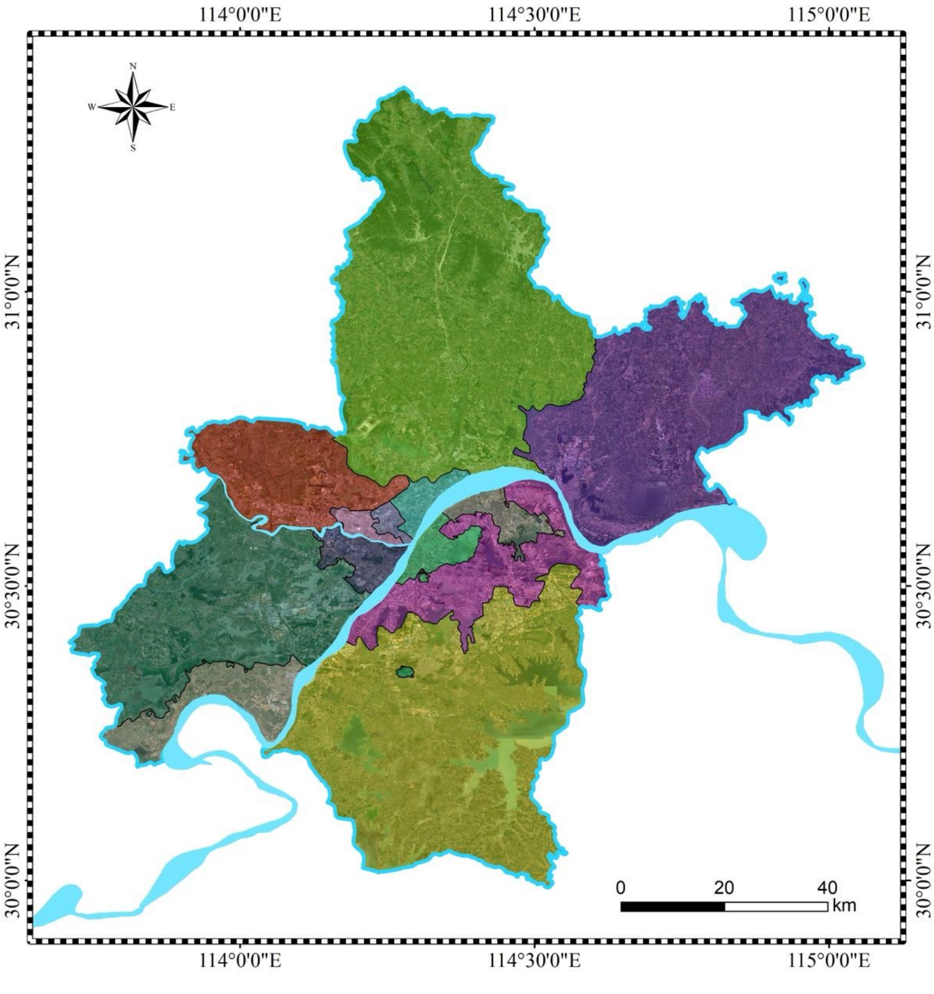


Figure 4.1: Map of Wuhan and the division of administrative areas

4.1.2 E-hailing industry

China's E-hailing market began a decade of prosperity and dramatic changes with the entry of Yidao Company in 2010 as a symbol. In 2012, Kuaiche was established, in the same year the famous DiDi entered; in 2014, American companies entered the Chinese E-hailing market to get a share of the pie, and in 2015, Shenzhou was established. At this point, the exploration period of the China E-hailing market is over.

The year 2015 to 2016 was a launch period for the E-hailing market in China. At the beginning of the year, DiDi annexed Kuaiche, more new companies entered the market, and Shouqi went into the pool as a government company providing E-hailing services. At the end of year 16, DiDi took over Uber's business line in China. At this point, DiDi's almost monopoly was officially in place. The next seven years of rapid growth saw more companies launch E-hailing business lines. As of May 21, 2021, Wuhan has at least 18 E-hailing platforms. According to JiGuang Data's forecast, the beginning of 2025 is the maturity period of the E-hailing business (JiGuangg BigData 2019).

Figure 4.2: E-hailing platforms in Wuhan

According to the survey report of Yiguan analysis (analysis 2019), the usage of E-hailing in China in 2020 is shown in the figure below. February, March, and April were the three months when the Covid-19 epidemic hit China. In response to the national call, the people of Wuhan stayed at home for a full 76 days. Residents of many other cities in China have also reduced their travel accordingly. Therefore, a clear trough can be seen in the corresponding position on the graph(4.3). Subsequently, the number of people using E-hailing gradually rebounded.

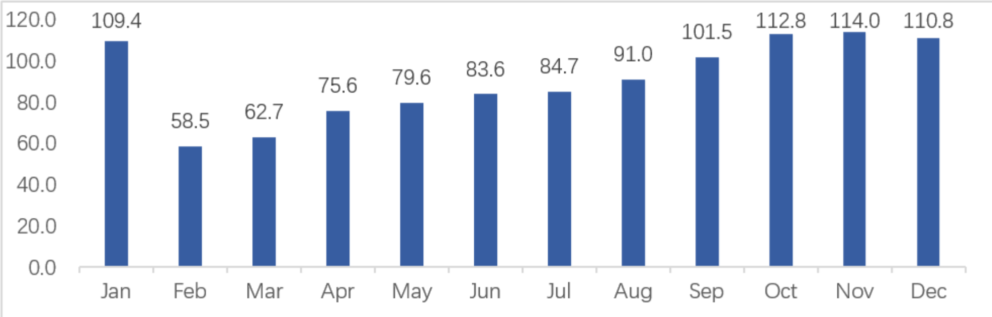


Figure 4.3: Volume of active users on mainstream platforms in 2020 (unit of y-axis is million)

4.1.3 Gender differences in E-hailing

Gender disparity in the E-hailing industry has a long history. It manifests itself in two main ways: gender inequality in the group that provides the service and gender imbalance in the group that receives the service. As described in subsection(2.2), many female drivers cannot join the E-hailing industry because of family opposition for safety or religious reasons and because of their safety concerns or lack of pay (compared to male drivers). An Uber study spanning the years 2017 to 2020(Uber 2020) shows that in recent years, globally, the ratio of male to female drivers in the E-hailing industry has improved somewhat. From twice as many male drivers as female drivers in 2017 to nearly 3 to 2 male drivers over female drivers in 2020. As shown in the figure(4.4) below.

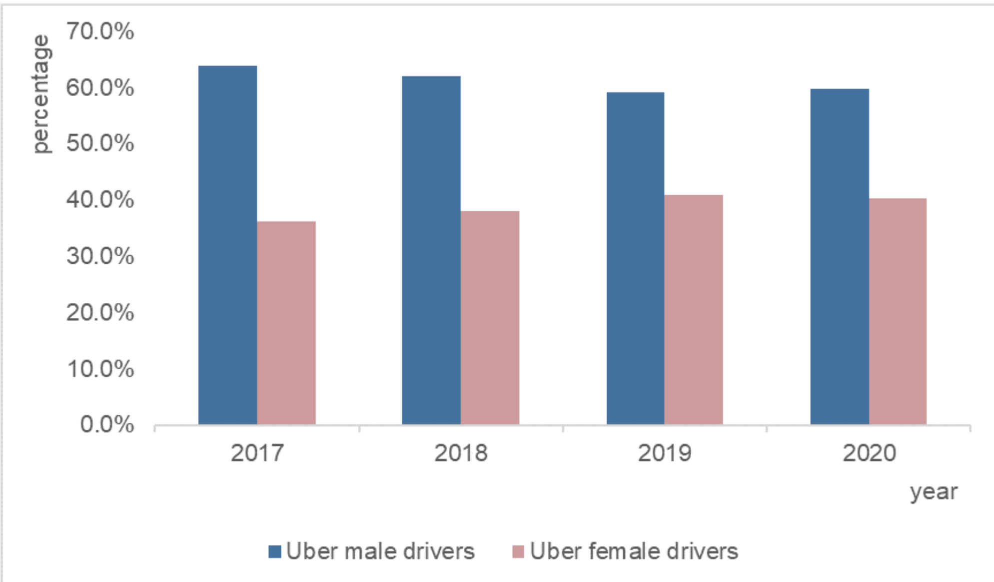


Figure 4.4: Change in the ratio between male and female Uber drivers from 2017 to 2020

A similar theme, however, plays out very differently in China. In 2018, DiDi, the Chinese ride-sharing company that captures over 87% of the market share(Statista 2021), had only 10% of female drivers (DiDi Chuxing 2018). In 2018, there were only 100,000 female drivers on the DiDi platform in Wuhan.

From a user perspective, gender differences in E-hailing are not as pronounced as the gender imbalance in the service group. Data provided by two data companies in China reveals that in 2017, E-hailing reached almost 60% of male users and only 40% of female users(JiGuangg BigData 2019). However, in 2019, the difference in this value became even more pronounced, with the ratio of men to women to almost 63% to 37% (analysis 2019). This phenomenon is extraordinary because, in 2018, DiDi introduced a series of protection measures for female drivers and users (chuxing 2018). The gender gap in this industry, however, is much more significant. The main reason for this, according to some scholars (He et al. 2020), is the series of crime time incidents against E-hailing female users that occurred during these two years. The specific crimes will be discussed in the following subsection.

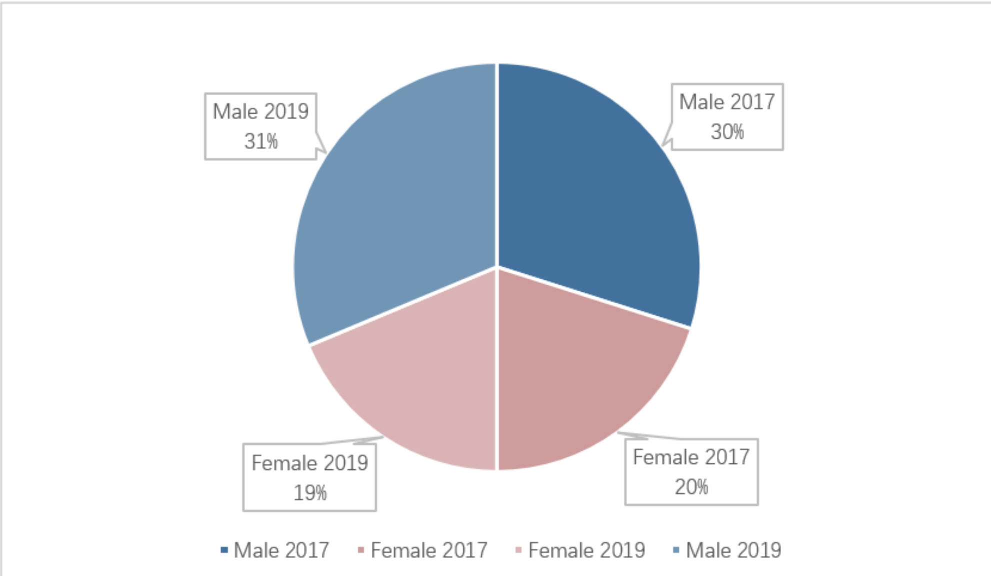


Figure 4.5: Change in the ratio between male and female users of E-hailing in 2017 and 2019

Gender-based violence

At the beginning of 2018, the safety issue of E-hailing was brought to the forefront. According to Weibo, the largest social media site in China, from 2017.5.18 to 2021.7.13, online ride-hailing has been on the hot search list 244 times, and 44 of those cases were linked with safety concerns (sexual harassment, inappropriate physical contact, rape, murder, etc.). According to a crime report released by Uber, 3,045 of its ride-related sexual assaults occurred in the U.S. from 2017 to 2018 (Uber 2018).

Furthermore, in China, according to the most authoritative Chinese media reports, there have been at least 50 malicious incidents related to E-hailing by the end of 2018. All of the victims were women (CCTV 2018).

4.2 Survey conduction

This survey was carried out online and offline simultaneously, which both lasted four months from August to December in 2021. The online questionnaire distribution platform is a Chinese professional online survey platform called WenJuanXing (https://www.wjx.cn/).

The offline, face-to-face interviews were conducted to ensure the equilibrium of the experimental data. Sampling was conducted simultaneously in five locations. Wuhan's largest railway station, residential neighborhoods in the city center, residential neighborhoods on the edge of the city, large public squares, and shopping mall entrances. The specific locations are shown in the figure(4.6) below.

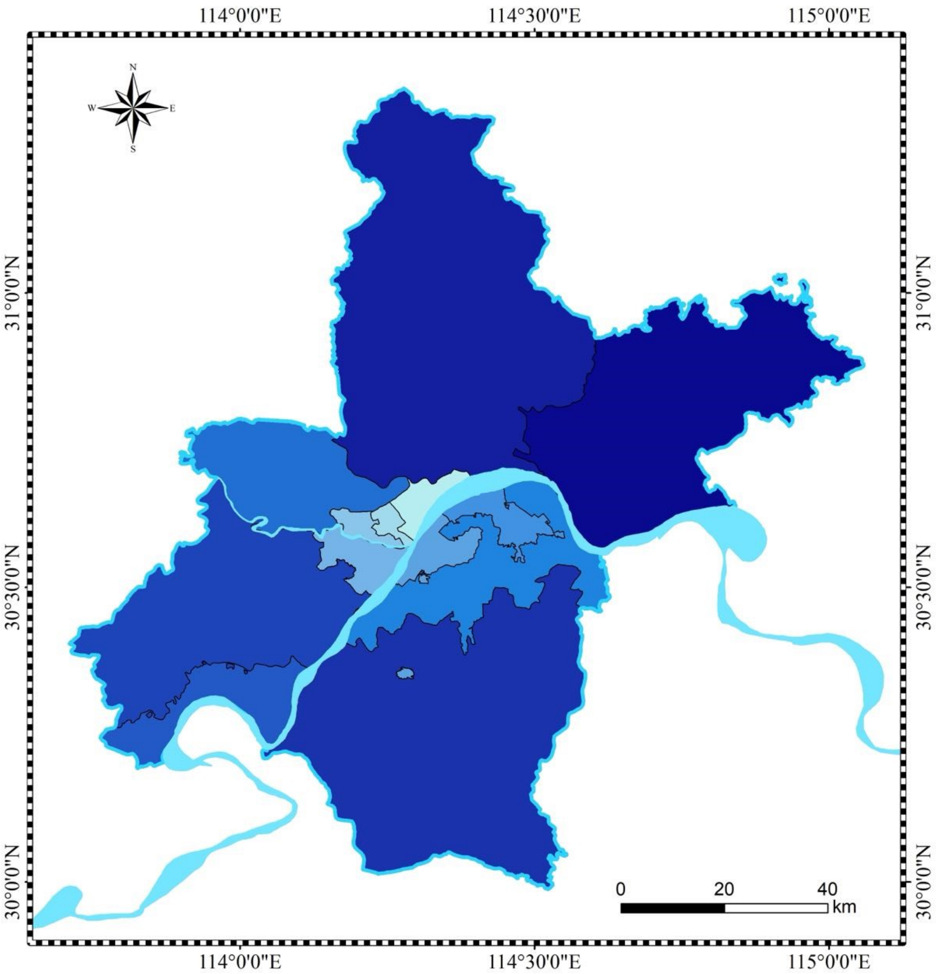


Figure 4.6: face-to-face interview survey spots (pink dots)

Pilot survey
After the questionnaire design was completed, it was sent to three friends who are transportation majors, one undergraduate, one graduate student, and one Ph.D. student to answer and give advice. And ten respondents from non-transportation majors. Five were male, five were female, two were older respondents collected offline, four were company employees aged 40-60, and four were younger. After listening to their opinions, some unclear expressions were revised, and explanations were attached to vague concepts. For example, the regulation appended notes on the concept of family and the number of generations under the related questions. Some icons were added to increase view-ability and pictorial explanations. Please see the appendix for the finalized questionnaire.

