Shared Ownership and Ridership of Driverless Cars in Edinburgh

By

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1.Declaration

I hereby declare that the work presented in this thesis has not been submitted for any other degree or professional qualification and is the result of my independent work.

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30th June 2024

2.Abstract

The research explores the attitudes towards sharing driverless cars (DC) among Edinburgh residents. DC Use is characterised by two dimensions: ownership and ridership. The personal mobility landscape has the potential to experience a paradigm shift over the coming decades due to the advent of level 5 DC, allowing people to enjoy hassle-free travel independent of the ability to drive. Therefore, DC use may generate more trips and miles travelled, aggravating further congestion and emissions, reducing the viability of traditional public transport services and people's propensity to walk and cycle. The shared use of DC could increase vehicle usage efficiency, make mobility more sustainable and affordable, and make cities more liveable.

Existing research has investigated the impact of shared DC use on travel behaviour through simulations and choice experiments. These studies examined shared ownership and ridership separately. Few studies investigated the impact of travelling with family members and strangers of mobility choice; no attention is paid to household dynamics. To fill these gaps, the present study (a) identifies the propensities to share ownership and ridership of DC in different travelling scenarios; (b) analyses the impact of current travel behaviour socio-economic characteristics on such propensities; (c) jointly considers personality traits and social norms attitudes as factors explaining shared use of DC. The scenarios consider three shared DC ownership models (private DC, partially owned DC, driverless taxis) and three shared DC ridership models (riding alone, with close contacts, with strangers), with and without the presence of family members. Regular and occasional trips are investigated.

Data is collected through an online questionnaire with 500 respondents, three-quarters of whom are of working age and owning a car. The questions are based on a literature review and interviews with mobility experts. Four areas are covered: current carsharing and ridesharing attitudes; determinants of attitudes towards carsharing and ridesharing; likelihood of adopting different DC ownership and ridership models; personality traits, social norms, and socio-demographic characteristics. Classes of carsharing and ridesharing behaviour are identified using cluster analyses. Discrete choice models are estimated to explain respondents' propensity for selected DC shared ownership and ridership scenarios, using the sharing behaviour, personality, social norms, and socio-demographic characteristics as determinants.

Frequent household-car users are inclined to adopt private DC, whereas highly educated respondents older than 55 are less inclined to private DC. Higher-earners, younger-aged, cooperative and resource-sharing behaviour are significant determinants of driverless taxi use. City-centre dwelling, cooperative millennials are more willing to share DC with a stranger.

People's reluctance to share trips with strangers is a crucial barrier to shared DC use. Privacy-preserving DC design can help people feel safer in sharing with a stranger. Public transport integration with DC should be investigated to promote further the shared use of DC.

Keywords: driverless car, shared ownership, shared ridership; online survey; discrete choice analysis

3. Publications associated with this research

1. Faruque, Sayed, (2022); Determinants of shared ownership and use of driverless cars in Edinburgh; 54th Annual UTSG conference, Edinburgh Napier University, from 4th- 6th July 2022 Edinburgh. For this paper, the Runner-up position was achieved in the SMEED prize competition for the best student paper in the 2022 UTSG conference (July 2022 – UTSG)

2. Faruque, S., Fonzone, A., & Fountas, G. (2022). Explaining expected non-shared and shared use of driverless cars in Edinburgh. *Transportation Research Procedia*, *62*, 286–293. https://doi.org/10.1016/j.trpro.2022.02.036

3. Faruque, Sayed, (2021); Non-shared and shared use models of driverless cars; Modelling World 2021, 5 -6th October 2021, Edgbaston Cricket Ground, UK (face-to-face)

4. Faruque, Sayed; Fonzone, Achille; Fountas, Grigorios, Explaining expected non-shared and shared use of driverless cars in Edinburgh; Transport Planning Procedia; 24th EURO Working Group on Transportation Meeting, EWGT 2021, 8-10 September 2021, Aveiro, Portugal

5. Faruque, Sayed, (2021); Models for shared ownership and use of driverless cars in Edinburgh; Geographies of Autonomous Urban Transport; RGS (Royal Geographic Society) - IBG Annual International Conference 2021; August 31st to September 3rd, 2021; Greenwich, London (online)

6. Faruque, Sayed, (2021); Shared ownership and ridership models of driverless vehicles; 19th Annual Transport Practitioners' Meeting, 7- 8 July 2021, Organised by PTV Group and SWECO, UK (online)

7. Except from the above, My abstract "Joint Analysis of Determinants for Non-shared and Shared Driverless Car Use in Edinburgh applying Multinomial Logit Model" was selected to be presented at the 17th International Conference on Travel Behavior Research, Vienna 2024, July 14th - 18th

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9. List of Abbreviations

List of Abbreviation	Meaning
DC	Driverless Cars
AV	Autonomous Cars
SMID	Scottish Index of multiple deprivations
UTSG	University Transport User Group
Ow_Pr_Re	Likelihood of private DC use for regular trips
Ow_Fr_Re	Likelihood of shared owned DC use for regular trips
Ow_Ta_Re	Likelihood of driverless taxis use for regular trips
Ow_Pr_Oc	Likelihood of private DC use for occasional trips
Ow_Fr_Oc	Likelihood of shared-owned DC use for occasional trips
Ow_Ta_Oc	Likelihood of driverless taxis use for occasional trips
Ri_ReNF_A	Likelihood of riding alone in a DC for regular trips
Ri_ReNF_K	Likelihood of riding with known people in DC for regular trips
Ri_ReNF_S	Likelihood of riding with a stranger in DC for regular trips
Ri_OcNF_A	Likelihood of riding alone in a DC for occasional trips
Ri_OcNF_K	Likelihood of riding with known people in DC for occasional
Ri_OcNF_S	Likelihood of riding with a stranger in DC for occasional trips
Ri_ReWF_A	Likelihood of riding in a DC in the presence of a family member
Ri_ReWF_K	Likelihood of riding in a DC with known people in the presence
Ri_ReWF_S	Likelihood of riding in a DC with a stranger in the presence of
Ri_OcWF_A	Likelihood of riding in a DC in the presence of a family member
Ri_OcWF_K	Likelihood of riding in a DC with known people in the presence
Ri_OcWF_S	Likelihood of riding in a DC with a stranger in the presence of
Occ	Occasional Travel
Typ	Types of Sharing
Int	Interaction Term
Fam	Share the ride family member
JSHOP	Likelihood of accepting the shared use of DC than private DC
JSHARP	The greater or indifferent likelihood of accepting DC shared
RA	Riding alone
RK	Riding with known people
RS	Riding with stranger
PD	Private DC
DT	Driverless Taxi
SDC	Shared DC
DVT	Weak preference for Driverless Taxis over Private DC
RST	Weak preference for sharing the trip with a stranger than
RSF	Weak preference for riding with a stranger in the presence of a
BLR	Binary-logit Regression
MNL	Multinomial Logit model
LL	Log-likelihood
SPSS	Statistical Programme for Social Survey

1. Chapter 1: Introduction

1.1 Background

This Chapter introduces the research topic described in this PhD Thesis. This research investigates the determinants and impacts of shared ownership and shared ridership of Driverless Cars (DC) from household mobility perspectives. This Chapter starts with the context of the research study. The definition of terms related to DC sharing comes next, followed by the research questions. These research questions are presented along with the research methodology. Finally, the motivations and the structure of this thesis are presented.

1.2 Context

1.2.1 Driverless Car Emergence

The rapid development of carsharing (Shaheen and Cohen, 2013) and ride-sourcing (Rayle *et al.*, 2016) services has sparked the debate about the shared mobility concept. Shared mobility is the rapidly growing sector of the sharing economy that is primarily defined as the collaborative consumption of shared resources available in the marketplace (Acheampong and Cugurullo, 2019). According to Botsman and Rogers (2011), in a collaborative system, consumers have to pay for the company's respective service or product without needing to owe that. The transport sector shared mobility concept was discussed in terms of a) sharing the ownership of a car and b) sharing a passenger ride in a car. The integration of shared mobility with DC technology has the potential to bring positive changes to the environment (Schoettle and Sivak, 2015), and the usage of private cars (Haboucha *et al.*, 2017; Davidson & Spinoulas, 2016; Jiang *et al.*, 2018; Krueger *et al.*, 2016). This research concerns modelling shared mobility behaviour and shared DC adoption intentions within urban areas (Schoettle and Sivak, 2015).

Over the last few decades, passenger mobility patterns have evolved around innovative ideas. The use of private cars was challenged by technology-enabled mobility options (Westervelt *et al.*, 2017). Consequently, the demand for car ownership shows marked changes (Stocker and Shaheen, 2017). For instance, in the UK, London witnessed a high ratio of carsharing opportunities in the form of the car club, which offers easily accessible cars around neighbourhoods (TfL, 2016). By enhancing the supply of car-sharing facilities, 165000 car club members currently use this service (TfL, 2016). Therefore, car clubs offer an easy and flexible way to share a private car instead of owning it full-time.

Simultaneously, the emergence of DC will bring a paradigm shift in the mobility market and the traffic network. As reflected in some scientific papers and news articles, the projected impact of DC will be an increase in car demand and the resultant increase in traffic congestion (Anderson *et al.*, 2016). The reason behind this high volume of traffic is related to DC's capability to drive without human interaction, which can reuse driving time (as there will be no driving task) and allow mobility for travel-restricted groups (e.g., disabled, elderly, low-income). In addition, empty runs DCs may lead to further increased vehicle miles travelled, and the congestion level may worsen unless these DCs can operate on shared services.

The number of carsharing systems is rising despite the increasing number of personal cars since personal cars are cost-intensive with fewer comparable options. Concerning this, sharing DC could reposition itself in response to demand shortage in a specific location, thus relieving the extra traffic pressure by reducing the number of cars to half (Fagnant and Kockelman, 2014). Due to the possible unavailability of one-way taxis on the return leg, shared driverless taxis could resolve these supply-side issues by matching the journey schedule and eliminating uncertainty (Firnkorn and Müller, 2015). By applying ride-matching services, shared DC can reposition itself on-demand to any geographic location (Haboucha *et al.*, 2017). Shared DC will run with zero human interactions and will be more cost-effective than conventional taxis and sharing systems (Krueger *et al.*, 2016).

Considering the flourishing market of shared mobility, DC can also be used on a shared basis to serve multiple car owners or occupants with similar travel interests. DC mobility can rejuvenate the mobility ecosystem by allowing shared ownership and ridership. For the proposed research, shared ownership and ridership are two dimensions of shared mobility. In this regard, a questionnaire survey was designed to understand the expected patterns of shared ownership and ridership of DC and the underlying behaviour of people. This knowledge will be the basis for designing transport policies that can steer the future of autonomous mobility in a more sustainable direction.

Reliance on sharing by car club might result in less use of the private car, reduced congestion, less demand for parking and reduced emissions. There is the possibility of fewer cars holding and urban trips, which will result in a cleaner environment (e.g., London's car club car fleet is 33% less pollutant than London's average) (TfL, 2016).

Similarly, car sharing reduces the burden of capital investment on private mobility ownership, thereby reducing the inefficiency of a personal car that remains idle for 95% of the time (Shoup, 2014). As of January 2013, there were more than a million car-sharing users in North America alone (Cohen and Shaheen, 2018). Alongside, ridesharing and ride-hailing services offer a more flexible and economical way to share a ride. With the growing trend of shared mobility, the car ownership concept got a paradigm shift affecting car ownership.

Nevertheless, DC technology has emerged as a new mobility concept in the urban travel market, enhancing shared mobility options. The reason behind this is two-fold. Firstly, there will be no driver in DC and, therefore, no cost for the driver, so per ride will be relatively cheaper than traditional rides. Secondly, since these cars will be operated by on-demand functionality, the reason to own a private car will be reduced with the same freedom of mobility a private car holder enjoys today.

1.2.2 Existing Shared Mobility Market

Our mobility landscape is full of mobility resources, but uncontrolled utilisation can create scarcity for some parts of society. As of 2018 statistics, 780 per 1000 people in Europe own private cars (Statista, 2018), which is underutilised 95% of the day (Bates and Leibling, 2012). A third of these cars do not move at all for the entire length of the day (Moli *et al.*, 2019). This inefficiency in mobility behaviour creates a distributional imbalance that results in a mobility gap for some parts of society. A possible solution can be reusing these underutilised private cars during their idle time. My present research theme evolves from this inefficiency of using mobility resources within some parts of society through DC.

Mobility demand is increasing with the growth of the population. Within the next 20 years, 59% of the world's population will live in urban areas (Department of Economic and Social Affairs, 2015). Besides these, economic austerity associated with higher energy demand with the growing number of cars is the reason to search for an alternative to traditional mobility and car ownership. Findings from 2013 suggest that mobility demand has shifted from private ownership to sharing among millennials (Shaheen and Cohen, 2013). From this point of view, within the next 20 years, due to the emergence of DC and the scope to integrate into the future mobility ecosystem, travel behaviour might face changes to accept shared cars or shared ridership of cars to satisfy the overarching demand for mobility in society.

Mobility sharing can be discussed with the concept of a sharing economy to tackle multiple effects of changing travel behaviour and car demand, where the mobility user possesses the right to borrow, lend, and rent mobility facilities through a digital platform (Shaheen *et al.*, 2017). The shared economy concept is flourishing to facilitate short-term access to goods or cars in exchange for monetary compensation (Cohen and Shaheen, 2018). In practical terms, the sharing economy allows the consumption of goods and facilities at low prices, which would otherwise be costly (Pasimeni, 2020). For instance, the Bla Bla carsharing system allows the drivers/owners of a car to share the car journey with others, and Uber divers use their cars to allow the ride to others in exchange for money.

Considering social and economic variations, under the umbrella of shared mobility, the modes of transport are multifaceted, including concepts such as carsharing, bike sharing, ridesharing (e.g., carpool, vanpool), public transit services, on-demand ride services, and scooter sharing, and alternative transit services, such as shuttles and micro transit. According to Roukouni et al. (2020), shared mobility by their innovativeness to date can be represented by the following Figure 1.1 :

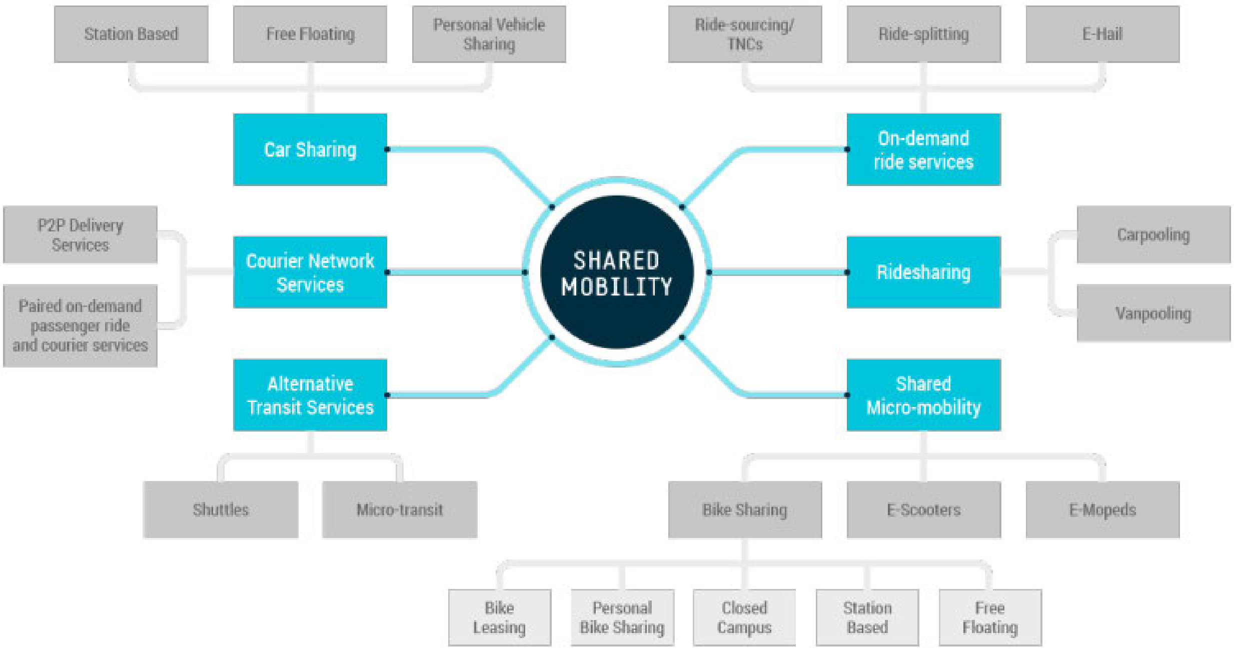


Figure 1.1: The range of shared mobility options in the urban mobility market - adopted from the classification of Roukouni et al. (2020)

Along with Figure 1.1, ride-sourcing (e.g., Lyft and Uber), ride-splitting (e.g., Uber POOL, Lyft Line) (which allows passengers to split the fare and ride) and e-Hail (app-enabled taxis) services are also termed as ridesharing services. Finally, shard mobility also includes app-enabled flexible goods delivery services where private cars, bicycles, or scooters (e.g., food and packages) are the carriers. Pangbourne et al. (2020) referred to MaaS as an innovative mobility solution that gathered shared mobility options within a standard interface to help users purchase mobility options. This interface is the key to providing the best and cheapest ride matching for the user.

Within the taxonomy of shared mobility, the form of sharing that casts a stringent effect on people's mobility behaviour is carsharing (Steininger *et al.*, 1996). Carsharing is a membership-oriented short-term mobility service where members should pay by the hour, day or month (Duncan, 2011). In this system, members have access to various cars that can allow them to customise their journey based on their purpose. This system is an alternative to car ownership with reduced car maintenance costs and liabilities (e.g., initial capital cost, fuel, maintenance, insurance, etc.) The fundamental difference between car ownership and carsharing is that the cost is proportional to the actual use in the case of carsharing. For less frequent trip makers and leisure travellers, carsharing offers ease of access and a low-cost travel option rather than holding the car full-time in their possession (Litman, 2000).

[redacted]

Figure 1.2: Development of shared cars and members in Germany by year and mode (Kolleck, 2021)

The very early adoption of car sharing was founded in 1948 in Switzerland. This concept has undergone experimental projects (e.g., 1983 – 86 in Indiana, 1984 – 1986 in Sun Francisco) to attain the modern carsharing form in 1994 in Quebec, Canada. After that, in the mid-1990s, several carsharing practices became popular in several North American cities. This kind of carsharing strategy became popular with the emergence of telematics in 1998 (Cohen and

Shaheen, 2018). As of July 2015, Canadian carsharing programs hit 20 compared to 22 in the US. As an approximation, 1530190 members used 25527 roundtrip cars in the US in 2014 (Shaheen *et al.*, 2014). Figure 1.2 shows the carsharing number growth in Germany over the past 10 years.