4.3 Data analysis

4.3.1 Socio-demographic variables

A total of 1346 responses were received, and after data cleaning was completed to remove samples that did not meet the consistency criteria, 1054 responses remained, the socio-demographic variables table is shown in Appendix B Table(B.4).

The values of the socio-demographic variables obtained from the survey are compared with the values of the statista portrayal of Di users in the Chinese market in 2021(Statista 2021). This will assist in verifying the correctness of the values for Wuhan.

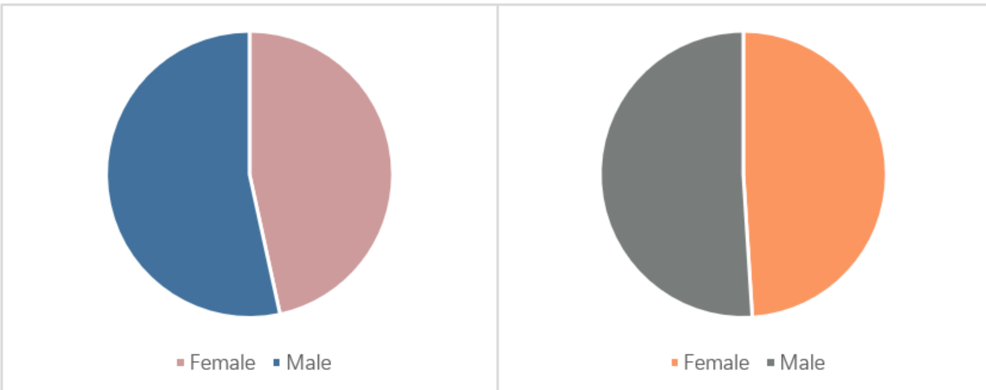


Figure 4.7: The gender ratio of E-hailing users in Wuhan region obtained from the survey(left)/The gender ratio of DiDi users in China by statista(right)

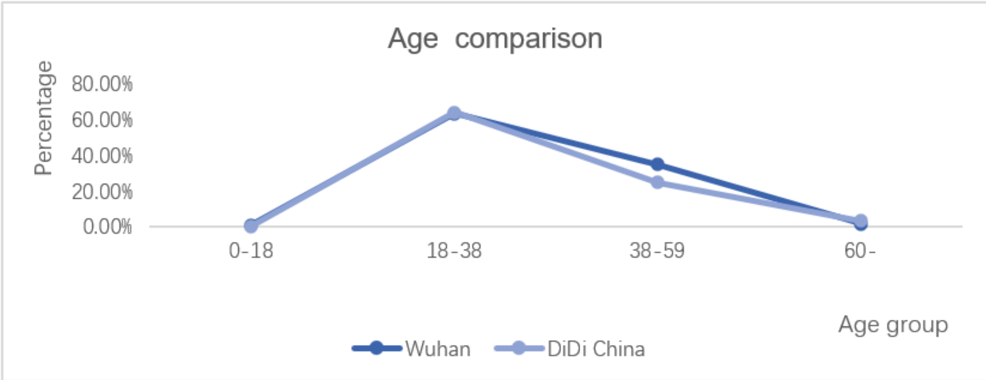


Figure 4.8: Surveyed data from Wuhan and DiDi China of age group distribution

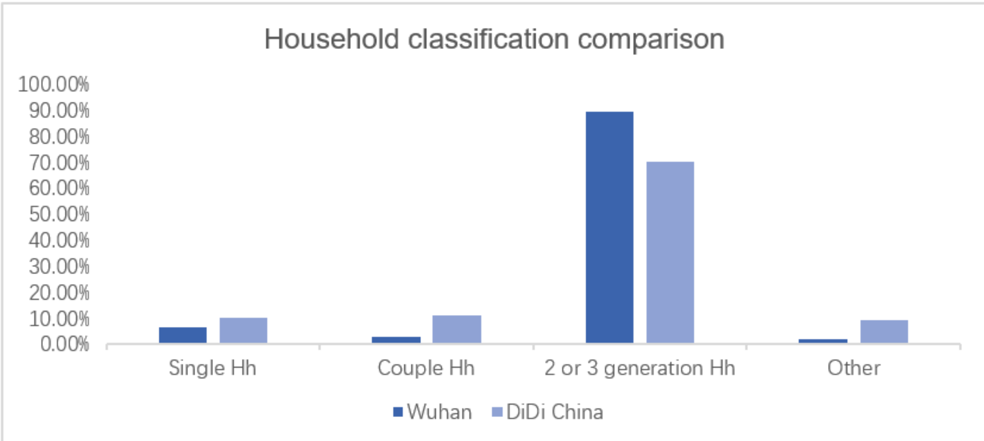


Figure 4.9: Surveyed data from Wuhan and DiDi China of household classification

From the comparison of the three charts above, it can be found that there is a high degree of similarity between the data obtained from the questionnaire using Wuhan as the scope of the study and the data obtained by statista from Chinese DiDi users through the questionnaire. Thus, it shows that the survey data is valid.

4.3.2 Travel behavior

The second part of the questionnaire investigates the travel behavior of the respondents, which was divided into two parts, travel mode and travel purpose. A total of six travel purposes and six travel modes are set. As in Figure(4.10) survey structure.

Table 4.1: For each travel purpose, the percentage of each travel mode

		Travel purpose					
		Work	School	Home	Entertainment	Business	Others
	PuT	30.45%	32.12%	32.65%	25.96%	30.10%	30.98%
	PrT	22.76%	15.21%	23.69%	22.19%	20.73%	19.08%
Travel mode	Walking	13.92%	22.89%	11.52%	8.99%	6.33%	9.76%
	Cycling	16.02%	18.47%	14.65%	11.38%	9.71%	12.35%
	Taxi	6.23%	4.42%	6.12%	11.44%	13.70%	9.99%
	EH	10.62%	6.89%	11.37%	20.05%	19.43%	17.85%

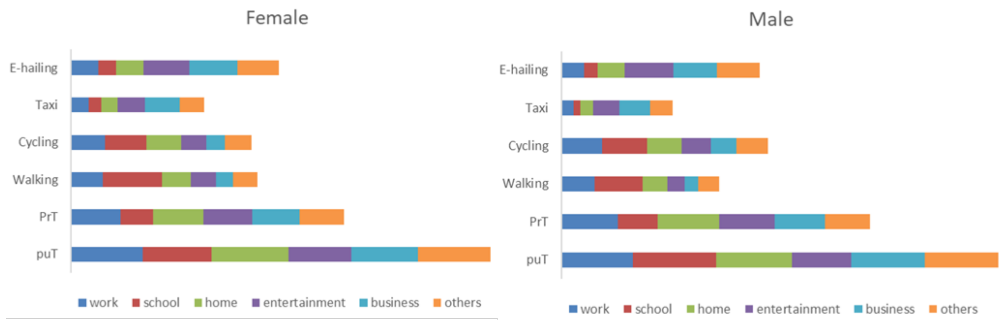


Figure 4.10: Distribution of travel purpose and travel mode by gender

Using gender as the classification rule, we get the different transportation modes used by females and males separately for different travel purposes, as shown in the Figure above. A clear difference is that men are less likely to walk and use a personal vehicle. In the case of E-hailing, it is clear that female users use E-hailing to get to school more often than male users.

4.3.3 E-hailing usage

Part three of the survey questionnaire is about E-hailing usage; the questions are asked from five aspects, as shown in Figure (4.10).

Frequency of using E-hailing
The Figure below reveals that regardless of gender, nearly half of the respondents use E-hailing several times a week, which is still a high frequency of use. Nearly 20% of respondents use E-hailing services almost every day, making them heavily dependent on E-hailing services.

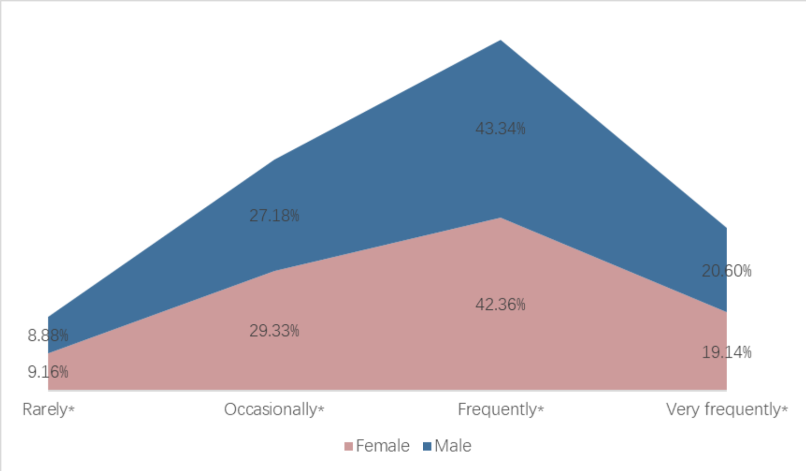


Figure 4.11: Frequency of using E-hailing by gender

*Rarely used: a few times a year
*Occasionally use a few times a month
*Frequently used: several times a week
*Very frequent used: almost every day

Satisfaction with E-hailing service

In order to better grasp the user's overall satisfaction with the E-hailing service, it is necessary to ask the user a general perception about the E-hailing service before asking follow-up risk perception questions. The 7-point Likert scale was selected for the options. For specific reasons for selecting the 7-point Likert scale, please see section(3.1.3).

According to the survey data, it can be concluded that the majority of the population take the positive attitude of neutral level and above for E-hailing services. The share of men who find E-hailing services either very satisfying or unsatisfying is much larger than that of women who make the same choice.

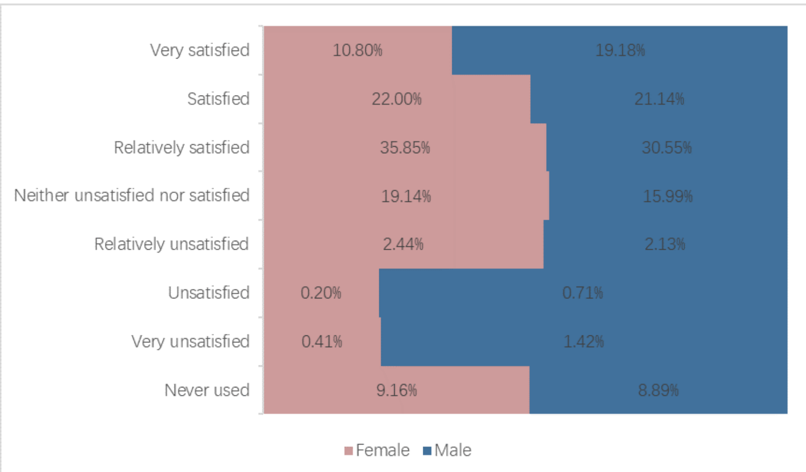


Figure 4.12: Users' satisfactory of current E-hailing service by gender

E-hailing using situation
The difference between this question and the travel purpose in travel behavior is that this question does not focus on other travel modes but only on the travel scenario for E-hailing. For those who use E-hailing, 21.33% of the population uses it for their daily commute home. Nearly 42% of respondents said they use E-hailing for their relaxation and entertainment needs; they use it under shopping, dining, visiting friends and family, and entertainment situations.

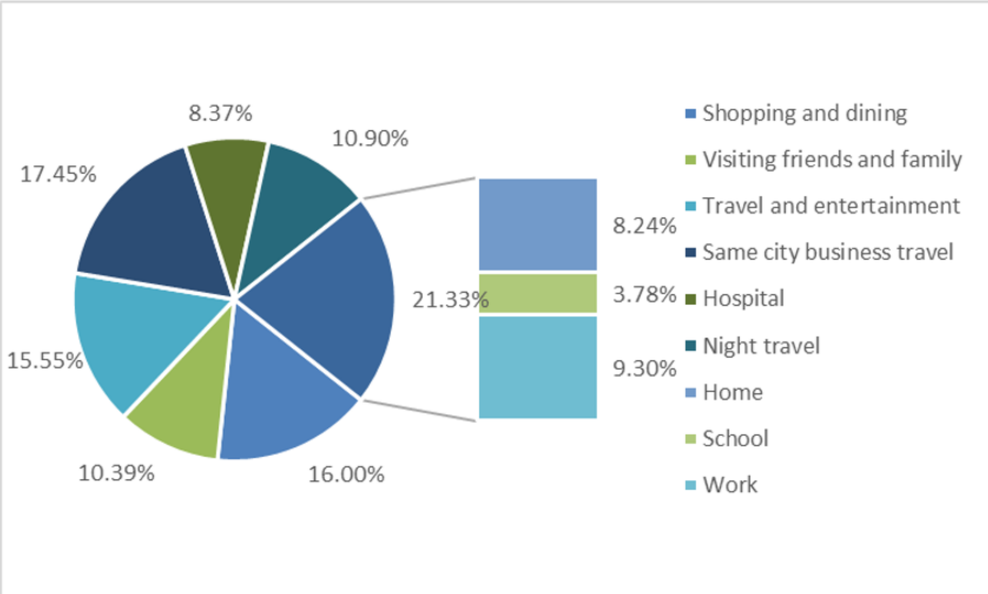


Figure 4.13: E-hailing using scenarios

Reasons that hinder the use of E-hailing
For those who have used E-hailing services, there must be a reason why they use E-hailing less frequently. Likewise, for those who have never used the E-hailing service, there are reasons why they have rejected using E-hailing.

The data cited here shows gender differences in the reasons for not using E-hailing. More than 30% of female users do not use E-hailing because of safety concerns, and more than 30% of men do not use E-hailing because of the price factor. Longer wait times may push customers toward other modes of transportation, such as choosing to travel by public transportation or stopping at the curb for a traditional cab while waiting for an E-hailing vehicle.

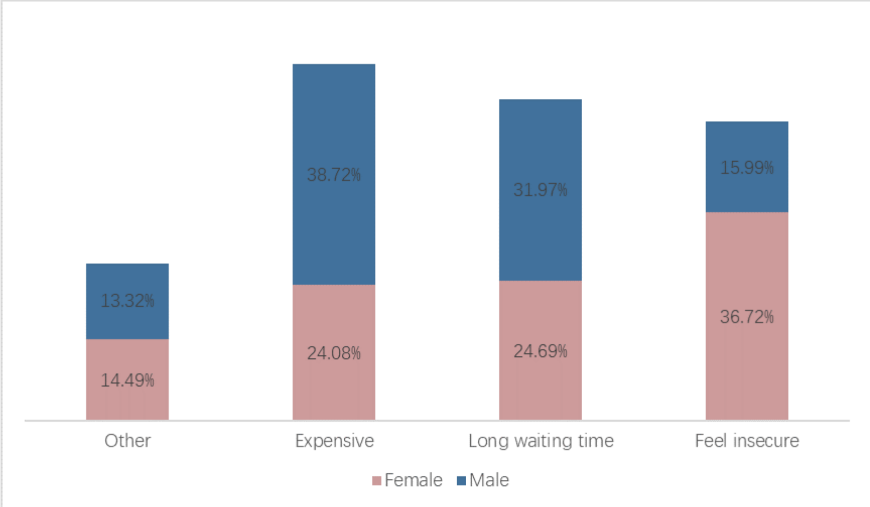
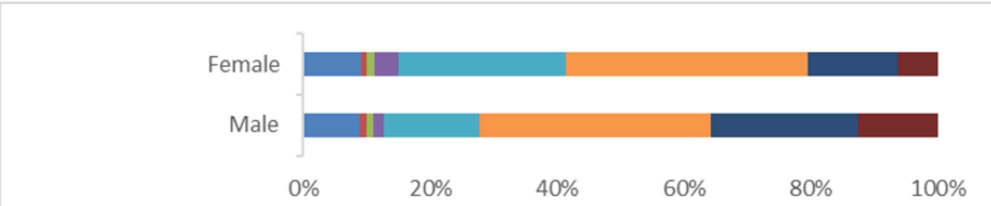


Figure 4.14: Reasons prevent users from using E-hailing

4.3.4 Risk perception of E-hailing

As the last part of the questionnaire, the fourth part, this section explores the factors that affect the perception of security of users using E-hailing and lists some of the existing protection measures, thus verifying those measures that are effective and those that could be strengthened. In order to explore the overall perceived safety of the E-hailing environment, respondents were asked to choose how safe they felt when using E-hailing.

Perceived safety when using E-hailing



	Male	Female
Never used	8.88%	9.16%
Very unsafe	1.07%	0.81%
Unsafe	1.07%	1.22%
Relatively unsafe	1.78%	3.87%
Neither unsafe nor safe	14.92%	26.27%
Relatively safe	36.59%	38.29%
Safe	23.27%	14.05%
Very safe	12.43%	6.31%

Figure 4.15: Perceived safety when using E-hailing by gender

The perceived safety of the E-hailing environment is viewed by gender grouping. It can be judged that although most of the respondents, both male, and female, feel that the E-hailing environment is relatively safe. However, when the focus falls on the range of perceived insecurity of E-hailing by gender, it can be seen that the percentage of female respondents is much higher.

More vulnerable group in E-hailing

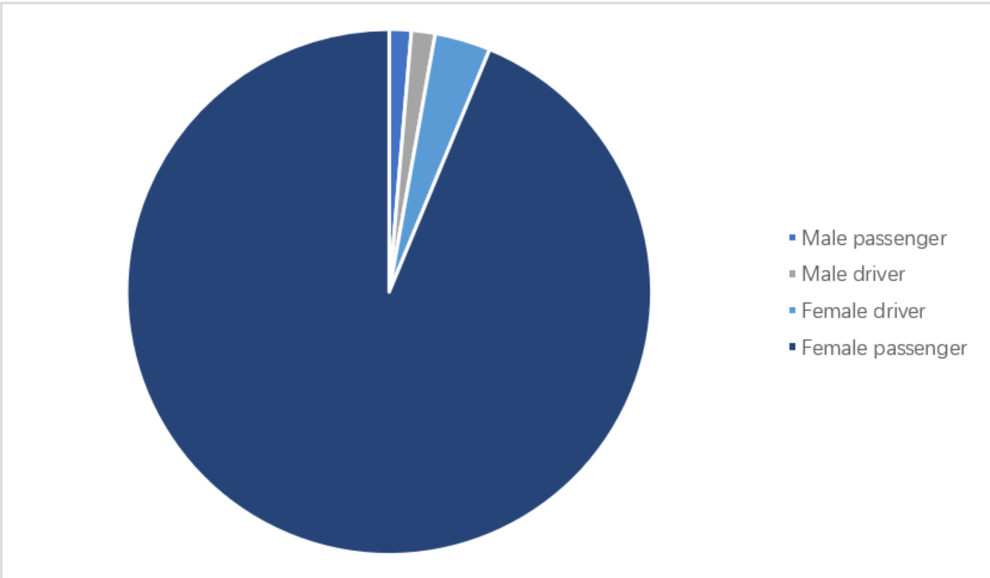


Figure 4.16: More vulnerable group in E-hailing

On the question of which group is more dangerous and vulnerable in the E-hailing environment, female passengers are overwhelmingly the most dangerous group in the E-hailing environment.

Risk perception

For the other risks perceived by users, these are classified according to the criteria from the literature(L. Ma et al. 2019) into five categories: Physical risk, Financial risk, Functional risk, Psychological risk, and Trust in the driver. The specific questions are shown in the table(4.2) below.

Table 4.2: Risk perceived factors

Factor	Measure items
Financial Risk	I am worried about my property security by using E-hailing service.
Functional Risk	I have encountered more male drivers than female drivers.
Physical Risk	I am worried about encounter traffic accidents when using E-hailing.
Psychological Risk	Using E-hailing service is relatively dangerous for personal safety.
	Female drivers are less likely to be physical threat than male drivers.
	I will be more nervous when using E-hailing alone.
	I feel insecure when using E-hailing after 10pm.
Trust in Driver	I will check the navigation route when using E-hailing.
	I will check the driver's rate before I get in the E-hailing car.
	I will inform my friends or family before or during the trip with E-hailing.
	I am worried about the driver might violate the traffic lows.
	I am worried about some inappropriate actions from the driver.
	I am worried about the harassment, insults and physically threatening behavior from the driver.

The topic of E-hailing safety has been very much in the limelight since 2018. Over the years, many regulations and protection measures, guardianship measures, and penalties have come out accordingly. Regulatory protections include, for example, drivers must be licensed, must be registered, must be dedicated to a specific vehicle, must not use another person's license plate, the driver-car-license trio must match exactly, and so on. Monitoring measures are mainly installed in the vehicles providing E-hailing services, such as surveillance cameras, cell phone app background monitoring to sensitive words during the service period, etc. Punitive measures are also introduced; for example, the driver rating system from the platform is connected to the owner's income; once there are serious bad reviews complaints, the driver may be forced to stop taking orders and other measures. Protection measures are implemented mainly from the passengers. For example, many E-hailing platforms now provide a one-click alarm function, real-time positioning sent to friends or family members, and the function of early and immediate termination of the trip to inform the background platform. Does the presence of these measures or regulations improve respondents' sense of security in the E-hailing industry or not? It is another element that this thesis would like to discuss.

Measures to be taken in the face of risks

Respondents were asked to answer what measures they would most likely take in encountering the various risks mentioned in the previous subsection.

21.47% of respondents said they would call the police as a priority, followed by 18.1% who would choose to complain to the platform, 18% who would notify friends or family for help, and nearly 18% who said they would end their trip early. As shown in the below figure(4.17).

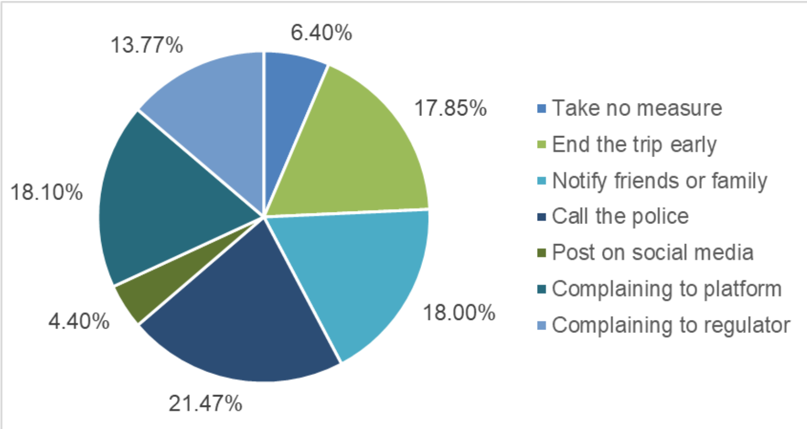


Figure 4.17: Measures to be taken in the face of risks

Perception of malignant accidents
Respondents were asked to answer whether, in their impression, they agreed that the frequency of crimes against women in the E-hailing industry was high over these years. (i.e., the number of times is high?) Furthermore, whether their perception of these incidents would influence their subsequent choice of E-hailing service. The responses to the two questions were given on a 7-point Likert scale, which allowed respondents to correspond their feelings to the corresponding level in the scale, described by words—shown as follows.

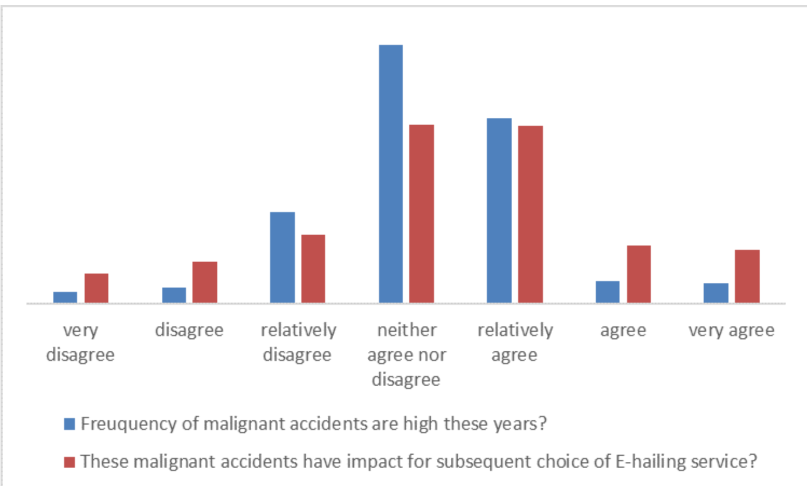


Figure 4.18: Perception of malignant accidents

The summary percentage table according to gender for all the survey data is shown in Appendix B Table(B.5).

4.4 Data preparation

Data cleaning

The cleaning process revealed that the data obtained had some conflicting options for a few respondents. For example, in the question "Have you ever used E-hailing," the respondents chose never used of E-hailing service, and in the question "Please choose the frequency of your usage of E-hailing," they choose "Frequently used." In this case, the questionnaire was considered invalid. Of the 1346 questionnaires obtained, 132 had similar problems.

Some other similar inconsistent questions and the reasonable answers are listed below:

Table 4.3: inconsistent questions and the reasonable answers

Previous Questions and choice of answer	Later Questions and choice of correct answer
Household kid amount: >= 1	Household generation: >= 2-generation family
Travel mode: Private vehicle	Household Vehicle amount: >=1
Have you ever used of E-hailing service: No	Frequency of using E-hailing: Never used
Measures you would take when facing the listing safety hazards: Complaining to affiliated company or regulator.	Frequency of your complaining to corresponding company or regulator: Options other than Never complained.

Creating dummy variables

Using the *dummyVars*() function in the caret package in *R*(Kuhn et al. 2021) can be used to create a series of dummy variables. If all the variables are put in one table. Before generating dummy variables, there are 25 variables in total, but after the step of generating dummy variables, there are 100 variables in total.

Mistakes and missing value

As stated in subsection(3.3) above, some of the incorrectly selected values can be converted to some apparent number of marked nature, such as -3, by the *mutate*() function in the tidyverse package (Wickham et al. 2019b), while other missing values due to other reasons, such as leaving the page without finishing the whole survey, missing selections, etc., in the data preparation phase before each model estimation process, it is been removed using the *drop_na*() function.

Spot outliers

In this questionnaire, most of the questions are discrete categorical variables. Therefore, the process of screening them for outliers was relatively simple. The following figure(4.19) shows some of the process, which filters the categorical outliers.

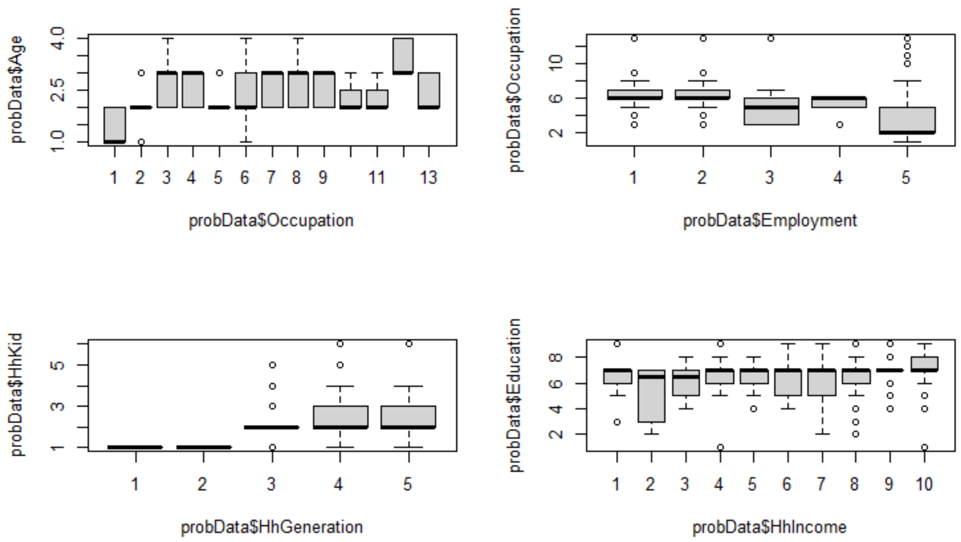


Figure 4.19: four examples of categorical outliers

Zero- and Near Zero-Variance variables

For the Zero- or Near Zero-Variance variables, the following contingency table(4.4) shows the age and frequency of E-hailing use as examples.

Table 4.4: Contingency table of Age and Use frequency of E-hailing

Age (Before)	Use frequency of E-hailing (Before aggregate)				
	Never used	Rarely used	Occasionally used	Frequently used	Very frequent used
0-18	0	4	3	2	0
18-38	39	159	303	146	18
38-59	52	130	139	42	1
60-	4	4	7	1	0
Age (After)	Use frequency of E-hailing(After aggregate)				
	Rarely used	Occasionally used	Frequently used		
Young	202	306	166		
Old	190	146	44		

Values of zero variance appear in the table, and values of near-zero variance. The measure used here combines the ages into two groups of values, a younger group of 0-38 years old and an older group of 38 years old and above. The underuse frequency groupings were aggregated into three groups: rarely used, occasionally used, and frequently used.

Multicollinearity

The procedure for testing for Multicollinearity for variables in each model is described in subsection(3.3) below. The $vif()$ function from the car package is used (Fox and Weisberg 2019).