DC will offer free in-vehicle time, as there will be no driving task, and allow easy leisure activities that can be done on the traditional cars while riding. This zero-driving task can attract riders from distinct traveller groups, especially older adults, disabled people, and other travel-restricted groups (Mestres *et al.*, 2017). With these benefits, DC can create induced travel demand and alter user behaviour, attracting higher traffic volume and extra vehicle miles travelled on the road (Harper *et al.*, 2016; Fagnant & Kockelman, 2014). Fagnant and Kockelman (2014) proved that shared DC could reduce the extra vehicle miles by 50%. In response to the anticipated higher volume of traffic and highway capacity issues with the advent of DC, these DCs will be platooned and leave the unused road space for other cars' usage. DCs' will be connected to road infrastructures to disseminate road usage data, thereby reducing congestion and avoiding road incidences (Tientrakool *et al.*, 2011). In terms of sharing, a modelling exercise by a study conducted in Singapore found that shared DC could operate at the same operational efficiency as one-third of the present car demand to support the mobility demand of an entire city (Spieser *et al.*, 2014).

Nonetheless, in this shared mobility paradigm, the average idle time enjoyed by conventional cars is of concern to support its use through a shared basis. Personal cars remain parked and idle for 95% of the time, unused until they are needed by their owner (KPMG, 2012). In DC sharing, this unutilised time can genuinely offer the opportunity to share the DC other than the owner to serve and then satisfy their mobility needs.

1.2.3 Shared Mobility and Driverless Cars

Empirical research suggests that the emergence of DC will likely flourish the carsharing system in idle car time (Tian *et al.*, 2021). For instance, a peer-to-peer carsharing system allows a private car owner to rent their car to another individual through an intermediate company or sharing system (Dill and Mcneil, 2021). DC adoption will likely popularise this carsharing in the mobility market because DCs are not operated by drivers, allowing them to relocate according to the user's demand. Therefore, operating the DC sharing system might be much cheaper, allowing the shared economy concept to flourish after DC implementation. Thus, DC technology and shared mobility options can change the carsharing and ownership model in various ways.

As the Society of Automation Engineers (SAE, 2018) specified, DC technology applies to the spectrum of driver assistance systems where the highest level refers to the complete hands/feet/brain off driving. These cars can also interact with the surroundings with seamless data sharing by intelligent devices (e.g., Front camera, GPS, Lidar, etc.). DC technology will also bring benefits related to safety, congestion, and mobility behaviour for society's travel-restricted group (Trommer et al., 2016; Milakis et al., 2017).

Based on empirical research, the anticipated zero driving tasks in the DC era, in-vehicle time, will be perceived more positively; hence, the value of travel time (VTT) might be lower (Kolarova *et al.*, 2017). Hence, there is a chance that DC can redefine the in-vehicle time use pattern by influencing more economical spending of travel time in DC. Simultaneously, DC will allow door-to-door travel opportunities with less waiting time by relocating, avoiding congestion (Zmud *et al.*, 2016) and influencing on-demand mobility options like existing ride-sourcing services (e.g., Uber, Lyft). An early evaluation of Level 5 DC technology features might cost an additional $10,000 to $50,000 per DC than its non-automated counterpart, and this higher initial cost might increase average consumers' propensity to share the DC on the grounds of affordability issues.

With the cost as a barrier to implementing private DC, empirical findings suggested that 25% of individuals will prefer a private DC over a shared DC (Haboucha *et al.*, 2017) irrespective of the high fidelity, user friendliness and environmental benefit (Greenblatt and Shaheen, 2015). Despite many positive mobility benefits of shared DC, the potential uptake of shared DC depends on trip characteristics (e.g., travel costs and parking availability) and behavioural factors (e.g., attitudes towards sharing and in-vehicle activities) still to be explored. Therefore to understand the perception of shared ownership and shared ridership in the DC era, factors influencing the use of shared mobility in the backdrop of present car ownership and sharing services need to be explored thoroughly.

1.3 Definition of Terms

Driverless Car definition

The term "autonomous vehicle (AV)" (sometimes known as the self-driving vehicle or driverless cars) refers to a form of a motorised vehicle that is computer-controlled and operates on current roadways with little or no direct human intervention (Fagnant *et al.*, 2015a). With the development in the hi-tech industry and improvements in computing, DCs can substitute human drivers with artificial systems that perform jobs in a human-like manner (Ionita, 2017). The paper stated that DCs are running through several learning stages and experiences to perform approximately like a human, which is more than true/false logic and behave autonomously.

DCs can apply the spectrum of driver assistance technologies as specified by the Society of Automation Engineers (SAE, 2018), where the highest level (Level 5) refers to the complete hands/feet/drain off driving. Besides, these cars can interact with the surroundings with seamless data sharing by intelligent devices (e.g., Front camera, GPS, Lidar, etc.). Experts expect DC will bring benefits related to safety and congestion and provide mobility for travel-restricted groups (Trommer et al., 2016; Milakis et al., 2017) with all the following technology features:

1. Driving assistance with some intelligent devices (e.g., front camera, GPS, Lidar, etc.)
2. Can drive itself without human interaction by making travel time free for other work
3. Can detect the presence of other vehicles and pedestrians from a reasonable distance to avoid the collision
4. Can control its speed with the speed of the surrounding traffic flow
5. Onboard backup and communication system to communicate with other cars and devices nearby

DC Functions

DCs operate in a three-phase functional process known as "sense-plan-act" (Behere and Törngren, 2015). Figure 1.3 depicts a high-level overview of the components required for DCs and their subsidiary duties to organise satisfactory automation. These components are the following (Behere & Törngren, 2015):

1. Perception of the external environment/context in which the vehicle operates.
2. Decisions and control of the vehicle motion concerning the external environment/context that is perceived.
3. Vehicle platform manipulation mainly involves sensing and acting the Ego vehicle to achieve the desired motion.

[redacted]

Figure 1.3: Driverless cars' functional components (Behere & Törngren, 2015)

Figure 1.4 depicts the very high-level structure of modern DC systems (Talpaert *et al.*, 2018). Functional components of DC are the conceptual building blocks of how DC works, while the structure depicted in Figure 1.4 is the application mechanism of the building blocks. First, DCs collect low-level data through cameras, radars, LiDARs (Light detection and ranging), and GPS-IMUs (GPS and Inertial Measurement Units provide an instantaneous position) before transforming them into DCs lane positions and obstacles. ADAS (Advanced Driver Assistance System) is implemented for lane keeping, collision avoidance and low-speed cruise control. At the next stage, scene detection, classification, and localisation analysis are fed into the path-planning process to predict cars' travel trajectories and manoeuvres. Dynamic traffic information is passed through a high-level control mechanism and identifies constraints as the DC path progresses through a continuous closed-loop system (Talpaert *et al.*, 2018).

[redacted]

Figure 1.4: Fixed modules describing the DC driving task flow (Talpaert et al., 2018)

DC Shared Ownership

In detail, while private DCs refer to the private ownership model, shared DCs belong to the shared or shared ownership option. Private DC mean that each traveller uses the car individually, such as a conventional personal car. On the contrary, shared DCs allow more than one rider/sharer to share a DC (Stoiber et al., 2019; Turon & Kubik, 2021). Regarding sharing types, shared DCs are of two types: (1) sharing the ownership (e.g.,cat-club, peer-to-peer, car-rent from close contacts/company), and (2) sharing a ride (e.g., ridesharing, carpools, vanpools, shared taxis).

Following the literature, with the emergence of DC, people can choose between full-time DC ownership or sharing/hiring a DC in case of need. In this research agenda, the first DC concept is a privately owned DC with a single occupant for personal use. The car is owned by the users or their household for private ownership.

The second concept is the shared owned DC among 3 - 4 members, which combines the features of a taxi (Uber) and carsharing with the facility of on-demand service. The purchase cost, maintenance and other liabilities will be divided for this ownership model. But to access a shared-owned DC, someone should wait and spend on parking costs. In shared ownership, the car is partially owned by the users, which may happen following different models, e.g., people living in the same building or owning the same car jointly.

Another form of shared ownership is the driverless taxi, for which people will not spend on purchases except paying the rental cost. People can also share the trip with others, which may require longer journey times but could make your trip less expensive (per journey). The usage cost will depend upon the time usage inside the driverless taxi. Taxi services are operated by a company that runs the cars, and the user does not participate in the ownership.

DC Shared Ridership

Ridesharing is sharing a trip where drivers and passengers have similar origins and destinations (SAE, 2018). The driving responsibility and cost may be split among the passengers for the entire trip. Ridesharing includes carpooling and vanpooling among 7 to 15 passengers. Alongside ride-sourcing (e.g., Lyft and Uber), ride-splitting (e.g., Uber POOL Lyft Line) (allows passengers to split the fare and ride) and e-Hail (app-enabled taxis) services are also termed as ridesharing services. The ride/trip can be shared with different categories of people: 1) members of the household, 2) acquaintances (friends, colleagues), and 3) strangers. The attitudes towards sharing a ride are expected to change with the category of people you share a ride with.

It is possible to combine each form of shared car ridership with each type of people in sharing the trip or ride (e.g., someone can share a trip with members of the household in a private car or ride with a stranger in a taxi) and explore these shared ridership attitudes in further research.

1.4 Research Questions

1.4.1 Research Questions

Questions for this research are identified based on the extensive literature search and after discussion with industry experts. The first research question focused on behaviour related to present shared ownership and shared ridership. In this question, options of present shared ownership and ridership, trip purposes, and in-vehicle activity preferences are the variables. The second research question assessed the attitudes and behaviours determining DC shared ownership and shared ridership. Assessments of the respondents' personality traits, social norms, and socio-demographic status in influencing DC shared mobility choices were performed under the third research question. The proposed research questions are the following:

Question 1. What is the current behaviour in terms of shared mobility?

1a. What are the current shared ownership behaviours by different travel modes?

1b. What are the current ridesharing behaviours by different travel modes?