4.4.1 Correlation test

Because continuous variable data were not gathered in this thesis questionnaire, the Spearman correlation coefficient was utilized to assess the data's correlation.

Socio-demographic Variables

The first category comprises sociodemographic data that may be considered ordinal categorical variables: gender, age, occupation, employment status, education level, household income, household generation number, household kids number, household vehicle amount, living area, and the corresponding accessibility. The variables were arranged ascendingly, and the correlations between them were estimated using the complot package (Wei and Simko 2021), with the method argument chosen as spearman.

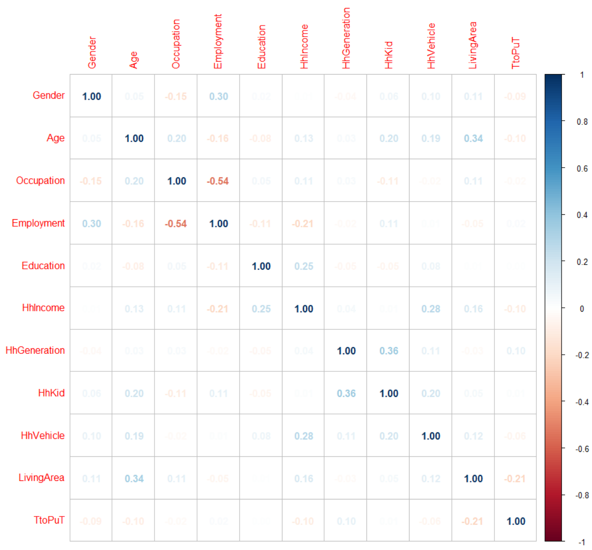


Figure 4.20: Socio-demographic Variables Correlation Coefficient

According to the above graph, there is a relatively strong correlation between occupation and employment status, but it does not exceed 0.6, so there is no need to do much processing. However, the negative correlation between these two variables is reasonable, meaning that the higher the occupation level, the more stable the respondents' employment status, and the less likely they are to be short-term workers or temporary workers. There is indeed some correlation between these two variables, even if from the logical aspects. Other variables, such as the correlation between household kid number and household generation number and household income and education level, are very weak. Therefore, these variables are used in the subsequent modeling process.

E-hailing Usage Variables

Performing the same procedure for the variables related to E-hailing usage yields the following results.

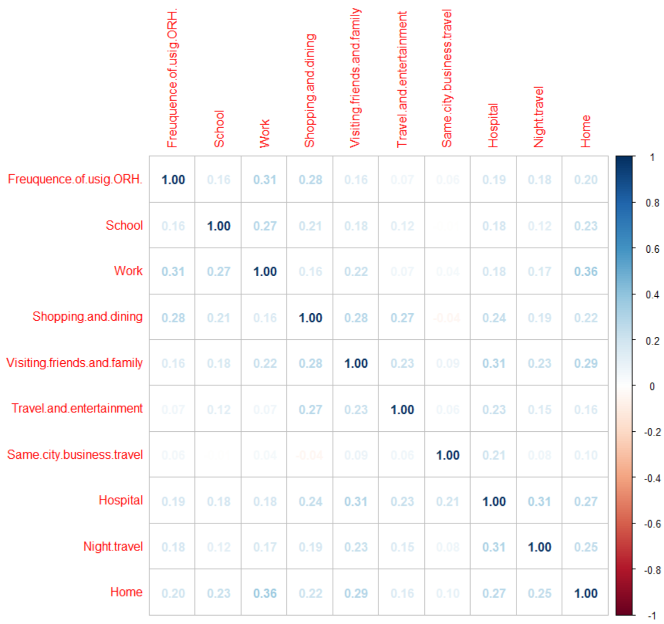


Figure 4.21: E-hailing Usage Variables Correlation Coefficient

4.5 Model estimation

Following the research methodology given in Chapter 3, this chapter demonstrates the models' estimating process and the estimated models' coefficient interpretation.

4.5.1 User Profile

Binary Logit Model

In order to test the correlation between the independent variables, the model is fitted several times; the first time is simple binary logistic regression, also called univariate logistic regression, and then in multivariate binary logistic regression. If the odds ratio of each variable is similar, it means they are independent of each other.

Dependent Variable The first step in developing the model was to define the dependent variable.

E-hailing choice: This dependent variable is a binary variable, where 0 means never used the E-hailing service, and one means used the E-hailing service. The task of this model is to find out whether there are group differences in the use or non-use of E-hailing services and, more importantly, whether there are gender differences.

Table 4.5: E-hailing choice Binary Logit Model results

		95CI	
Independent variables	β	LL	UL
age: 0-38			(base)
age: 38-59	-0.979***	-1.508	-0.449
age: 60-	-1.029	-2.403	0.346
occupation: student			(base)
occupation: inferior	-0.881*	-1.800	0.039
occupation: superior	-1.437***	-2.497	-0.377
employment: long-term			(base)
employment: fixed-term	-0.164	-0.793	0.466
employment: unfixed-term	-0.694**	-1.358	-0.030
education: low			(base)
education: middle	1.790***	0.639	2.941
education: high	1.967***	0.810	3.124
education: top	2.530***	1.194	3.867
hhincome: 0-5kRMB			(base)
hhincome: 5k-10kRMB	0.236	-0.330	0.801
hhincome: 10k-RMB	1.119***	0.469	1.769
ttoput: <8min			(base)
ttoput: 8-12min	-1.017***	-1.702	-0.331

ttoput: 12-20min	-0.584	-1.331	0.163
obstruction reason: Other			(base)
obstruction reason: Long waiting time	0.978**	0.152	1.805
obstruction reason: Expensive	0.277	-0.484	1.038
obstruction reason: Feel insecure	-0.640*	-1.347	0.068
Intercept	1.699**	0.110	3.288
Observations			1,050
Residual Deviance			530.443
AIC			566.443
BIC			655.661

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficient interpretation

The table above shows the estimated coefficients of the final model. P-values are based on the robust standard errors and are not shown the specific value here but with the asterisk. The confidence interval (CI) set for each coefficient is 95%. The interpretation of the significant variables is as follows. All of the following interpretations of variables obey the principle that the other variables are considered as constant when focusing on a particular variable.

Age: Age is a categorical variable that is divided into three categories, one for below 38 years old, one for 38 to 59 years old and one 60 years old and above. The youth group (0-38 years old) is used as a reference variable. The negative coefficient indicates that the middle-aged group (38-59 years old) will have a lower probability of using E-hailing services than the youth group. The estimate coefficient of old group (60 years old and above) do not have a P-Value, which is smaller than 0.5.

Occupation: Occupation is aggregated into three levels to avoid the appearance of zero- and near zero-variance. When compared to the student population, the more advanced the career level, the less likely it is to use E-hailing.

Employment: Employment status is divided into three levels, from the most stable one long-term, to the most unstable one unfixed term. Unfixed term employee will be less likely to use E-hailing than the long-term employees. When compared to long-term employees, fixed-term employees do not show a significant likelihood of using E-hailing services.

Education: Similar to Employment above, the education level, as a categorical variable, is aggregated. Education variables were divided into low (from illiterate till junior high school), middle (from high school to specialty school), high (undergraduate) and top (master and Ph.D) categories. The likelihood of using E-hailing is lower for people with a lower education level than for people with a higher education level. Moreover, as the education level is higher, the more likely it is to use E-hailing.

Household income (HhIncome): Monthly household income is a categorical variable divided into three categories: households with less than 5,000 RMB, households with monthly income between 5,000 and 10,000 RMB, and households with monthly income above 10,000 RMB. People with higher monthly household incomes are more likely to use E-hailing than those with lower monthly household incomes. However, this is only noticeable for household monthly income higher than 10,000RMB, the difference between 0-5,000RMB and 5,000-10,000RMB household monthly income is not significant.

Accessibility (TtoPuT): TtoPuT is the variable that represents the accessibility of the respondent's daily commuting origin. It has been divided into four levels, measured by the time for walking to the nearest public transportation, less than 8 min (the reference variable), 8-12 min, 12-20min and longer than 12 min. The sign of the corresponding coefficient indicates that, when the walking time is between 8 to 12 minutes, the respondent will be less likely to use E-hailing than the one who takes less than 8 minute to walk to the nearest public transportation station.

Obstruction reason: In the obstruction reason, two reasons are proven to differ from zero significantly, Feeling insecure about E-hailing and Long waiting time. The negative sign for the estimated coefficient of reason Feel insecure indicates that the respondents who feel insecure about E-hailing services are less likely to have used E-hailing. Moreover, the positive sign for a reason Long waiting time indicates that the respondents who feel the waiting time for an E-hailing vehicle is long are more likely to have used the E-hailing service.

For the dependent variable of ever using E-hailing, the gender difference was present in the previous descriptive analysis part, but in the modelling part, it is not significant.

Goodness of fit

Multicollinearity analysis was performed on the variables retained in the model, using the $vif()$ function of the car package in R(Fox and Weisberg 2019). The results obtained are shown below. Since no variable has a VIF value greater than 5, it can be determined that there is no multicollinearity among these variables.

Table 4.6: VIF value of retained variables in BNL

Var	Age	Occupation	Employment	Education	HhIncome	Obstruction reason	TtoPuT
VIF	1.533	2.384	1.838	1.492	1.307	1.176	1.137

To analyze whether a model with predictor variables has a better fit than a model with only an intercept (i.e., a null model). The residual deviation difference between the model with predictor variables and the null model is first calculated. Then the difference in degrees of freedom between the two models is calculated to equal the difference in predictor variables, and finally, the difference in p-value is calculated. The chi-square value of 111.6353 with 20 degrees of freedom and an associated $p - value$ less than 0.001 indicates that this BNL model is generally better than the null model. This test is called the likelihood ratio test (the deviance residual is -2*log likelihood). Alternatively, the model's log-likelihood can be viewed directly, using the $logLik()$ function.

Table 4.7: Goodness of fit when comparing BNL with predictor variables and without

Diff. residual deviation	Diff. degrees of freedom	Diff. p-value	log Lik.
107.197	17	4.054091e-15	-265.222 (df=18)

It is also possible to generate diagnostic plots for judging the model's goodness of fit, as shown in the figure(4.22) below.

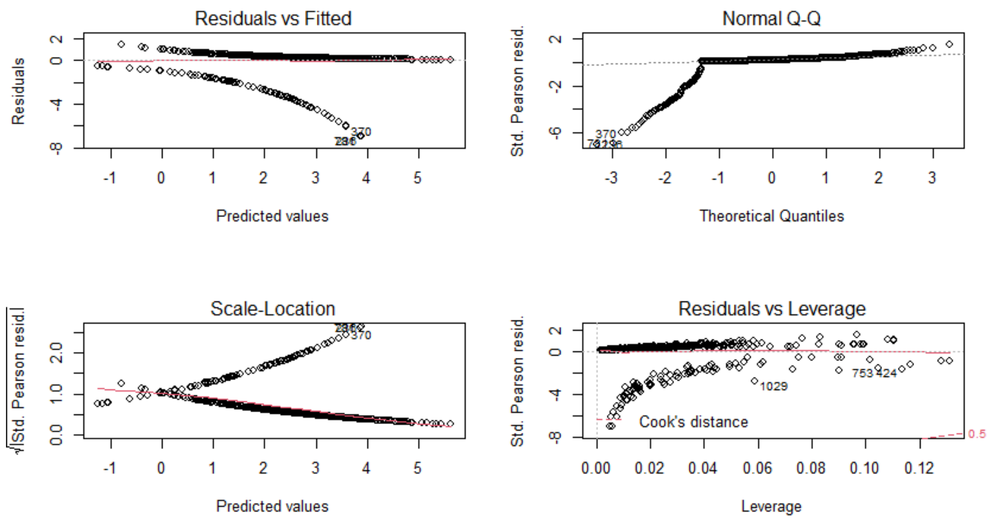


Figure 4.22: diagnostic plots for judging the BNL model's goodness of fit

Because Logit models, unlike linear models, do not have r-squared, many methods define pseudo-r-squared in measuring model superiority, here using McFadden as an example (Logit models use Maximum Likelihood Estimation).

Table 4.8: $pseudo - R^2$ BNL1: Ever used

llh	llhNull	G2	McFadden	r2ML	r2CU
-265.221	-318.820	107.197	0.168	0.0971	0.213

llh: The log-likelihood from the fitted model
llhNull: The log-likelihood from the intercept-only restricted model
G2: Minus two times the difference in the log-likelihoods ($G2 = (-2) * (llhNull - llh)$)
McFadden: McFadden's $pseudo - R^2$
r2ML: Maximum likelihood $pseudo - R^2$
r2CU: Cragg and Uhler's $pseudo - R^2$

Ordered Logit Model

Use frequency

The following three models, Use frequency, Satisfaction about E-haling, and Sense of security, are all Ordered Logit Models.

Dependent Variable The first dependent variable is the frequency of E-hailing use, which itself is a categorical variable in the order of never used E-hailing, rarely used (used only a few times a year), occasionally used (unused several times a month), frequently used (used several times a week), and very frequently used (used almost every day).

First, the respondents who never used E-hailing were eliminated because it is not the object of concern. Categorizing the dependent variable according to independent variables such as age revealed that the values under this dependent variable were minimal. The same procedure was conducted with the dependent variable, finally grouped into three factors: rarely used (a few times a year), occasionally used (a few times a month), and frequently used (several times a week).

Table 4.9: ONL1: use frequency

	Dependent variable: Use frequency				
	β	LL	UL	Std. Error	odds ratio
age: young					(base)
age: old	-0.627***	-0.898	-0.356	0.138	0.534
hhincome: 0-5kRMB					(base)
hhincome: 5k-10kRMB	0.407**	0.047	0.766	0.183	1.502
hhincome: 10k-RMB	0.550***	0.206	0.893	0.175	1.733
hhgeneration: 1-generation					(base)
hhgeneration: 2-generation	-0.699***	-1.156	-0.243	0.233	0.497
hhgeneration: >= 3-generation	-0.712***	-1.168	-0.257	0.232	0.491
hhvehicle: 0					(base)
hhvehicle: 1	-0.108	-0.414	0.198	0.156	0.898
hhvehicle: >=2	-0.392*	-0.808	0.024	0.212	0.676
obstruction reason: other					(base)
obstruction reason: Long waiting time	0.656***	0.250	1.062	0.207	1.927
obstruction reason: Expensive	0.734***	0.326	0.208		2.082
obstruction reason: Feel insecure	0.100	-0.327	0.527	0.218	1.106
Threshold 1:a few times a year / a few times a month	-0.977			0.321	
Threshold 2: a few times a month / several times a week	1.242			0.322	
Observations					955
Residual Deviance					1925.061
AIC					1949.061
BIC					2007.401

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficient interpretation

The interpretation for all the significant variables could be explained in control of other variables as follows, given that all other variables in the model are held constant.

Age: Younger users are more likely to use the E-hailing service more frequently than older users.