1c. What are the factors influencing present shared ownership and ridesharing behaviour?

Question 2. What are the expected behaviours and attitudes regarding shared mobility using DC?

2a. How do sharing behaviours influence propensity towards shared DC?

2b. What are the attitudes determining weak propensities to accept shared DC use over non-shared DC options?

2c. What are the attitudes determining non-shared and shared DC use?

Question 3. What are the personal characteristics influencing shared mobility choices with DC?

3a. How do socio-demographic characteristics influence the sharing choices concerning DCs?

3b. How do personality traits influence the sharing choices concerning DCs?

3c. How do social norms influence the sharing choices concerning DCs?

1.4.2 Research Methodology

This study utilises an online questionnaire data collection methodology to use the data to answer the research questions. Revealed preference (RP) data summarised the present mobility-sharing behaviour of Edinburgh residents and the likelihood of adopting different DC-sharing mobility options. Among the RP data, demographic, socioeconomic, personality and social-norm data variables are transformed into binary variables to ensure the data non-linearity in the econometric analysis. Collected data was then analysed through statistical and econometric modelling. Among the discrete choice analysis types, Binary probit, ordered probit, binary-logit, and multinomial-logit are the econometric methods used in this research analysis.

1.5 Motivation

This study tried to unearth the DC shared ownership and ridership possibilities and associated factors among the people of Edinburgh. Understanding people's preferences for different DC shared mobility options and the need for them are essential indicators in identifying the future use of shared DC. Therefore, through this research, an effort was made to find the link between present mode-sharing behaviour and potential DC-sharing possibilities.

KPMG (2015) identified DC as the benefits provider to a wide range of people with significant environmental, economic, and social benefits, including improved social inclusion. Besides, in the proposed research, in-vehicle time use can help deliver better service provision for future transport modes.

The proposed research can bring in-vehicle comfort, convenience, and privacy for DC users and design the car fleet more purposefully. Discussing journey purpose and in-vehicle activity preference can help create a more user-friendly service for specific trip purposes. For instance, a local carsharing club can provide more entertainment facilities for off-peak leisure travellers than commuters (e, g., newspapers, news channels or FM radio).

Moreover, having understood different in-vehicle activity preferences and their sensitivity for different types of travellers, car manufacturers can ensure better interior design for their DC fleet. The user-friendly design of car interiors is essential for journey comfort and convenience, and these facilities can attract more passengers to use them rather than their present car options.

The shared ownership concept can determine the willingness to pay for future DC options compared to traditional car hire and car club schemes. Discussion of factors may help shape the future mobility market along these choices. This research concept may help develop user-centric future transport policies (i.e., local, regional and national). When users' sensitivities for private DC and shared DC concerning other travel aspects (trip purposes and in-vehicle activities) can be well understood, ridesharing companies can maintain a more economical car fleet size and lower maintenance costs. In the same way, the local council can reduce their expenditure on labour-intensive, on-demand ridesharing facilities for the elderly and disabled people of the community.

Building upon the assumptions on valuable aspects of DC stated above research efforts were made through the growing number of literature related to DC sharing adoption and the impacts of this disruptive technology. However, the underlying features of these studies are based on hypothetical population choices and some agent-based simulations, where observed choice data was ignored. Besides, these studies assessed market penetration and general adoption patterns of DC without considering shared DC demand from the household perspective. A few of these studies applied a segmented DC choice method with latent DC choice parameters, where travel patterns and frequency are insignificant. A few studies investigated shared mobility concerning strangers but failed to consider the presence of family members in sharing. Although very few of these studies focused on carsharing and ridesharing behaviour jointly, shared DC use in ownership at the household level is missing from the present research arena.

Motivated by these gaps in the present literature, my present study employed a discrete choice modelling method to analyse observed household travel behaviour (regular or occasional shared car ridership, car ownership) data to assess the propensities for DC shared ownership and ridership in association with socio-economic characteristics, personality traits and social norms attitudes.

1.6 Organisation of this Thesis

The core part of this research is presented in this dissertation with seven chapters, outlined in the following paragraphs. Several appendices at the end of the dissertation are attached that elaborate on the materials and findings used to describe this research.

Chapter 2 presents the literature review on shared DC ownership and ridership models. This Chapter defines DC-shared ownership and ridership before elaborating on the determinants and impacts of these DC-sharing options. A comprehensive review of present research gaps on DC shared ownership and ridership is discussed at the end of this Chapter.

Chapter 3 is the methodology chapter that describes the data collection and data analysis methodology. The theoretical framework used in this research and its implications are discussed at the beginning of this Chapter. After that, the 'Expert Interview Questionnaire' and analysis of the 'Expert Interview' data are described. The final data collection methods and data sample size estimation are then described. This Chapter ends with discussing econometric methods used in the data analysis.

Chapter 4 elaborated on the descriptive analysis of the data about shared DC ownership and ridership choices, socioeconomic and personality characteristics, and attitudes towards the social norm.

Chapter 5 elaborated on cluster analysis results to describe the present carsharing and ridesharing behavioural groups. This Chapter started with the clustering methodology and described these behavioural groups and their characteristics concerning the socioeconomic groupings, sharing reasons, personality, and social-norm status. This Chapter concluded with an analysis connecting respondents' present sharing behaviour with the likely behaviour of DC sharing.

Chapter 6 deals with several econometric modelling techniques associated with answering the research questions. This Chapter is divided into four sections, designed to describe four econometric methods. All the facts and figures in this Chapter are the direct output of DC choice models and the factors determining the shared DC usage possibilities.

Chapter 7 summarises how the research was carried out, answering the research questions and achieving the objectives. Implications, limitations, and further research opportunities are discussed at the end of this Chapter.

2. Chapter 2: Literature Review

2.1 Introduction

The main objective of this Chapter is to discuss relevant literature in the field of shared DC use with its deployment strategy, anticipated business models, policies related to shared DC use, determinants and impacts. This Chapter primarily focused on Level 5 DC, and bike–sharing and scooter–sharing systems are not part of this literature review. Journal papers, conference papers, policy papers and technical reports, book chapters and other PhD dissertations are among the reviewed literature. A structured approach was followed in collecting studies representing different DC sharing types from the Web of Science and Google Scholar search, using 12 keywords (Milakis et al., 2017; Narayanan et al., 2020). This method is structured by using several categorical phrases (e.g., shared ownership and shared ridership) and associated keywords while collecting studies from the web. These keywords helped me identify different types of shared DC services (e.g., shared taxi, private DC, driverless shuttle, shared ride with DC), methods (e.g., discrete choice modelling, stated preference survey, cluster analysis) used for each of the identified studies for shared DC use. Based on these studies, the impacts of expected shared DC services were categorised evaluated the expected demand for them, and tried to uncover policy and operational requirements for channelising the development and deployment of shared DC services.

Shared driverless mobility systems with the convergence of shared rides, mobile services (e.g., smartphones and wireless data), and automation are among the most innovative disruptions in the present transport industry (e.g., Greenblatt & Shaheen, 2015; Stocker, Lazarus, Becker, & Shaheen, 2016). These shared services were observed in practice within a few cities around the worldfor the last ten years, where different prototypes and usages are available. Amongst them, several studies termed public transit systems as shared driverless mobility with various functionality and applications in the literature (Narayanan *et al.*, 2020; Xu *et al.*, 2019; Cohen and Shaheen, 2018).

2.2 Emergence of shared DC

DCs are likely to introduce the next paradigm shift in sharing transport. With some anticipated benefits associated with DC introduction, several critical evaluation stages will follow through. In these stages, the active involvement of car manufacturers and technology companies will likely induce the demand for the world's first DC car. The recent interest in DC and the technical jargon used to describe its benefits indicated that DC systems are at the doorstep to be introduced sooner with full functional capability (Brown, 2018). Even though the deployment of DC is fully thought, having looked through recent actions of automobile manufacturers and technology traders, DC is likely to deploy as shared mobility services (Stocker and Shaheen, 2018). BMW Group had planned to bring ridesharing with DC to the streets by 2021 in collaboration with Intel and Mobileye (BMW, 2016). Following the same path, Ford Motor introduced ridesharing with DC service in 2021 (The Ford Company, 2016). Volkswagen Group and Hyundai have teamed with Aurora Innovations to set up an on-demand DC service in 2021 (O'KANE, 2018). Daimler has teamed up with Uber to bring DC within Uber's Global ridesharing network (Daimler AG, 2017). Japanese car maker Toyota partnered with Uber in a £388m investment deal destined for the same goal (Monaghan, 2018). After millions of miles of testing, Waymo has started commercial DC ridesharing services surrounding Phoenix, Tempe, Mesa and Chandler (LeBeau, 2018).

2.3 Shared DC Classification

Typifying shared DC is essential when policymakers organise to implement a shared DC system in a region. Typology is essential to characterise the working principles in the future implementation of shared DC and its deficiencies. To envisage the likely benefits and risks of DC implementation, investors sometimes need information about shared DC types for ease of implementation (Litman, 2022). An inclusive assessment of the demand for shared DC and associated guidance on policy and supply mechanisms could further develop the shared DC system (e.g., operation, sharing types, integration with other modes, service types, reservation structure, ownership and network operations).

As mentioned in the existing literature (Narayanan *et al.*, 2020), shared DC systems are categorised based on their operation types (e.g., booking time frame, sharing system, and integration with other mode types). Based on the booking time frame, shared DC can be divided into on-demand (Alonso-Mora et al., 2017; Fagnant & Kockelman, 2018; Gurumurthy & Kockelman, 2018; Sebastian, 2017; Hyland & Mahmassani, 2018; Lokhandwala & Cai, 2018), reservation-based (Levin, 2017; Ma et al., 2017; Pimenta et al., 2017) and mixed systems. These systems allow users to book DC sharing systems in real-time, in advance or allow them to use both.