Household income (HhIncome): The higher the monthly household income, the more likely it is that E-hailing will be used more frequently. And, as the monthly household income increases, the greater the odds ratio means the greater the likelihood of more frequent use compared to the group with lower monthly household income.

Number of family generations (HhGeneration): Multi-generational households will use E-hailing less frequently compared to households of one generation.

Household vehicle number (HhVehicle): Households without a vehicle are used as a reference variable to compare with households with only one vehicle and households with multiple vehicles. Although, the frequency of use with only one private vehicle in the house is not significant compared to the frequency of use without a vehicle in the house. Households with multiple vehicles are significantly more likely to use E-hailing less frequently than households without vehicles.

Obstruction reason (Reasons prevent you from using E-hailing): two obstruction reasons show significance, which is, feeling that E-hailing services are expensive and Long waiting time. Both estimated coefficients are preceded by a positive sign, indicating that those who expensive when using E-hailing services are more likely to use them, and similarly, those who feel the waiting time for E-hailing is long are more likely to use E-hailing services.

The $vif()$ function of the car package in R was used to check the multicollinearity of the model's variables. The result is as follows table(4.10).

Table 4.10: VIF value of retained variables in ONL1: use frequency

Var	Age	HhIncome	HhGeneration	HhVehicle	Obstruction reason
VIF	1.100	1.120	1.066	1.148	1.071

Although, the proportional odds assumption is a very controversial topic, this check is still performed in this thesis. Please see the Table(B.1) in Appendix B.

Satisfaction about E-hailing

Dependent Variable

The dependent variable for the second ONL model is the satisfaction with the E-hailing service, the final grouped five indicators are: 3,4,5,6,7. Combine 1 (Very unsatisfied), 2 (Unsatisfied), and 3 (Relatively unsatisfied) into a set of 3 (Unsatisfied) because the number of respondents choosing 1, 2, and 3 is small.

Table 4.11: ONL2: Satisfaction

	Dependent variable: Satisfaction				
	β	LL	UL	Std. Error	odds ratio
hhgeneration: 1-generation					(base)
hhgeneration: 2-generation	-0.699***	-1.156	-0.243	0.221	0.625
hhgeneration: >= 3-generation	-0.712***	-1.168	-0.257	0.221	0.846
living area: CBD					(base)

living area: suburban	0.280**	0.025	0.534	0.130	1.323
ttoput: <8min					(base)
ttoput: 8-12min	-0.132	-0.403	0.139	0.138	0.877
ttoput: 12-20min	0.066	-0.370	0.503	0.223	1.069
ttoput: >20min	0.399**	0.0002	0.798	0.203	1.490
use frequency: Rarely used					(base)
use frequency: Occasionally used	0.240*	-0.035	0.515	0.140	1.271
use frequency: Frequently used	0.277	-0.065	0.618	0.174	1.319
obstruction reason: other					(base)
obstruction reason: Long waiting time	-0.647***	-1.037	-0.257	0.199	0.524
obstruction reason: Expensive	-0.725***	-1.111	-0.339	0.197	0.484
obstruction reason: Feel insecure	-1.182***	-1.600	-0.764	0.213	0.307
vulnerable group: Mdriver					(base)
vulnerable group: Mpassenger	1.539**	0.031	3.048	0.770	4.661
vulnerable group: Fdriver	1.791***	0.502	3.081	0.658	5.997
vulnerable group: Fpassenger	0.733	-0.384	1.850	0.570	2.082
risk perception: FuR					(base)
risk perception: PR	-0.797*	-1.690	0.095	0.455	0.451
risk perception: PsyR	-0.134	-0.692	0.424	0.284	0.874
risk perception: TD	-0.526*	-1.119	0.067	0.303	0.591
high accidents frequency: Very frequent					(base)
high accidents frequency: Frequent	0.318	-0.211	0.847	0.270	1.374
high accidents frequency: Fair	0.653**	0.128,	1.178	0.267	1.921
high accidents frequency: Rarely	0.672**	0.090	1.253	0.297	1.957
high accidents frequency: Almost none	1.205***	0.467	1.943	0.377	3.336
impact on use: No effect					(base)
impact on use: Little effect	-0.286	-0.777	0.206	0.251	0.751
impact on use: Has effect	-0.869***	-1.304	-0.434	0.222	0.419
impact on use: A lot of effect	-0.670***	-1.112	-0.229	0.225	0.512
impact on use: Strong effect	-0.839***	-1.337	-0.341	0.254	0.432
Threshold 1: unsatisfied / neutral	-3.6365				0.7118
Threshold 2: neutral / relatively satisfied	-1.5818				0.7003
Threshold 3: relatively satisfied/satisfied	0.1472				0.6998
Threshold 4: satisfied/very satisfied	1.4933				0.7005
Observations					952
Residual Deviance					2,634.700
AIC					2692.70
BIC					2833.599

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficient interpretation

The interpretation for all the significant variables could be explained in control of other variables as follows, given that all other variables in the model are held constant.

Household generation number(HhGeneration): Families of two generations are more likely to be dissatisfied with E-hailing than those of only one generation. The difference in perceptions on this issue between multi-generational and one-generation households was not significant.

living area: Respondents living in the suburbs are 32% more likely to be somewhat more satisfied with E-hailing overall than those living in the city center.

Accessibility (TtoPuT): The estimated parameters are significant only for respondents who live or work in the least accessible places (requiring more than 20 minutes to walk to the nearest public transport station) compared to respondents in the most accessible places (requiring less than 8 minutes to walk to the nearest public transport station). That is, respondents with the worst accessibility are generally more likely to feel more satisfied with E-hailing than those with the best accessibility.

Use frequency: Respondents who occasionally use E-hailing are more likely to feel more satisfied with it than those who rarely use it. The coefficient for those who use E-hailing frequently is not significantly different from zero, so it is not significant.

Obstruction reason (Reasons prevent you from using E-hailing): Similar to that in the first ONL model. Users who are apprehensive about E-hailing services because they feel insecure are more likely to be dissatisfied with E-hailing services. Furthermore, users are more likely to be satisfied with the E-hailing service because they feel that E-hailing is expensive and the waiting time is long.

Vulnerable group: Take male driver as the reference variable, the respondent who believe it is the male passenger are more vulnerable will be more likely to feel satisfied. Same situation can be applied with the respondent who believe the female driver are more vulnerable.

Risk perception: Because the categorical variables of risk perception are classified too many, and the contingency table generated by the dependent variable satisfaction is as follows(4.12) shown, so it is integrated. The final contingency table generated is shown in the following table (4.12). The variables that show significance compared to Functional Risk (FuR) are Physical Risk (PR) and Trust in Driver (TD). the estimated coefficients of both variables are negative, indicating that, compared to FuR, the two risk factors, PR and TD, cause users to be more likely to be less satisfied with E-hailing.

High accidents frequency (Do you feel the frequency of the malignant accidents against women are high in these years?): The very frequent was chosen as the reference variable, and it was felt that people with less frequent malignant accidents against women in recent years would be more likely to be more satisfied with E-hailing.

Impact on use (Will these malignant accidents affect your later used of E-hailing?): No effect, as a reference variable. The greater the influence on the future choice of E-hailing as a mode of travel, the less likely users are to be satisfied with E-hailing.

Table 4.12: Contingency table of Risk perception and Satisfaction

Risk perception (Before)	FiR	FuR	PR	PsyR	TD
Very dissatisfied	0	0	2	7	1
Dissatisfied	0	0	0	3	2
Relatively dissatisfied	0	1	0	19	4
Neutral	4	6	10	121	47
Relatively dissatisfied	0	22	9	239	73
Dissatisfied	0	6	3	176	41
Very dissatisfied	0	13	7	113	28
Risk perception (After)	FuR	PR	PsyR	TD	
Dissatisfied	3	3	29	7	
Neutral	4	6	121	47	
Relatively dissatisfied	5	22	239	73	
Dissatisfied	6	6	175	41	
Very dissatisfied	7	13	113	28	

The $vif()$ function of the car package in R was used to check the multicollinearity of the model's variables. The result is as follows table(4.13).

Table 4.13: VIF value of retained variables in ONL: use frequency

Var	VIF
hhgeneration	1.106
living area	1.134
ttoput	1.187
use frequency	1.128
obstruction reason	1.254
vulnrable group	1.155
risk perception	1.197
high accidents fre	1.316
impact on use	1.371

The proportional odds assumption table(B.2) for this model is in Appendix B, Table. The $H0$ assumption holds, means it obey the proportional odds assumption.

Sense of security

Dependent Variable

Feeling safe about E-hailing is the third dependent variable for the third ONL model, with three indicators: feel unsafe, feel neither unsafe nor safe and feel safe about the E-hailing service.

Table 4.14: ONL3: Sense of security

	Dependent variable: Sense of security				
	β	LL	UL	Std. Error	odds ratio
gender: male					(base)
gender: female	-0.483***	-0.738	-0.229	0.130	0.617
use frequency: Rarely used					(base)
use frequency: Occasionally used	0.397***	0.119	0.676	0.142	1.488
use frequency: Frequently used	0.665***	0.325	1.0058	0.174	1.945
obstruction reason: other					(base)
obstruction reason: Long waiting time	-0.251	-0.639	0.137	0.198	0.778
obstruction reason: Expensive	-0.408**	-0.791	-0.024	0.196	0.665
obstruction reason: Feel insecure	-1.195***	-1.618	-0.771	0.216	0.303
vulnerable group: Mdriver					(base)
vulnerable group: Mpassenger	0.768	-0.698	2.234	0.748	2.155
vulnerable group: Fdriver	2.019***	0.749	3.2908	0.648	7.532
vulnerable group: Fpassenger	0.871	-0.220	1.963	0.557	2.390
risk perception: FuR					(base)
risk perception: PR	-0.754*	-1.644	0.136	0.454	0.470
risk perception: PsyR	-0.234	-0.806	0.3384	0.292	0.792
risk perception: TD	-0.697**	-1.302	-0.092	0.309	0.498
high accidents frequency: Very frequent					(base)
high accidents frequency: Frequent	0.050	-0.500	0.601	0.281	1.052
high accidents frequency: Fair	0.621**	0.077	1.165	0.278	1.861
high accidents frequency: Rarely	0.904***	0.304	1.505	0.306	2.470
high accidents frequency: Almost none	1.625***	0.867	2.383	0.387	5.079
impact on use: No effect					(base)
impact on use: Little effect	-0.536**	-1.023	-0.049	0.249	0.585
impact on use: Has effect	-1.243***	-1.671	-0.815	0.218	0.288
impact on use: A lot of effect	-0.906***	-1.346	-0.467	0.224	0.404
impact on use: Strong effect	-1.152***	-1.652	-0.653	0.255	0.316
Threshold 1: unsafe / neutral	-3.498				0.673
Threshold 2: neutral / relatively safe	-1.384				0.665
Threshold 3: relatively safe / safe	0.723				0.663
Threshold 3: safe / very safe	2.295				0.666
Observations					952
Residual Deviance					2463.712
AIC					2511.712
BIC					2628.317

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficient interpretation

The interpretation for all the significant variables could be explained in control of other variables as follows, given that all other variables in the model are held constant.

Gender: Compared to male users, female users are more likely to feel more insecure about the overall environment of E-hailing. According to the odds ratio, female users are nearly 63% more likely to feel unsafe about E-hailing than male users.

Use frequency: People who use E-hailing more frequently are more likely to feel that E-hailing is safe as a mode of travel than those who rarely use it (the reference variable). And as the frequency of use increases, the likelihood of feeling safe from E-hailing will continue to increase.

Obstruction reason: People who reduce or stop using E-hailing because they feel it is unsafe rightfully feel that E-hailing is even more unsafe. Furthermore, those who find it expensive are more likely to find E-hailing unsafer.

Vulnerable group: Compared to male drivers (the reference variable), those who feel that female drivers are more vulnerable will perceive E-hailing as safer overall. None of the other variables showed significance compared to male drivers.

Risk perception: Using Functional Risk as the reference variable, people who feel that there is Physical Risk and Trust in Driver in E-hailing services are more likely to feel that E-hailing is more unsafe.

High accidents frequency (Do you feel the frequency of the malignant accidents against women are high in these years?): The very frequent was chosen as the reference variable, and it was felt that people with less frequent malignant accidents against women in recent years would be more likely to feel safer with E-hailing as a travel mode.

Impact on use (Will these malignant accidents affect your later used of E-hailing?): No effect, as a reference variable. The greater the influence on the future choice of E-hailing as a mode of travel, the less likely users are to feel safe with E-hailing.

The $vif()$ function of the car package in R was used to check the multicollinearity of the model's variables. The result is as follows table(4.15).

Table 4.15: VIF value of retained variables in ONL3

Var	Gender	Education	HhKid	LivingArea	Use frequency	Obstruction reason
VIF	1.079	1.010	1.027	1.028	1.031	1.131

Although, the proportional odds assumption is a very controversial topic, this check is still performed in this thesis. Please see the Table(B.3) in Appendix B.

The above models, a BNL model three ONL models from different aspects, portrayed the group using E-hailing. Thus, an attempt is made to identify group variability, and more importantly, gender differences. It can be seen that group differences exist in the E-hailing market environment in Wuhan. Furthermore, the last ONL model proves that gender differences exist, and they are huge in terms of the perceived safety of E-hailing services.

4.5.2 Gender gap

Gender is a dependent variable of binary, which here, female is referred to as 1, and male is referred to as 0. A BNL model can be estimated to explore the factors contributing to gender differences in the E-hailing industry.

Dependent Variable

Gender: 1 as female, and 0 as male.

Table 4.16: E-hailing choice Binary Logit Model results

Dependent variable: Gender(1:Female, 0:Male)			
Independent variables	beta	LL	UL
age: young			(base)
age: old	0.596***	0.214	0.978
occupation: student			(base)
occupation: inferior	-0.714**	-1.378	-0.049
occupation: superior	0.049	-0.730	0.828
employment: long-term			(base)
employment: fixed-term	0.182	-0.239	0.603
employment: unfixed-term	1.619***	1.077	2.162
hhkid: 0			(base)
hhkid: 1	-0.432**	-0.830	-0.034
hhkid: >=2	0.013	-0.853	0.880
living area: CBD			(base)
living area: suburban	0.352**	0.004	0.700
ttoput: <8min			(base)
ttoput: 8-12min	-0.057	-0.410	0.297)
ttoput3: 12-20min	-0.236	-0.793	0.322
ttoput: >20min	-0.872***	-1.442	-0.302
use frequency: rarely used			(base)
use frequency: occasionally used	0.030	-0.333	0.393
use frequency: frequently used	0.403*	-0.043	0.850
obstruction reason: other			(base)
obstruction reason: Long waiting time	-0.662***	-1.153	-0.172

obstruction reason: Expensive	-0.761***	-1.260	-0.263
obstruction reason: Feel insecure	0.200	-0.345	0.745
risk perception: FuR			(base)
risk perception: PR	0.374	-0.863	1.612
risk perception: PsyR	1.415***	0.568	2.262
risk perception: TU	0.773*	-0.122	1.668
sense of security: unsafe			(base)
sense of sercurity: neutral	0.181	-0.585	0.947
sense of sercurity: relatively safe	-0.365	-1.132	0.402
sense of sercurity: safe	-0.833*	-1.671	0.005
sense of sercurity: very safe	-0.799*	-1.728	0.130
high accidents frequency: Very frequent			(base)
high accidents frequency: Frequent	1.045***	0.374	1.716
high accidents frequency: Fair	0.464	-0.198	1.127
high accidents frequency: Rarely	0.424	-0.320	1.168
high accidents frequency: Almost none	0.250	-0.730	1.230
impact on use: No effect			(base)
impact on use: Little effect	-0.180	-0.839	0.480
impact on use: Has effect	0.311	-0.262	0.884
impact on use: A lot of effect	0.426	-0.164	1.0174
impact on use: Strong effect	0.634**	0.005	1.262
Constant	-2.594***	-4.231	-0.958
Observations			952
Log Likelihood			-504.729
AIC			1,081.457
BIC			1256.365
Note: *p<0.1; **p<0.05; ***p<0.01			

Model coefficient interpretation

The table above shows the estimated coefficients of the final model. P-values are based on the robust standard errors and are not shown the specific value here but with the asterisk. The confidence interval (CI) set for each coefficient is 95%. The interpretation of the significant variables is as follows. All of the following interpretations of variables obey the principle that the other variables are considered constant when focusing on a particular variable.

Age: Compared to the older respondents, the younger respondents were more likely to be male.

Employment: Female respondents are more likely to be hired in a unfixed-term manner.

Household kid amount (HhKid): Female respondents were more likely to have no kid at home compared to families with one child.

LivingArea: The female respondents are more likely to the resident in the suburban area compared to city center area.

Accessibility (TtoPuT): The reference variable is the best reachable ($TtoPuT < 8min$) and the estimated parameters show strong significance when the accessibility is extremely poor. That is, female respondents are less likely to live or work in places with very poor accessibility compared to those with excellent accessibility.

Use frequency: Female respondents were more likely to use E-hailing more frequently.

Obstruction reason (Reasons prevent you from using EH): Male respondents were more likely than female respondents to abandon to use E-hailing service or stop using it because of price factor in the E-hailing environment. Similarly, male respondents would be more likely to stop using E-hailing services because of the waiting time.

Sense of security: Female respondents are more likely to feel that E-hailing is not a safe mode of travel compared to male respondents.

Risk perception: In using E-hailing, female respondents are more likely to feel threatened by Psychological Risk and the sense of danger due to distrust of the driver, when compared with the Functional Risk.

High frequency of accidents (targeting women): Respondents feel that malicious incidents against women in the E-hailing field have been more frequent in recent years are women.

Accidents impact on choosing EH: When asked if it would affect their continued choice to use E-hailing services after so many malignant incidents against women. Female respondents were more likely to choose that it would strongly affect their continued use of E-hailing.

Goodness of fit

Multicollinearity analysis was performed on the variables retained in the model, using the $vif()$ function of the car package in R(Fox and Weisberg 2019). The results obtained are shown below. Since no variable has a VIF value greater than 5, it can be determined that there is no multicollinearity among these variables.

Table 4.17: VIF value of retained variables in BNL

Var	VIF
Age	1.495
Occupation	2.712
Employment	2.470
HhVehicle	1.122
LivingArea	1.272
TtoPuT	1.234
Obstruction reason	1.200
Satisfication with EH	1.392
Sense of security	2.886
Risk perception	1.195
High frequency of accidents	3.035
Accidents impact on choosing EH	1.517
impact on use	1.643

To analyze whether a model with predictor variables has a better fit than a model with only an intercept (i.e., a null model). The residual deviation difference between the model with predictor variables and the null model is first calculated. Then the difference in degrees of freedom between the two models is calculated to equal the difference in predictor variables, and finally, the difference in p-value is calculated. The chi-square value of 305.143 with 35 degrees of freedom and an associated p-value less than 0.001 indicates that this BNL model is generally better than the null model. This test is called the likelihood ratio test (the deviance residual is $-2 * log$ likelihood). Alternatively, the model's log-likelihood can be viewed directly, using the $logLik()$ function.

Table 4.18: Goodness of fit when comparing BNL with predictor variables and without

Diff. residual deviation	Diff. degrees of freedom	Diff. p-value	log Lik.
305.143	35	7.637353e-45	-504.729 (df=36)

It is also possible to generate diagnostic plots for judging the model's goodness of fit, as shown in the figure(4.23) below.

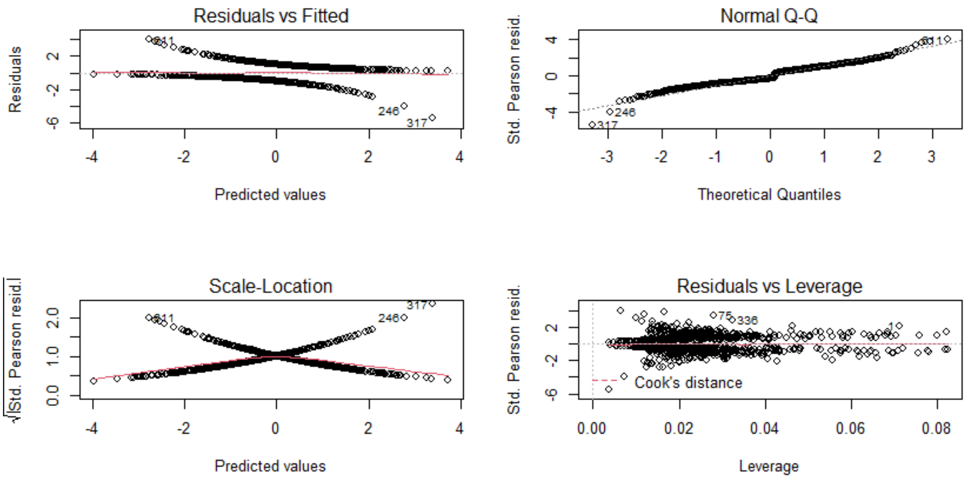


Figure 4.23: diagnostic plots for judging the BNL model's goodness of fit

Because Logit models, unlike linear models, do not have r-squared, many methods define pseudo-r-squared in measuring model superiority, here using McFadden as an example (Logit models use Maximum Likelihood Estimation).

Table 4.19: $pseudo - R^2$ BNL1: Ever used

llh	llhNull	G2	McFadden	r2ML	r2CU
-504.729	-657.300	305.143	0.232	0.274	0.366

llh: The log-likelihood from the fitted model
llhNull: The log-likelihood from the intercept-only restricted model
G2: Minus two times the difference in the log-likelihoods ($G2 = (-2) * (llhNull - llh)$)
McFadden: McFadden's $pseudo - R^2$
r2ML: Maximum likelihood $pseudo - R^2$
r2CU: Cragg and Uhler's $pseudo - R^2$

4.5.3 Measurement model

From the research that evaluates the effectiveness of the DiDi ride-hailing security measures(Jing et al. 2021), seven methods were selected to enhance the sense of security during E-hailing services. These seven measures are: Take no measure, End the trip early, Notify friends or family, Report to the police, Post on social media, Complaint to the platform providing EH services, and Complaining to the regulator. Respondents were asked to answer which measure they would choose to respond to when faced with a risk related to security.

Dependent Variable

Measures: After conducting zero-variance and near zero-variance analysis for the seven measures provided for selection, it was found that when a contingency table was formed with variables of many categories, there were cases where the values were zero. Therefore, the seven measures were combined, and those with similar properties were merged. Finally, six measures were generated, which are:
0- Take no measure
1- Asking for help from others (including friends, family members, netizens etc.)
2- End the trip early
3- Report to the police
4- Complaint to the platform providing EH services
5- Complain to the regulator

Because the dependent variable is an unordered multicategory variable, it is modeled using the Multinomial Logit Model. The final modeling result is as follows the table(4.20). Specify measures0 (Take no measure) as the reference category.

Table 4.20: Multinomial Logit Model: Measures model

Multinomial logistic regression			Independent variable: Measures		
measures	Coefficient	Std. err.	z	P>∣z∣	RRR
0: Take no measure					(base)
1: Asking for help from others (including friends, family members, netizen etc.)					
gender					
male		0 (base)			1
female	0.644	0.448	1.440	0.150	1.905
2: End the trip early					
gender					
male		0 (base)			1
female	-0.014	0.323	-0.040	0.965	0.986
3: Report to the police					
gender					
male		0 (base)			1
female	0.647	0.294	2.200	0.028	0.028
4: Complaint to the platform providing EH services					gender
male		0 (base)			1
female	-0.120	0.358	-0.340	0.736	0.736

Note: *p<0.1; **p<0.05; ***p<0.01

Multinomial logistic regression			Independent variable: Measures		
measures	Coefficient	Std. err.	z	P>|z|	RRR
5: Complain to the gender					
male		0 (base)			1
female	0.443	0.274	1.620	0.106	1.557
Number of obs = 957					
LR chi2(5) = 15.33					
Prob > chi2 = 0.0090					
Log likelihood = -1347.0372					
Pseudo R2 = 0.0057					

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficient interpretation

The coefficients of a standard Multinomial Logit Model can only reflect the direction of their influence by the positive or negative of the coefficient sign. However, they cannot portray the magnitude of the influence of the independent variables on the choice behavior. In order to quantitatively interpret the MNL, the relative risk ratio (RRR) can be calculated.

Take measure0 (Take no measure) as the reference variable, the measure1 (Asking for help from others) has a significant estimated coefficient, with the sign of positive, and the RRR is 1.905. Female users will has a high potential to ask for help from others when they need help, compared with take no measure. Same situation with measure3 (Report to the police), and measure5 (Complain to the regulator).

Goodness of fit

The above table results show that the pseudo R^2 of this thesis is 0.289, indicating that the selected independent variables explain the dependent variable (choice of measures) in the above table to an average extent and not particularly low. Various goodness-of-fit indicators for the standard MNL can be output by entering the first command in STATA, which outputs the goodness-of-fit indicators for the above model.

Table 4.21: Measures of Fit for mlogit of measures

Log-Lik Intercept Only: -1347.037	Log-Lik Full Model: -1354.704
D(947): 2694.074	LR(df=5):15.334
Prob > LR: 0.109	McFadden's R2: 0.006

McFadden's Adj R2: -0.002	ML (Cox-Snell) R2: 0.016
Cragg-Uhler(Nagelkerke) R2: 0.017	Count R2: 0.493
Adj Count R2: 0.000	AIC: 2714.074
AIC divided by N: 2.836	BIC(df=10): 2762.712

The below table(4.22) shows that the predicted values of a total of 472 samples are equal to the actual values, and the prediction accuracy reaches 49.32%, indicating that the model has a average accuracy in fitting the samples.

Table 4.22: Predicted values table

count	Freq.	Percent	Cum.
-5	64	6.69	6.69
-4	30	3.13	9.82
-3	113	11.81	21.63
-2	7 206	21.53	43.16
-1	72	7.52	50.68
0	472	49.32	100.00
Total	957	100.00	

5 Discussion and conclusion

This chapter is to analyze the results, draw conclusions, and look ahead to present the shortcomings of this thesis.

5.1 Findings

In this last chapter, firstly, the discussion from the data analysis aspect on the descriptive findings of the Wuhan E-hailing industry. Secondly, from the modeling aspect on the research findings on the group differentiation in the E-hailing market in Wuhan, the gender gap situation, and the proven measures to handle the security problems in the E-hailing industry and respond to the research questions. Lastly, the lessons learned from the survey, the limitation of this research, and the expected future work will be explained.

5.1.1 Data analysis findings

A total of 1346 questionnaires were collected, and for those who had used E-hailing, the ratio of men to women was 53% to 47%. In terms of age group, less than 1% of respondents were non-adults (under 18 years old), young people between 18 and 38 years old made up the majority of respondents, accounting for 63%, while middle-aged and older people older than 38 years old made up 36% of respondents overall. For respondents' occupations, the leading ratios and their corresponding percentages are Company employers 34.25%, Professional and technical personnel 13.09%, Students older than 18 years old 15.28% and Ordinary civil servants (ordinary employees of government agencies or institutions) 7.4%. Of this, permanent workers account for more than half of the share, 54.08%. The shares of short-term and temporary workers are 16.32% and 2.28%, respectively. More than half of the respondents' education level is bachelor's degree graduates, and the rest are mostly graduate and high school graduates. There are more undergraduate graduates among the female respondents than the male respondents, while more male respondents have graduate degrees than the female respondents. Less than three female respondents had never attended school, while only three male respondents were semi-literate. The vast majority of respondents had a monthly household income of more than 5,000 RMB or 625 Euros. The difference between the monthly household income of male and female respondents was not significant. Because of the importance of the concept of family in Chinese culture, nearly 90% of those surveyed reported that their families are two- and multi-generational. Because of China's one-child policy in the 1990s, most of the respondents had only one child in their families, and now that the policy is being liberalized, the number of multi-child families is gradually increasing. More than 60% of respondents said they had only one private vehicle at home, while 23% of respondents did not have a car at home. In this study, 62% of the respondents live in the suburbs, while only 37% live in the city center. Even though more than 60% of the respondents in this survey are from the suburbs, the accessibility of where they live and work is still very optimistic, with nearly 50% of the respondents living and working within an 8-minute walk of a public transportation station. This is thanks to the 12 existing subway lines in Wuhan, with nine more expected to open in the future.

Wuhan residents are no strangers to E-hailing, with over 90% of respondents having used the service. 42.88% of the respondents use E-hailing several times a month, and nearly 2% of them are heavy E-hailing users. For the satisfaction of E-hailing service, most of the respondents' perception of E-hailing service is above the neutral value, which is very positive. When asked what caused respondents not to use or to stop using E-hailing as their mode of travel, a gender gap emerged, with nearly 70% of female respondents saying it was because they felt unsafe, while 67% of male respondents said it was because of the price factor.

Since there is such a significant gender difference in the issue of the perceived safety of E-hailing, continue to explore the direction of perceived risk in the use of E-hailing. Although, in general, when looking at the E-hailing environment regardless of gender, most respondents felt relatively safe or at least above a neutral attitude. However, when looking at the female respondents individually, there is a risk that they feel that E-hailing services are much less safe on the Likert scale than the male respondents. Moreover, the almost lopsided perception is that both men and women feel that the most dangerous and vulnerable group in the E-hailing environment is the female passenger. The risks perceived during the use of E-hailing are classified into five categories: financial risk, function risk, physical risk, psychological risk, and Trust in the driver. Female respondents generally perceived Psychological risk in using E-hailing, while for male respondents, Trust in a driver also accounted for a large portion of the risk sources. When asked if the frequency of E-hailing accidents against women was high in the past few years, female respondents were more likely to agree with this statement than male respondents. Likewise, female users reported that these accidents impacted their continued choice of E-hailing as a mode of travel in the future.

In response to these safety issues, male and female respondents complained to the regulatory authorities. This was followed by calling the police and uploading to social media platforms. They also indicated that the probability of complaining when they encountered dangerous situations or high-risk scenarios was high.