Based on the sharing types, shared DC systems can be classified into carsharing (Alam & Habib, 2018; Allahviranloo & Chow, 2019; Bischoff & Maciejewski, 2016; Dia & Javanshour, 2017), ridesharing and mixed-sharing services. Ridesharing (Alazzawi et al., 2018; Alonso-Mora et al., 2017; Heilig *et al.*, 2017; Martinez & Viegas, 2017) allows two or more people to travel together, which is also one of the focus of this research. Between these two DC sharing types, a mixed system allows people to ride alone or with others (Cyganski et al., 2018; Lokhandwala & Cai, 2018). Based on the destination choice, ridesharing can be origin-destination-based or dynamic ridesharing en route (Hyland and Mahmassani, 2018).

When the integration types were considered, a shared DC system can be independent (which is not dependent on another mode), or integrated (W. Shen *et al.*, 2018; Moorthy *et al.*, 2017; Yap *et al.*, 2015), in which the shared system supports the public transport system. Based on the ownership of an independent system, this sharing system falls into mobility-on-demand service (Bischoff & Maciejewski, 2016; Bösch, Ciari, and Axhausen, 2017; Childress *et al.*, 2015a; Loeb, Kockelman, and Liu, 2018) and shared ownership system (Masoud & Jayakrishnan, 2017; Allahviranloo & Chow, 2019). Ownership is the other focus of my research. Except these, the particular type of shared DC system includes campus-based, industrial DC systems (S. Kim et al., 2017; Pimenta et al., 2017; Nordhoff et al., 2018).

Based on the service types, Földes & Csiszár (2018) identified four different DC applications: driverless taxis (independent car sharing), shared driverless taxis (ridesharing system), feeder pod (feeder system to a high capacity Public transport line) and fixed route pod (high capacity demand-responsive pod). According to Földes & Csiszár (2018), regarding capacity, the first three options of shared DC are demand-driven, while the last one is demand-responsive, which is flexible in timing and runs on a predetermined route.

Based on reservation structure, (Hyland and Mahmassani, 2017) classified shared DC into three types: (1) Short-term rentals, (2) Point-to-point service, and (3) Mixed service. This is based on reservation and pricing structures. For short-term rentals, passengers are allowed to use the service for a particular time slot, while for point-to-point service, DC is likely to move passengers between two fixed points. Concerning pricing structure, this paper divided shared DC into fixed pricing and dynamic pricing structure. For the fixed pricing structure, the passenger has to pay for the time and distance, while for the dynamic pricing, the passenger must pay based on origin-destination and time of the day.

Concerning vehicle ownership and network operations, Stocker and Shaheen (2017) introduced some potential shared DC business and service model scenarios. They also proposed four vehicle types regarding vehicle capacity. This study identified six future DC business models: (1) Business-to-Consumer (B2C) with a single owner-operator; (2) B2C with different entities owning and operating; (3) Peer-to-Peer with a third-party operator; (4) P2P with the decentralised operator; (5) Hybrid ownership with the same entity operating; (6) Hybrid ownership with a third-party operator. Besides, the shared DC scenarios concerning capacity are (1) large vehicles (20 + Pax), (2) mid-sized vehicles (7 to 20 Pax), (3) small vehicles (3 to 7 Pax) and (4) micro vehicles (1 or 2 Pax).

In light of this literature review, shared mobility services are likely more common in offering cost-effective and convenient services to users due to efficiency (Stocker and Shaheen, 2018). This paper also claimed that single-occupant cars would likely dominate in the preparatory stages of DC use.

2.4 Literature Review Methodology

The methodology followed in this literature review involved five steps. The research scope, defined in the **first step**, is the shared ownership and ridership possibilities with DC. Based on shared ownership and ridership choice perspectives, this literature review is comprehensive among current DC researchers (Milakis *et al.*, 2017; Faisal *et al.*, 2019). The literature selection process applied for this research is illustrated in Figure 2.1.

The **second step** was identification, where literature on driverless cars was searched throughout the web by following a set of keywords and phrases related to DC sharing (as described in Table 2.1). Besides, another set of keywords was used to systematically reflect a range of possible social and behavioural themes associated with DCs. To make a robust search and to investigate the recent trend in DC shared ownership and ridership possibilities, the search inclusion criteria were intended for online peer-reviewed English journal articles published between 2000 and 2022. While considering this literature review, a comprehensive search was made through different databases up to 2022, but only a few pieces of literature from 2021 and 2022 were selected to answer research questions. There was no commendable research for DC shared ownership and ridership among the published researchers during this time.

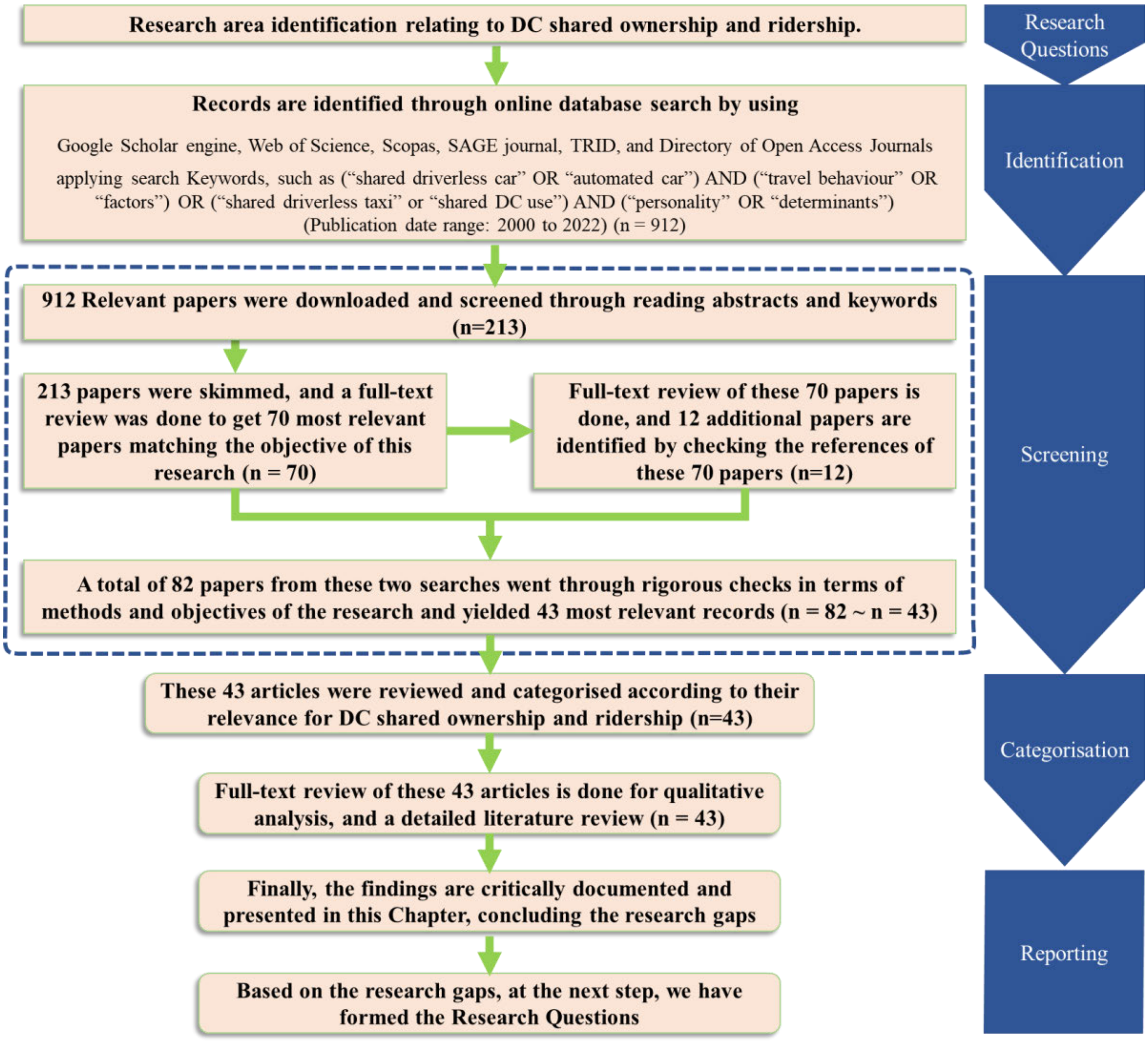


Figure 2.1: Literature review methodology

Table 2-1: Keywords for searching shared ownership and shared ridership of DC

Keywords: Literature for DC shared	**Keywords: Within document search**
Shared autonomous car use	Age band: millennials, centennials,
Shared driverless car services	Gender: Man, woman
Private driverless cars	Impact/ Challenges/
Shared ownership of autonomous cars	Car ownership/ No car ownership
P2P driverless car use	Travel behaviour
Shared ownership and driverless car	Safety
On-demand automated car	Convenience
Keywords: Literature for DC shared	Comfort
Shared autonomous electric vehicles	Personality traits
Shared driverless taxis	Social norm
Driverless taxi services	Society/Social influence
Shared self-driving car	

The exclusion criteria included those points not considered within the inclusion criteria. Amongst them, public transport, bike sharing, cyclists and pedestrians are not included in the search. Besides, the exclusion criterion relating to the publication date was determined before

2000, with the end date fixed in July 2022. An online search was conducted using the Google Scholar engine, Web of Science, Scopas, SAGE journal, TRID, and Directory of Open Access Journals. The query strings used for database searches were formed with one keyword from the first column and one from the second, such as (“shared driverless car” OR “automated car”) AND (“travel behaviour” OR “factors”) OR (“shared driverless taxi” or “shared DC use”) AND (“personality” OR “determinants”). These keywords finally focused on the titles and abstracts of the articles searched. These keywords and their combination are used here for examples only.