Lesson learned During this survey, a lot of resistance and difficulties were encountered, and at the same time, much help from people was received. In the process of face-to-face interviews, many of the comments were pointed out on the spot, which was not found in the pilot survey stage, which is the advantage of the online survey cannot be compared. The main lesson is that the questions should be as concise and straightforward as possible, for some of the more professional concepts should be explained and clarified. This problem was discovered during the first face-to-face interview and was immediately revised; before that, nearly 200 survey samples had been obtained through online methods. After the initial cleaning of the data, it was discovered that specific issues were not explained clearly, leading to significant discrepancies in the responses. For example, the definition of the number of generations in a family, the definition of a family, a child (a minor under the age of 18), etc. Therefore, after cleaning the data, only a tiny portion of the sample was left for the first round of research.

5.1.2 Model findings

A total of six models, two BNL, three OBL, and one MNL, were used to model the reasons and factors behind the gender gap of the E-haling market in Wuhan.

The user profile related to E-hailing in Wuhan is that middle aged people (38-39 years old) are less likely to use the E-hailing service than youth people (0-38 years old), and no significant difference between old group (above 60 years old) and youth group.

BNL1: Ever used
Moreover, for the different gender groups, the BNL model of whether or not they had used E-hailing services did not show significance. Compared to students, both lower and higher level workers use EH less frequently, which may be related to them owning their own vehicles. Employees who do not work regularly are less likely to use EH than employees who work regularly and permanently. Therefore, commuting works occupy a certain importance for EH. And the higher the education level, the higher the possibility of having used EH. In turn, how to simplify the functions of EH is a major key for EH to penetrate into the low-education market. For monthly household income, there is only a significant difference in the use of EH between those with a monthly household income of 10kRMB or more and those with less than 5k. Similarly, for accessibility, users within 8 to 12 minutes' walk of a public transport station were less likely to use EH than those with the best accessibility, and as accessibility became worse, the likelihood of using EH was not significant. This may be due to other modes of transportation, such as private transportation. If the waiting time for EH vehicles is long, the likelihood of have ever used of EH will increase. Because not having used EH, it may not create this feeling. Feeling insecure about EH naturally makes the possibility of using EH less likely.

ONL1: Use frequency
For the first ONL model on the frequency of EH use, the factors associated with EH use were age, number of generations in the household, location of residence, and factors that prevented (or continued) EH use. Older adults will be less likely to use EH services. Multi-generational households will be less likely to use EH, and they will choose to travel

more often by private car. Those who feel EH is an expensive mode of transportation use it less frequently than those who feel it is unsafe. Households with two or more cars use EH much less frequently than households with none. There is no significant difference in frequency of use between households with one car and households with no one. However, gender was not a factor influencing people's use of e-hailing as a mode of travel. For the dependent variable of frequency of use, there were no gender differences.

ONL2: Satisfaction
The second ONL model explores the satisfaction of different user groups with E-hailing services. The higher the number of generations in the household, the lower the satisfaction with EH will be. Users living in the suburbs will be more satisfied with EH compared to those living in the city center. Compared to users with very good accessibility (TtoPuT<8min), only the values for users with very poor accessibility (TtoPuT>20min) show significance. Users who use EH occasionally give more positive comments compared to those who use it rarely, while those who use it frequently are not as satisfied with EH. Both Long waiting time, expensive and Feel insecure are the factors that make users less satisfied with EH. Those who perceive the risk of using EH to be physical risk and difficult to trust the driver are less satisfied with EH than those who perceive functional risk. Cognitively, the less frequent the number of malicious incidents against women in recent years, the more satisfied users are with EH. And those users who are left with a psychological shadow due to these malicious events, even though, these events did not happen to them, their satisfaction with EH will still be reduced.

ONL3: Sense of security
The third ONL model explores the relationship between the overall safety of the e-hailing environment and the user groups. A gender difference emerges regarding whether the overall environment of E-hailing is safe. Female users would feel that the overall environment of E-hailing is unsafe. The more frequently people use e-hailing, the more they trust the safety of e-hailing.

BNL4: Gender gap
The fourth model is a BNL model where gender is set as a binary option as the dependent variable. The socio-demographic variables that showed significance with the dependent variable of gender were age, occupation, and residential environment. This is due to the characteristics of the selected respondents and is not a concern here. Female respondents were more likely than male respondents to abandon to use E-hailing service or stop using it because they felt unsafe in the E-hailing environment. Women are optimistic about their satisfaction with E-hailing, although they are more likely to feel a bit insecure about the overall environment of E-hailing. Among the factors that cause women to feel threatened, psychological risk and the inability to trust the driver are two significant factors. Similarly, the frequency of accidents against women in the E-hailing industry in recent years is perceived to be higher by the female population, while the male population does not have such a perception. When asked whether these incidents would affect their subsequent choice of E-hailing, the effect was more substantial for the female group.

MNL5: Measurements
For the last MNL model, the validity of some of the measures proposed for gender-specific insecurities when using E-hailing is addressed. The reference group is Take no measure, and the measures that proved to be significant for female users are Asking for help from other, Report to police and Complain to the regulator.

5.2 Conclusion

The final section of this research will describe the overall conclusion, research limitation, and potential future research.

5.2.1 Research questions

The research questions listed in the first chapter can finally be answered in the final section.

1. Is there user group differentiation in the E-hailing market in Wuhan, especially gender differentiation?

User group differentiation existed in the E-hailing market in Wuhan. For different gender groups, obstruction reasons, sense of security, perception of different kinds of risks, and perception of the incidence of nasty accidents against women in recent years are important factors influencing women's choice of E-hailing services.

2. What factors affect female users to adopt E-hailing?

Age, Occupation status, Employment, household vehicle numbers, living area, living or working place accessibility, obstruction reasons, sense of security, the risk from the psychological aspect and the hardness to trust in driver, and the frequency of malignant accidents against women in recent years are all factors which will affect female uses to adopt E-hailing.

3.What regulations/measures will help to fix this gender gap in the E-hailing market?

By enhancing the ability to end a trip early with one click, making the alarm function more straightforward and faster, and strengthening the supervision of rectification of complaint cases, all can enhance women's sense of security in the case of using E-hailing, thus narrowing the gender gap.

5.2.2 Limitation and future work

In this thesis, the exploration of E-hailing as a transportation mode focuses only on E-hailing as a whole in terms of travel mode. There is no subdivision of E-hailing, such as

’hitchhiking’, ’special car (special car for business travel)’ and some other refined categories to differentiate and set weights. This also leads to a more challenging interpretation of the relationship between significant and dependent variables. Second, the sample collected is not representative of the entire population and is not balanced. Because the questionnaire was diffused online and offline, face-to-face interviews were conducted in a single location, and it was mainly focused on families living in the suburbs, company employees, and people with higher education levels. Finally, this thesis does not explore the different brands of platforms that provide E-hailing services separately but selects the most common standard features among them. In this way, the conclusions drawn are not specific to certain E-hailing platforms that offer special services (e.g., ShouQi, which provides escort luggage services).

This thesis does not organize the analysis for some latent attitude variables. After reading some literature (Jing et al. 2021)and(L. Ma et al. 2019), it was found that PCA and CFA or some other factor analysis methods could be used for the reduction of multivariate data. To explore the deep connections between variables and propose new classifications that would reduce such deep connections between variables. Also, SEM could be used to analyze the relationship between intention to use, perceived safety, perceived risk, and attitude towards the E-hailing service, without a specific independent variable. These can be added in a future study.

In addition, some derivative topics can be discussed, such as how much the gender disparity behind the E-hailing industry costs the weaker sex (not limited to women) (macroscopic concepts, including time, money, inconvenience, etc.) furthermore, whether these gender differences cost the weaker gender users, which affects the experience of the more robust gender users or other factors.

A Appendix

Wuhan online ride-hailing safety perception questionnaire survey

Hello to all the folks of River City!
I'm a Master's student in Transportation and I'm currently conducting research for my Master's thesis. The topic of my master's thesis is "The Gender Gap Behind the E-hailing Market", and I grew up in Wuhan, so of course I had to choose Wuhan as the location for my research.

This questionnaire takes 8 minutes to complete, according to Chapter 3, Article 25 of the Statistics Law, the statistical survey process to identify or infer the identity of the individual statistical survey data, any unit or individual shall not provide or disclose to the public, and shall not be used for purposes other than statistics. So please rest assured. I will achieve strict confidentiality.

In order to appreciate everyone's active participation and patience, this questionnaire set a bonus draw link, please leave a cell phone number or email at the end, the whole process is all voluntary.

Finally, welcome everyone to participate and actively forward. Together we can build a safe and harmonious Wuhan! Thank you!

*Required

"socio-demographic" section

1. What city do you currently live in? *

Mark only one oval.

- ◯ Wuhan
- ◯ Others

2. What is your gender? *

Tick all that apply.

- [ ] Male

- [ ] Female

3. How old are you? *

Mark only one oval.

- ( ) <= 18
- ( ) 18 - 38 (38 included)
- ( ) 38 - 59 (59included)
- ( ) >= 60

4. What's your occupation? *

Mark only one oval.

- Student (< 18 years old)
- Student (> 18 years old)
- Freelance
- Self-employed
- Skilled workers
- Company employers
- Professional and technical personnel (teachers, doctors, lawyers, etc.)
- Ordinary civil servants (ordinary employees of government agencies or institutions)
- Senior management (senior civil servants, senior management of enterprises abover the managerial level, etc.)
- Housewives, husbands
- Unemployed or looking for a job
- Retires
- Others

5. What is your employment status? *

Mark only one oval.

- Permanent workers
- Fixed-term workers
- Short-term and temporary workers
- Paid apprentices, corporate trainees and interns
- Others

6. What is your highest level of education completed? *

Mark only one oval.

- Never attend school
- Illiterate, semi-literate
- Elementary school
- Junior high school
- High school/ vocational school
- Specialty
- Undergraduate
- Master's degree
- Ph.D

7. What is your monthly income category of households in RMB? *

Long-term residence together or related by blood, that is, based on marriage, blood, adoption or cohabitation and other relationships formed by the common living unit, that is, considered family members, children away from home, in order to achieve economic independence or not moved to block residence is still considered family members.

Mark only one oval.

- 0-500
- 500-800
- 800-1000
- 1000-1500
- 1500-2000
- 2000-3000
- 3000-5000
- 5000-10000
- 10000-20000
- >20000

8. What's your household size? *

Father-son means two generations, female-mother-mother means three generations, and so on.

Mark only one oval.

- 1 person (living alone)
- 2 people (with cohabiting partner)
- 2-generation family
- 3-generation or multigenerational families
- Other

9. How many kids in your household? *

Mark only one oval.

- 0
- 1
- 2
- 3
- 4
- >4

10. How many vehicles do your household have? *

Mark only one oval.

- 0
- 1
- 2
- 3
- 4
- >4

11. Please choose your living area. *

Mark only one oval.

- City central
- Suburban

12. How long will it take for you to walk from your home/workplace to the nearest public transport station? *

Mark only one oval.

- <8min
- 8-12min
- 12-20min
- >20min

"travel behavior" section

13. Which of the following travel modes do you use frequently in underlying scenarios? *

Mark only one oval per row.

	public transport	Bike (Electric bike, shared bike, motorbike)	private vehicle	walk	Traditional taxi	E-hailing
Work	⬭	⬭	⬭	⬭	⬭	⬭
School	⬭	⬭	⬭	⬭	⬭	⬭
Entertainment (shopping, dining, visiting friends)	⬭	⬭	⬭	⬭	⬭	⬭
Business	⬭	⬭	⬭	⬭	⬭	⬭
Others	⬭	⬭	⬭	⬭	⬭	⬭

"E-hailing usage" section

14. Have you ever used online ride-hailing? *

Tick all that apply.

- [ ] yes
- [ ] No

15. Your frequency of using online ride-hailing per week? *

Mark only one oval.

- ⬭ Rarely used (A few times a year)
- ⬭ Occasionally used (A few times a month)
- ⬭ Frequently used (a few times a week)
- ⬭ Very frequent used (almost every day)

16. When will you choose online ride-hailing? *

Mark only one oval.

- Go to school
- Shopping and dining
- Travel and recreation
- Go to hospital
- Go home

17. please choose the reason that prevent you from using E-hailing the most or no longer to use E-hailing service. *

(even it just happened 1 time, please choose it)

Mark only one oval.

- Feel insecure
- Expensive
- Long waiting time
- Others

18. Are you satisfied with the service provided by the online ride-hailing company? *

1 = very unsatisfied, 2 = unsatisfied, 3 = neutral, 4 = satisfied, 5 = very satisfied

Mark only one oval.

	1	2	3	4	5	6	7	
very unsatisfied								very satisfied

"risk perception of online ride-hailing" section

19. Do you think the current online ride-hailing environment is safe? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unsafe	◯	◯	◯	◯	◯	◯	◯	Very safe

20. Which groups of people do you think are more vulnrable when using E-hailing? *

Mark only one oval.

- ◯ Female passenger
- ◯ Female driver
- ◯ Male passenger
- ◯ Male driver

21. Please choose the one you agree with most from the following statements. *

Mark only one oval.

- ◯ Do you meet more male drivers than female drivers?
- ◯ The female drivers will threaten you more than male drivers?
- ◯ If I'm alone, I will be more nervous to ride than having accompany.
- ◯ I don't feel safe using E-hailing after 10pm.
- ◯ During the trip, I will check the route with the given on my phone multiple times.
- ◯ I pay attention to rate and reviews of the driver.
- ◯ I will tell friends or relatives about the information of this ride-hailing trip.

22. What safety hazards do you think online ride-hailing has? *

Mark only one oval.

- Drivers violate traffic rules
- Traffic accidents
- Inappropriate behaviour of driver
- Harassments, insults, and threat from the driver
- Challenge of personal safety
- Challenge of property safety

23. What do you do when you encounter one of these listing safety hazards? *

Mark only one oval.

- Ends the trip earlier
- inform friends and family, call for help
- report to the police
- Post it through social media platforms to remind others
- complaining to regulator
- Take no measure
- complaining to the corresponding plateform

24. Do you agree that, if you meet something uncomfortable during the ride-hailing, you will complaint to the service provided company? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very disagree								Very agree

25. Do you agree that, the frequency of the occurrence of female online ride-hailing accidents in recent years is high? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very disagree	◯	◯	◯	◯	◯	◯	◯	Very agree

26. Do you agree that, the previous ride-hailing accidents will affect your willingness to choose ride-hailing? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very disagree	◯	◯	◯	◯	◯	◯	◯	Very agree

B Appendix

Table B.1: ONL1: Brant test for parallel regression

Test for	X2	df	probability
Omnibus	13.13	10	0.22
age2	0	1	0.95
hhincome2	0.2	1	0.66
hhincome3	0.06	1	0.81
hhgeneration2	4.18	1	0.04
hhgeneration3	0.81	1	0.37
hhvehicle2	0.13	1	0.72
hhvehicle3	0.19	1	0.66
obstruction reason2	6.13	1	0.01
obstruction reason3	3.21	1	0.07
obstruction reason4	2.85	1	0.09

H0: Parallel Regression Assumption holds

Table B.2: ONL2: Brant test for parallel regression

Test for	X2	df	probability
Omnibus	220.74	75	0
hhgeneration2	0.72	3	0.87
hhgeneration3	1.24	3	0.74
living area1	5.59	3	0.13
ttoput2	0.76	3	0.86
ttoput3	9.98	3	0.02
ttoput4	4.72	3	0.19
use frequency2	8.51	3	0.04
use frequency3	12.14	3	0.01
obstruction reason2	1	3	0.8
obstruction reason3	5.56	3	0.14
obstruction reason4	1.59	3	0.66
vulnrable group2	3.17	3	0.37
vulnrable group3	0.73	3	0.87
vulnrable group4	1	3	0.8

risk perceptionPR	3.83	3	0.28
risk perceptionPsyR	10.89	3	0.01
risk perceptionTD	6.64	3	0.08
high accidents fre2	7.34	3	0.06
high accidents fre3	4.83	3	0.18
high accidents fre4	6.71	3	0.08
high accidents fre5	3.55	3	0.31
impact on use2	10.58	3	0.01
impact on use3	7.78	3	0.05
impact on use4	21.99	3	0
impact on use5	0.56	3	0.91

H0: Parallel Regression Assumption holds

Table B.3: ONL3: Brant test for parallel regression

Test for	X2	df	probability
Omnibus	136.91	60	0
gender1	1.32	3	0.73
use frequency2	5.11	3	0.16
use frequency3	0.61	3	0.89
obstruction reason2	4.25	3	0.24
obstruction reason3	1	3	0.8
obstruction reason4	1.93	3	0.59
vulnrable group2	3.67	3	0.3
vulnrable group3	1.31	3	0.73
vulnrable group4	5.69	3	0.13
risk perceptionPR	1.62	3	0.66
risk perceptionPsyR	3.71	3	0.29
risk perceptionTD	4.3	3	0.23
high accidents fre2	7.83	3	0.05
high accidents fre3	12.37	3	0.01
high accidents fre4	7.39	3	0.06
high accidents fre5	4.18	3	0.24
impact on use2	1.39	3	0.71
impact on use3	2.74	3	0.43
impact on use4	4.11	3	0.25
impact on use5	6.84	3	0.08

H0: Parallel Regression Assumption holds

Table B.4: Survey Sample Sociodemographic Summary Statistics

Variable		Survey sample	
	Levels	No	Pct%
Gender	Male	563	53.42%
	Female	491	46.58%
Age	(0,18]	9	0.85%
	(18,38]	665	63.09%
	(38,59]	364	34.54%
	(60,-)	16	1.52%
Occupation	Students(under 18)	7	0.66%
	Students(above 18)	161	15.28%
	Freelance	56	5.31%
	Self-employed	24	2.28%
	Skilled workers	99	9.39%
	Company employers	361	34.25%
	Professional and technical personnel (teachers, doctors, lawyers, etc.)	138	13.09%
	Ordinary civil servants (ordinary employees of government agencies or institutions)	78	7.40%
	Senior management (senior civil servants, senior management of enterprises, etc.)	34	3.23%
	Housewives, husbands	7	0.66%
	Unemployed or looking for a job	4	0.38%
	Retired	23	2.18%
	Others	62	5.88%
Employment	Permanent workers	570	54.08%
	Fixed-term workers	172	16.32%
	Short-term and temporary workers	24	2.28%
	Paid apprentices, corporate trainees and interns	13	1.23%
	Other	275	26.09%
Education	Never attend school	2	0.19%
	Illiterate, semi-literate	3	0.28%
	Elementary school	3	0.28%
	Junior high school	11	1.04%
	High school/ vocational school	102	9.68%
	Specialty	155	14.71%
	Undergraduate	582	55.22%
	Master's degree	174	16.51%
	PhD	22	2.09%
HhIncome (RMB)	0-500	7	0.66%
	500-800	6	0. 57%

Variable	Levels	Survey sample No	Pct%
	800-1000	14	1.33%
	1000-1500	18	1.71%
	1500-2000	19	1.80%
	2000-3000	34	3.23%
	3000-5000	111	10.53%
	5000-10000	338	32.07%
	10000-20000	314	29.79%
	>20000	193	18.31%
Generation	1 person (living alone)	67	6.36%
	2 people (with cohabiting partner)	28	2.66%
	2-generation family	486	46.11%
	3-generation or multigenerational families	454	43.07%
	Other	19	1.80%
HhKid	0	271	25.71%
	1	539	51.14%
	2	205	19.45%
	3	30	2.85%
	4	6	5.69%
	>4	3	2.85%
HhVehicle	0	247	23.43%
	1	635	60.25%
	2	148	14.04%
	>2	24	2.28%
LivingArea	Suburban	659	62.52%
	CBD	395	37.48%
TtoPuT*	<8 min	519	49.24%
	[8, 12)	308	29.22%
	[12, 20)	106	10.06%
	>20 min	121	11.48%

Table B.5: Descriptive statistics of participant characteristics

Variable	Levels	Survey sample Pct%	Female	Male
Socio-demographic				
Gender	Male	53.42%		
	Female	46.58%		
Age	(0,18]	0.85%	0.19%	0.66%

TtoPuT* : Walking time to the nearest public transportation station, as defined in 3.1.2 accessibility.

Variable	Levels	Survey sample Pct%	Female	Male
	(18,38]	63.09%	36.05%	27.04%
	(38,59]	34.54%	16.79%	17.74%
	(60,-)	1.52%	0.38%	1.14%
Occupation	Students(under 18)	0.66%	0.19%	0.47%
	Students(above 18)	15.28%	3.61%	11.67%
	Freelance	5.31%	2.47%	2.85%
	Self-employed	2.28%	1.23%	1.04%
	Skilled workers	9.39%	8.63%	0.76%
	Company employers	34.25%	23.72%	10.53%
	Professional and technical personnel(teachers, doctors, lawyers, etc.	13.09%	5.98%	7.12%
	Ordinary civil servants (ordinary employees of government agencies or institutions)	7.40%	2.09%	5.31%
	Senior management (senior civil servants,senior management of enterprises, etc.)	3.23%	2.28%	0.95%
	Housewives, husbands	0.66%	0.00%	0.66%
	Unemployed or looking for a job	0.38%	0.19%	0.19%
	Retired	2.18%	0.19%	1.99%
	Others	5.88%	2.85%	3.04%
Employment	Permanent workers	54.08%	33.59%	20.49%
	Fixed-term workers	16.32%	10.25%	6.07%
	Short-term and temporary workers	2.28%	1.71%	0.57%
	Paid apprentices, corporate trainees and interns	1.23%	1.14%	0.09%
	Other	26.09%	6.74%	19.35%
Education	Never attend school	0.19%	0.19%	0.00%
	Illiterate, semi-literate	0.28%	0.09%	0.19%
	Elementary school	0.28%	0.09%	0.19%
	Junior high school	1.04%	0.57%	0.47%
	High school/ vocational school	9.68%	4.36%	5.31%
	Specialty	14.71%	9.01%	5.69%
	Undergraduate	55.22%	31.40%	23.81%
	Master's degree	16.51%	6.74%	9.77%
	PhD	2.09%	0.95%	1.14%
HhIncome (RMB)	0-500	0.66%	0.38%	0.28%
	500-800	0. 57%	0.09%	0.47%
	800-1000	1.33%	0.85%	0.47%
	1000-1500	1.71%	0.95%	0.76%
	1500-2000	1.80%	0.85%	0.95%
	2000-3000	3.23%	1.42%	1.80%
	3000-5000	10.53%	4.93%	5.60%
	5000-10000	32.07%	18.41%	13.66%
	10000-20000	29.79%	16.51%	13.28%

TtoPuT* : Walking time to the nearest public transportation station, as defined in 3.1.2 accessibility.

Variable		Survey sample		
	Levels	Pct%	Female	Male
	>20000	18.31%	9.01%	9.30%
Generation	1 person (living alone)	6.36%	3.61%	2.75%
	2 people (with cohabiting partner)	2.66%	1.42%	1.23%
	2-generation family	46.11%	23.34%	22.77%
	3-generation or multigenerational families	43.07%	24.00%	19.07%
	Other	1.80%	1.04%	0.76%
HhKid	0	25.71%	16.70%	9.01%
	1	51.14%	23.91%	27.23%
	2	19.45%	10.91%	8.54%
	3	2.85%	1.42%	1.42%
	4	5.69%	0.19%	0.38%
	>4	2.85%	0.28%	0.00%
HhVehicle	0	23.43%	14.61%	8.82%
	1	60.25%	31.40%	28.84%
	2	14.04%	5.88%	8.16%
	>2	2.28%	1.52%	0.76%
LivingArea	Suburban	62.52%	36.53%	26.00%
	CBD	37.48%	16.89%	20.59%
TtoPuT*	<8 min	49.24%	24.38%	24.86%
	[8, 12)	29.22%	14.99%	14.23%
	[12, 20)	10.06%	6.07%	3.98%
	>20 min	11.48%	7.97%	3.51%
E-hailing usage				
EH using scenario	Home	1.88%	0.63%	1.25%
	Hospital	0.84%	0.84%	0.00%
	Night travel	35.49%	15.97%	19.52%
	Same city business travel	34.86%	14.20%	20.67%
	School	0.94%	0.52%	0.42%
	Shopping and dining	7.31%	3.24%	4.07%
	Travel and entertainment	13.99%	8.98%	5.01%
	Visiting friends and family	2.61%	1.04%	1.57%
	Work	2.09%	1.04%	1.04%
EH choice	No	9.01%	4.74%	4.27%
	Yes	90.99%	48.67%	42.31%
Use frequency	Never used	9.01%	4.74%	4.27%
	Rarely used (a few times a year)	28.18%	14.52%	13.66%
	Occasionally used (a few times a month)	42.88%	23.15%	19.73%
	Frequently used (several times a week)	18.12%	9.96%	8.16%
	Very frequent used (almost every day)	1.80%	1.04%	0.76%
Satisfaction about EH	Very unsatisfied	0.95%	0.76%	0.19%

TtoPuT* : Walking time to the nearest public transportation station, as defined in 3.1.2 accessibility.

Variable	Levels	Survey sample Pct%	Female	Male
	Unsatisfied	0.47%	0.38%	0.09%
	Relatively unsatisfied	2.28%	1.14%	1.14%
	Neither unsatisfied nor satisfied	17.46%	8.54%	8.92%
	Relatively satisfied	33.02%	16.32%	16.70%
	Satisfied	21.54%	11.29%	10.25%
	Very satisfied	15.28%	10.25%	5.03%
Obstruction reason	Feel insecure	25.64%	17.09%	8.55%
	Expensive	31.91%	11.21%	20.70%
	Long waiting time	28.59%	11.49%	17.09%
	Other	13.87%	6.74%	7.12%
Risk perception				
Feeling safe about EH	Very unsafe	0.95%	0.38%	0.57%
	Unsafe	1.14%	0.57%	0.57%
	Relatively unsafe	2.75%	1.80%	0.95%
	Neither unsafe nor safe	20.21%	12.24%	7.97%
	Relatively safe	37.38%	17.84%	19.54%
	Safe	18.98%	6.55%	12.43%
	Very safe	9.58%	2.94%	6.64%
Vulnerable group	Fdriver	3.89%	2.37%	1.52%
	Fpassenger	92.98%	43.36%	49.62%
	Mdriver	1.14%	0.28%	0.85%
	Mpassenger	1.99%	0.57%	1.42%
Perceived safety hazard	Financial Risk	0.76%	0.47%	0.28%
	Functional Risk	4.55%	0.76%	3.80%
	Physical Risk	4.17%	1.23%	2.94%
	Psychological Risk	64.52%	33.59%	30.93%
	Trust in Driver	26.00%	10.53%	15.46%
Frequency of EH accidents relating women	Very disagree	3.18%	0.85%	0.79%
	Disagree	4.03%	1.44%%	2.06%
	Relatively disagree	30.55%	12.14%	18.41%
	Neither disagree nor agree	42.60%	24.67%	17.93%
	Relatively agree	15.09%	9.11%	5.98%
	Agree	3.30%	1.08%	1.17%
	Very agree	1.25%	2.05%	1.21%

TtoPuT* : Walking time to the nearest public transportation station, as defined in 3.1.2 accessibility.

Variable	Levels	Survey sample Pct%	Female	Male
Impact of accidents for subsequential use	Very disagree	3.81%	4.34%	1.27%
	Disagree	3.40%	3.53%	2.43%
	Relatively disagree	30.55%	7.59%	3.70%
	Neither disagree nor agree	42.60%	17.08%	12.33%
	Relatively agree	15.09%	12.81%	16.41%
	Agree	1.57%	6.39%	8.03%
	Very agree	2.98%	1.58%	2.31%
Measures				
Measures	Take no measures	6.74%	5.70%	7.64%
	End the trip early	0.47%	0.41%	0.53%
	Notify friends or family	3.42%	4.48%	2.49%
	Call the police	12.05%	9.37%	14.39%
	Post on social media	22.11%	24.44%	20.07%
	Complaining to company	7.21%	5.70%	8.53%
	Complaining to regulator	48.01%	49.90%	46.36%
High frequency of complaining	Very disagree	3.30%	0.28%	1.32%
	Disagree	2.56%	2.85%	1.15%
	Relatively disagree	4.65%	0.66%	1.90%
	Neither disagree nor agree	12.14%	2.75%	1.90%
	Relatively agree	67.65%	6.74%	5.41%
	Agree	7.40%	31.88%	22.03%
	Very agree	2.30%	4.08%	9.66%

TtoPuT* : Walking time to the nearest public transportation station, as defined in 3.1.2 accessibility.

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List of Abbreviations

BNL	Binary Logit Model
ONL	Ordered Logit Model
MLM	Multinomial Logit Model
EH	E-hailing
RRR	Relatively risk
OR	Odds ratio
Pct	Percentage
CI	Confident interval
LL	Lower interval
UL	Upper interval
DiDi	DiDi Company
AIC	Akaike Information Criterion
BIC	Bayesian Information Criteria
MLE	Maximum Likelihood Estimation
P2P	Peer-to-Peer
Put	Public Transport
Prt	Private Transport
SD	Standard Deviation
Var	Variable
Diff	Difference
df	degree of freedom
log Lik	log-likelihood
Std. Error	Standard Error
D	Deviation
Adj	Adjusted
Freq	Frequency
Cum	Cumulative Value
ICT	Information and Communication Technology
RF	Random Forest
DCM	Discrete Choice Model
NHTS	National Household Travel Survey
MLP	Multilayer Perception Neural Networks
NL	Nested Logit Model
RH	Ride-hailing
CHFS	China Household Finance Survey
PMCC	Product-moment correlation coefficient
BRT	Bus Rapid Transit
RUM	Random Utility Maximization
PDF	Probability Density Function

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