The **third step** is the screening, which involves reviewing relevant articles with their keywords and relevant abstracts. Abstracts of the selected articles were reviewed to screen out the non-relevant ones. My search primarily resulted in 912 papers relevant to DC sharing. After screening and evaluating the abstracts, relevancy for DC shared ownership and ridership was checked, and this process identified the 213 most relevant papers/articles. Only the relevant papers and journal articles are thoroughly skimmed and put in the chosen directory. The intention was to find those papers that used stated choice modelling in DC research and apply this technique to my experiment. Finally, a full-text review of the selected articles was performed in line with the aim of this study, and the number of reviewed papers was narrowed down to 70 articles.

Additionally, 12 extra papers were identified by reviewing references of these screened articles. All these 82 papers went through rigorous checking in terms of methods and objectives of the research and yielded 43 most relevant papers concerning shared owner DC and shared ridership with stated choice experiments. After the initial review, the screened-out papers/articles are listed in an Excel document to help further analyse them. These 43 articles were reviewed, categorised and analysed in the **fourth step**. Papers’/articles’ abstracts and results were reviewed to identify their relevance for DC shared ownership and ridership. After these primary categorisations, these papers/ articles are categorised according to the potential impacts of shared DC ownership and ridership on land use, travel behaviour, environment, and car ownership. The **final step** is the reporting and dissemination phase, which involves critically documenting and presenting my findings in this Chapter, concluding the research gaps. At the research question formation stage, these gaps were considered to form DC choice concepts and their potential implications.

Some studies not specific to shared DC were included, as they indicated the effects of driverless car use in terms of social and environmental changes, personal car use and sharing of cars. The literature for this thesis was collected from relevant sources, including “Transportation

Research Part C: Emerging Technologies", "Transportation Research Record", "Journal of Transport Geography", & "Transportation Research Procedia", which are the most frequently visited research records. These top three journals account for around 70% of the reviewed papers. These 43 papers/articles concerning their publication year revealed the growing interest in DC over the past couple of years. Nearly 70% of these papers were published between 2019 and 2021, about one-fourth (23%) of papers were published between 2017 and 2018, and the rest (6% - 7%) were published in 2016 or earlier. My findings include academic peer-reviewed journals, books/book chapters, professional reports and conference presentations published between 2000 and 2022. 62% of these 13 papers were chosen to discuss shared-owned DC that utilised econometric methods. Nine papers were published in the Transportation Research journal between 2015 and 2021.

2.5 Shared ownership with DC

2.5.1 Present shared ownership (car-sharing) trends

Car clubs can be taken as examples to identify the present car-sharing (shared car ownership) trend, where people can take short-term (e.g., hourly, daily, monthly). The terms and conditions of usage may vary in different countries of the world, and for which charges need to be confirmed before the journey starts. Car clubs' cars are traditionally owned and operated by an organisation for a commercial venture, responsible for distributing cars around the neighbourhood to which they belong (Sustrans, 2019). To increase the accessibility of cars, they can be parked near stations, job locations, public spaces or institutional campuses (e.g., Zipcar, City Car Club). Usually, reserved parking spaces for the car club cars save the drivers time searching for cars. Before booking a car, driving ability and annual subscriptions are ensured with an app-based communication portal. The car can be locked or unlocked with a mobile keypad or smart card that needs to be swiped to access the car.

Car clubs are a greater alternative to car ownership, allowing the owner to own it without the hassle of insurance, fuel, maintenance and tax burden. As of the present findings, one car club can replace 20 conventional cars to reduce road congestion and eliminate the need for higher parking demand (Sustrans, 2019). At the end of the time allocated to use the car, the car must be returned to the station, or it can be left at the journey destination to use by someone else.

On the other hand, car-sharing refers to sharing a car by two or more people with the same destination for the part or whole of the journey. Based on destination choice, another form of car club can be termed a '**One-way**' car share where the car will be left at the destination. All the traditional car club features are possible here with the enhancement of performing an unplanned journey. In this way, the driver will be charged by minutes for the times he drives. Figure 2.2 shows different car-club models.

[redacted]

Figure 2.2: Comparison of three types of car club operating models (Le Vine, 2012)

Peer-to-peer (P2P) car sharing is private car sharing through a broker office that makes the exchange possible (e.g., technology, customer service, driver and safety certificate, insurance). A 'P2P' car club operates as a broker between private car renters and car owners who wish to rent their cars out of their free time. The broker company that manages the digital transaction between the owner and the renter gets a fraction of the rental value. The P2P model also includes P2P car sharing, P2P marketplace, hybrid B2C and shared ownership model (shared ownership)(SAE, 2018).

Some P2P car clubs use telematics systems installed in the car to read smartcards and allow an authorised renter to access the car independently. An example for the UK is the Hiyacar, a newly formed P2P car-sharing club in London with 5000 members. According to Sarah Kilmartin of Hiyacar, sharing the under-utilised resources on a P2P basis can be a good earning source (£1000+/month) (Standard, 2019).

With nearly 100,000 global members, the car club's urban mobility model has been expanding since its initiation in Edinburgh in 2000 (Scotland, 2010). City Car Club was the first in Edinburgh to offer car hire facilities with various car models to suit the renter's short journey types. Besides, 31000 cars were removed from the road in London alone, covering 62 football pitches (CarPlus, 2017). During its 10-year tenure, London's car clubs formed with 18% electric cars as of 2018 survey results. Car clubs are the fast-growing shared car ownership venture in the UK's mobility market.

To date, numerous papers reveal the effects of car-sharing practices worldwide. Among these papers, the notable reasons mentioned are reduced car ownership and environmental and transportation effects. Due concentrate was given on motivation factors (Burkhardt and Millard-ball, 2006; Lane, 2005), changing car ownership patterns and social benefits of car sharing, focusing on the proposed research objective.

As of the Car Plus annual report of 2018, in Scotland, car club membership has grown 29% more than in 2017 during its 11-year tenure (CarPlus, 2018). The same report mentioned that 300 tons of extra CO_2 savings happened in one year, higher than the UK average. 32% of car club members sold their cars after joining the car-club. Figure 2.3 (next page) indicates why the household chose the car club membership for Scotland. Among those, the 'not having a household car and personal freedom of ridership' scored the topmost (31%), while 'additional car holding' scored second (13%).

As per the estimation from Zipcar, every 13 personal cars are likely to be replaced by one Zipcar. As a benefit, approximately £300 per month can be saved by Zipcar members alongside reduced carbon emissions and less parking demand (Zip Car Sharing, 2023). By 2020, approximately 120000 cars were supposed to be replaced on the road in the UK due to carsharing, as per the research done by TfL and Car Plus (Le Vine, 2012).

[redacted]

Figure 2.3: Household circumstances while joining a car club (CarPlus, 2018)

2.5.2 Shared Ownership Definition

The shared ownership scenario relating to the proposed research refers to the clustering of 3-4 households for regular and occasional DC use. It was assumed that the shared DC would be purchased and managed by the members of this DC shared ownership cluster. Ideally, when multiple individuals lease a car owned by a third party, this sharing can be termed shared ownership. Members of this venture bear the portion of the car purchase to use the shared car. This kind of car ownership venture could be run through a dealership or as a partnership with a company responsible for car purchase and operation. The benefit of shared car ownership can allow individuals to utilise high-end car models they might otherwise be unable to afford. Members can source additional income by renting the car to someone other than members, especially when their DC is not in use.

For this research, the idea of shared DC ownership was taken from a 2016 research (Masoud and Jayakrishnan, 2017) on shared ownership possibilities of DC, considering its initial market cost and possible maintenance. This study proved the 33% reduction in household car use with the advent of shared ownership of DC. Compared to that, the present study comprehensively unfolds shared DC ownership and ridership behaviour by frequency of use and in the presence of strangers and close contacts.

The shared ownership idea evolved from the collaborative consumption of higher-valued economic goods in a collective and joint activity. In shared ownership, all collaborative activities should not be organised simultaneously. Likewise, in shared ownership, the shared goods are owned by an individual (i.e., an apartment or a car) or a company (i.e., a fleet of shared cars) (Pasimeni, 2020). Most importantly, in the sharing economy initiatives, when people are organised and coordinated separately to consume luxury goods (i.e., cars, yachts, holiday homes) and services (i.e., energy initiatives, agricultural infrastructure), it can be termed shared ownership.

In transport research, the concept of sharing economy refers to the reuse of privately owned mobility resources (i.e., cars, bikes, scooters) within a business venture, where the shared/ shared access should be gained by dint of monetary benefits. For the merit of this research topic, the term shared mobility should not be mixed in place of shared ownership and vice-versa. The rise of the sharing economy since 2010 is inspired by distant interaction among users for temporary access to mobility resources (i.e., cars, bikes) without ownership status (Pasimeni, 2020). The symbolic identity and determination for some luxury goods, such as car ownership embedded in society, deter shared/shared ownership. Therefore, to gain successful shared ownership, the individual ownership feelings need to be transformed into a 'co-ownership' concept, as it deepens the community feel and sense of cooperation among the users (Mitchell *et al.*, 2012).

In the sharing economy, ownership is a perceived feeling associated with psychological ownership of resources (Atasoy and Morewedge, 2018) and sharing experiences (Kovacheva, 2019). Besides, sharing the resources in a shared ownership scheme requires cost-sharing and liabilities. In transportation, the sharing economy is backed up by different shared ownership options (as discussed in the subsequent sections). These are coordinated through community-based initiatives on long-term relationships and mutual trust (Hofmann and Hartl, 2017).

It can be mentioned that the 'social network' inspired the shared car ownership programme through the Nissan car model (Baldwin, 2016), launched in 2017 to represent the effort of the shared car ownership programme. Under this programme, users are supposed to be charged for their monthly usage of the local shared car fleet. Similarly, in partnership with Enterprise Car Club, BERYL operated a carsharing scheme that encouraged people to accept shared DC ownership (Simpson, 2023). As anticipated, this effort of shared ownership might influence people to take advantage of shared use and ownership. However, this shared ownership proposal is valid. The impacts of these schemes after their implementation were not yet available to the best of the author's knowledge.

2.5.3 Shared ownership possibilities with DC and their determinants

Shared DC ownership possibilities

DC facilities are still developing; therefore, DC sharing possibilities are still speculative, as discussed in the present research. Various DC ownership choices are tested around the world within different study frameworks. Among these studies, only a few handfuls simultaneously discussed shared/shared ownership.

Mourad et al. (2019) offered scenarios in their research where a private DC could be rented to other users when its owner is not using it. This system is not precisely like a P2P sharing system because, unlike P2P, this system will not be operated through a third-party operator.

Xu et al. (2019) researched the sharing of DC at a household level and tried to find the optimisation of car use in a Chicago sub-area network. In their model, they tried to understand how household size and travel behaviour can impact household activity scheduling and route planning for DC use.

Another activity scheduling study was conducted in New York by Allahviranloo & Chow (2019), which investigated passengers' willingness to pay for the use and reservation of cars within a group of users with a fleet of cars. The two-level model was used, in which the upper-level model guides the lower-level model to measure the willingness to pay by users under different activity scheduling, routing and pricing mechanisms. This study's findings suggested that a car club (shared DC ownership) system, where several cars operate, requires a pricing mechanism for trading cars at different time slots impacted by users' activity scheduling and fleet size. Time slot prices will be increased by the time of the day (AM to PM) when the trip demand and densities are also increased, indicating a perfect trade-off between the pricing and scheduling demand. Therefore, based on the available fleet size and activity scheduling demand, trip prices will be variable for the time of the day.

Similar to the P2P sharing program above, another study proposed shared DC ownership models within San Diego, California, due to the emergence of the DC era. This paper suggested that shared ownership might be an option for expensive DCs (Masoud and Jayakrishnan, 2016), where members must divide a DC's entire cost and liabilities (Jaynes, 2016). From the dynamic system perspective, this study proved that shared ownership of DC usage could reduce car ownership by 33% compared to individual DC ownership. This study was implemented with 1184 households and formed clusters among them, considering the proximity of their house locations.

An essential determinant of the present study is differentiating the choice of DC sharing options in contrast to current DC studies. To access the DC shared ownership and ridership, choice configurations followed the objectives of this study and explanatory factors were chosen from relevant studies of a similar nature. Similarly, the study by (Haboucha, Ishaq, and Shiftan, 2017) was chosen, where they compared a private DC with a shared DC and a conventional car. Although this study has not directly pointed towards various ownership choices, it compares DC and conventional car ownership (Haboucha *et al.*, 2017).

The study by Yoo et al. (2021) compared the willingness to buy (WTB) and the willingness to pay (WTP) for shared DC use. This study compared environmental concerns, fears of potential accidents, and merits regarding DC full utilisation as determinants for the willingness to purchase and pay for a ride in DC. Respondents who like to conserve nature are most willing to buy DC, as they appreciate DC in solving some pre-existing social problems. However, respondents who find merit in using DC are willing to buy and pay for DC service. Besides, those afraid of DC functionality are not willing to buy and are less willing to pay.

Stoiber et al. (2019) tested the differences in the likelihood of adopting pooled-use DC, privately owned DC, and driverless public transport shuttles. This study found that comfort, cost and time are crucial factors influencing shared DC use.

Nazari et al. (2018) examined the impacts of safety concerns, green travel patterns and mobility-on-demand (MOD) savviness factors on public interest concerning private DC ownership and different shared DC services (comprising carsharing, ride-sourcing, ridesharing, and access/egress mode) by joint modelling approach. Model assessment reveals that people are reluctant to use private and shared DC on safety concerns, while green travel patterns and MOD savviness factors indicate an interest in shared DC.

Concerning the green lifestyle preference, Lavieri *et al.* (2017) identified the factors explaining the attitude towards different DC ownership and sharing paradigms based on surveyed data. This study found that individuals who prefer green lifestyles and are technologically aware are more likely to choose shared DC in future.

Hao & Yamamoto (2018) assessed relative preferences among privately owned DC, privately owned but shared DC, and on-demand shared DC. High interest in shared DC use, socioeconomic status, car ownership and trip purpose are essential to this modelling exercise.

Wadud & Kumar (2021) experimented with privately owned DC, on-demand exclusive-use DC with ride services, and on-demand pooled/shared DC. This research proved a significant willingness to pay for DC ownership with a high heterogeneity among people regarding gender, income, and car ownership. Cost per mile, journey time, waiting time, reliability, gender variations, and car ownership are essential to provide these ownership values.

Determinants of DC shared ownership.

The anticipated determinants from the studies above are given in Table 2.2. While for most of these studies, socioeconomic status is a common determinant, travel behaviour changes, and car ownership is notable among them. A detailed list of studies concerning DC shared ownership with relevant impacts and determinants is given in Table 2-2.

Table 2-2: Determinants concerning DC shared ownership

Serial No.	Study Reference	Shared ownership/sharing types	Determinants of DC ownership/sharing
1	Mourad et al. (2019)	On-demand DC taxi service, private DC operating in P2P sharing	Lower vehicle execution time, higher fleet size, proper matching between DC owners and riders, use of meeting points
2	Xu et al. (2019)	Private DC and enhanced use of private DC to share within a family	Different household sizes, travel mode choice decisions, and travel behaviour
3	Allahviranloo & Chow (2019)	Driverless Car Club model	Fleet capacity, Activity scheduling, pricing mechanism
4	Masoud & Jayakrishnan (2016)	Shared Ownership of a DC in terms of cost and liabilities	Number of DC in the cluster, pricing
5	Haboucha et al. (2017)	Regular car, private DC, shared DC	Enjoy driving, environmental concern, and Pro-DC attitude
6	Yoo et al. (2021)	The study tried to differentiate between the willingness to buy and the willingness to pay behaviour of DC in terms of environmental consciousness.	Four latent attitudes related to natural environmental preservation, pollution reduction, possible accident preservation and convenience

7	Stoiber et al. (2019)	This study tested the difference among the likelihood of pooled-use DC, privately owned DC, and driverless public transport shuttles.	Socioeconomic status, car ownership, public transport subscription, and combined factors concerning comfort, cost and time
8	Nazari et al. (2018)	This paper examines the impacts of the various observable and latent factors on public interest in private DC ownership and different shared DC services (comprising carsharing, ride-sourcing, ridesharing, and access/egress mode) by jointly modelling these shared DC types.	Latent factors are traveller safety concerns about DC, green travel patterns, and mobility-on-demand savviness.
9	Lavieri *et al.* (2017)	This paper identifies the factors of different DC ownership and sharing paradigms based on surveyed data.	The propensity towards a green lifestyle and technological savviness
10	Hao & Yamamoto (2018)	This research assessed relative preferences among privately owned DC, privately owned but shared DC, and on-demand shared DC.	High interest in shared DC use, socioeconomic status, car ownership and trip purposes
11	Wadud & Kumar (2021)	The experiment described in this research considered privately owned DC, on-demand exclusive-use DC with ride services, and on-demand pooled/shared DC	Cost per mile, journey time, waiting time, reliability, gender variations, car ownership

2.5.4 Impacts of DC Shared Ownership

Appendix L listed some of the DC shared ownership studies, as mentioned below.

The reduction of car ownership is anticipated due to shared DC's integration in the carsharing fleet initiatives in the mobility ecosystem. DCs will transform car ownership by changing the operational model of car-owning through shared DCs (Zhang *et al.*, 2018). Within the present research arena, ownership and sharing propensities of DC are connected to incentivise the promotion of DC use (Haboucha et al., 2017; Krueger et al., 2016). With the advent of shared DC into the system, matters such as the cost-benefit analysis of ridesharing with DC (Gurumurthy *et al.*, 2007), the behavioural shift of ownership (Jiang *et al.*, 2018), future mode choice (Dissanayake & Morikawa, 2010; Levin & Boyles, 2015), individual preferences for shared mobility (Davidson & Spinoulas, 2016; Lavieri et al., 2017) and expected ownership pattern of DC (Menon et al., 2018; Schoettle & Sivak, 2015) should be taken into consideration. However, as reflected in the literature, individual ownership of DC is a burden due to the initial cost of DC, which can affect the inclusion of shared DC into the system (Menon *et al.*, 2018). The list in Table 2.2 reflects the study-specific determinants for shared DC use. This table is linked with Appendix L. By Column 'Type of intervention', each of these studies is categorised according to their possible impacts on mode choice behaviour and sharing propensity, car usage/car ownership, and likely environmental impacts of shared DC use. For all of the studies mentioned in Table 2.2, behaviour refers to mode choice behaviour.

Mode choice behaviour and sharing propensity

Mourad *et al.* (2019) Identified that even though shared DCs are likely to travel longer distances, shared rides can reduce up to 25% of the overall travel distances, significantly reducing traffic in big cities. Besides, when DC is used with an on-demand ridesharing system, a higher ride-matching ratio can be achieved with fewer DCs and shorter travel times. The outcome of this study also suggested that a greater number of DC fleets' meeting points are helpful factors in enhancing DC sharing.

Haboucha *et al.* (2017) experimented with the choices among using a regular car, private DC, and shared DC with choice variations due to driving enjoyment, pro-DC sentiment and environmental concerns. Besides these behavioural factors, this study found that 75% of the respondents are willing to use shared DC, while 44% are indifferent to using conventional cars.

Stoiber et al. (2019) assessed the sharing propensities among the pooled-use DC, privately owned DC, and driverless public transport shuttles. In this testing method, he assessed people's choices by their socioeconomic status, car ownership and public transport subscription. This study found that 61% of the respondents are more interested in the pooled use of DC and driverless shuttles than to prefer private DC.

In their study, Nazari *et al.* (2018) found that present car owners from multi-member households are more inclined to private DC, while individuals with larger inter-trip VMT variations are more inclined towards shared DC. Based on these findings, this study recommended that household car ownership is likely to be reduced as DC can serve multiple family members simultaneously.

In assessing the mode choice behavioural impact of shared-owned DC, Hao and Yamamoto (2018) found a low share of respondents who liked owning and sharing DC with others. Being male, having a high interest in DC, having low revenue expectations and having low car ownership are essential considerations in choosing shared DC use. In contrast, people are only willing to use shared DC, who are highly interested in DC and have part-time jobs, which will make them eliminate their cars in the future. Therefore, 20% - Shared DC can attract 30% of the trips, and 50% to 70% of the household vehicles will be sufficient to serve the demand without significant waiting time.

In identifying behavioural impact, Wadud and Kumar (2021) state that 60% of people will retain DC ownership without considering the convenience of ownership values, while 20% prefer pooled DC ride services. But considering heterogeneous convenience values, these shares will be 50% and 26%. Overall, this research outcome proved a significant willingness to pay for DC ownership with a high heterogeneity among people regarding gender, income, and car ownership.

Car usage/car ownership reduction

In estimating the possibilities of DC shared ownership, only a few studies highlighted the ownership impact due to shared-owned DC. Xu et al. (2019) applied integrated activity-based modelling and dynamic traffic assignment (ABM-DTA) framework to assess the preferences of private DC and enhanced use of private DC to share within a family. This research found that one shared DC for all household members could replace four conventional cars and reduce car miles travelled.

Allahviranloo & Chow (2019) applied a driverless Car club model with the willingness to pay under different pricing mechanisms. This study found that the DC car-club system requires a pricing mechanism for trading cars at different time slots impacted by users' activity scheduling and fleet size. Based on the available fleet size and activity scheduling demand, trip prices may vary for times of the day. Under the pricing substitution mechanism, shared-owned DC usage is supposed to be reduced by 20%, with a 4% higher trip cost.

A similar study by Masoud & Jayakrishnan (2016) investigated Shared Ownership possibilities of DC in terms of cost and liabilities. This research found that Shared DC sharing can reduce car ownership by 33%. If more households are interested in participating in the program, the efficiency will increase at a higher rate.

One study conducted among 347 Austin residents revealed that only 13% of the respondents are willing to choose shared DC over private DC, where the cost can be $1 / mile (Bansal *et al.*, 2016). In 2016, for different trip purposes, another study found that 70% of respondents were unwilling to use shared DC (Krueger *et al.*, 2016). This study suggested that travel time, waiting time and cost of the trips will be the significant determinants of shared DC use. Dynamic ridesharing capability will attract young travellers despite having some bias in the choice estimates.

Environment

Focusing on the environmental impact of DC shared ownership, Haboucha et al. (2017) found that driverless carsharing benefits the environment when environmental concern is a factor for shared DC choice. Considering the environment, another study by Yoo *et al.* (2021) utilised a latent attitude related to natural environmental preservation and pollution reduction. This study found that environmentally conscious people are more willing to buy DC than pay for it because DC can reduce pollution levels and congestion. Besides, Nazari *et al.* (2018) found that people who prefer green travel patterns are likely interested in shared DC use. Similarly, a propensity towards a green lifestyle indicates a better preference for shared DC Lavieri *et al.* (2017). This research outcome showed that 5% and 8% of respondents preferred DC sharing and ownership, respectively.

2.6 Shared Ridership with DC

A wide range of studies discussed DC shared ridership impacts on a broad range of topics. A structured literature review is presented in the subsequent paragraphs to provide an overview of various impacts in these fields. Some of these studies applied behavioural assumptions to recreate some DC travel behaviour and transport supply variables, including travel behaviour, car ownership, and sociodemographic variables. In addition, assumptions on DC types based on DC's acceptance level and functionality were also observed. Some studies tried to investigate DC operational models based on assumptions, while in most studies, the DC sharing scenarios are created based on different combinations of private DCs and shared DCs. Some studies also included assumptions concerning the use of DC in public transport.

Brief descriptions of shared ridership trials with DC are presented in Section 2.3.1. Additionally, impacts and determinants of shared ridership possibilities with DCs are described in Section 2.3.2, which highlighted study reference, modelling methods, shared ridership types, impacts, ownership change possibilities, and determinants of DC shared ridership.

2.6.1 Shared DC ridership trials and acceptances

Shared DC trials

Shared DCs are being piloted in several cities worldwide, and the most prominent of these locations are Phoenix in the US State of Arizona and Singapore. North America and Europe are two continents where shared DCs are mostly piloted and assessed. Regarding DC testing within Asian cities, Japan, China, and Singapore are pioneers. According to the DC Readiness Index, published in 2017, the Netherlands, Singapore and the US are the top three countries considering policy and legislation, technology and innovation, infrastructure, and consumer acceptance concerning DC (KPMG, 2017).

After the successful tests from car manufacturers, several laboratory and test-bed scenarios considered DC ridesharing evaluated through passengers' responses. Shuttle-like implementation of DCs was tested in several cities around the globe, such as London (Greenwich, 2018); New York (Mestres *et al.*, 2017); Berlin (Nordhoff *et al.*, 2018), Stuttgart (Heilig *et al.*, 2017) and Citymobil2 (several EU cities) to prioritise the ridesharing with DC. These studies collected the user's data from the test-bed scenario and analysed respondents' feelings to investigate ridesharing behaviour and acceptance patterns with the shared DC.

TRL of the UK is teamed up with technology company Agility 3 to guide GATEway researchers to deploy ridesharing with the driverless shuttle in Greenwich, London's poorly connected economic rundown area. This trial is over, and based on this trial, people expressed their views of the DC shuttle service and quality improvements. The result showed that, on average, people are willing to spend £2 for this driverless shuttle per person. Human factors engagement of this project identified that 79% of people took the driverless shuttle positively, while 53% said it would be environmentally beneficial (TRL, 2018). However, sharing with strangers was a significant barrier to accepting the DC journey. This study reveals that 20% of commuters are willing to share a ride at least once a week, while the corresponding figure is 33% for leisure at night. Greenwich is a limited area for testing and cannot answer the critical questions for geographic variation (e.g., inner-city, inner-suburb, and suburb-city). This study did not monitor how people react to different price variations for the journey (TRL, 2018).

CityMobil2 is a driverless ridesharing vehicle programme utilising Automated Road Transport Systems (ARTS) and has used EasyMile EZ10 and Robosoft Robucity vehicles at low speeds. This pilot programme attempted to research shared DC systems' technical, financial, cultural, and behavioural aspects and explored how they can best fit into existing transportation infrastructure across different cities (CityMobil2, 2016). To date, CityMobil2 has demonstrated in seven European cities to understand the design and implementation issues related to ARTS and to investigate the interaction between the driverless shuttle and other road users (Madigan *et al.*, 2017). People's motivation and enjoyment to use ARTS are strongly correlated with Behavioural Intentions to use ARTS in the future, along with the influence of performance expectancy, social influence and facilitating condition.

By utilising a similar type of driverless shuttle, another study conducted in Berlin-Schöneber was participated by 384 respondents (Nordhoff *et al.*, 2018). This study identified the overall appreciation for the shared ride with a driverless shuttle despite its slow operating speed and lack of luggage storage capacity.

Capri project was associated with another UK study conducted by the University of West of England. In a real-world environment, this project explored car users' preferences towards DC sharing based on the results of a stated preference task accomplished before and after the brief exposure in a shared driverless shuttle. The results showed that after experiencing the driverless shuttle, people's mode choice preference shifted from single-car use to shared DC use, even though people highlighted comfort as the guiding factor of DC choice (Paddeu *et al.*, 2021).

Shared DC implementation was found in several cities in the US. Perkins et al. (2018) outlined the shared DC pilot schemes and strategies to integrate DC within several municipalities in the US. As mentioned here, EasyMile shared DC (shuttle) was implemented in Arlington, Texas; Zoox in California; nuTonomy in Boston; Olli in Chandler, Arizona (Perkins *et al.*, 2018); and NAVYA in Florida (Morrow *et al.*, 2019). During the summer of September 2016, the nuTonomy driverless shuttle, in partnership with Grab, tested in the "One North" district of Singapore, a 2.5 square-kilometre business district (Tech Crunch, 2016).

EasyMile, the French driverless shuttle with 12 passenger capacity and 25mph operating speed, uses the EZ10 electric automated shuttles for pilots throughout Europe, the U.S., Singapore, Dubai, and Japan. Due to its low speed, this shuttle is being tested in campus settings and business parks. A 700-meter test route with EZ10 in downtown Dubai was piloted with free passenger rides (Shahbandari, 2016).

All these studies are tested within limited geographic areas where no abnormal impact on transport demand was recorded. Shared DC can be well suited for feeder services for long-distance public transit connections as an alternative to Cycling and Walking to these locations. A higher level of shared DC services can solve this accessibility issue when more people are attracted to these services with smarter mobility options.

Shared DC acceptance

Household car reduction is the most significant societal change that can be anticipated over the next few decades. Considering the availability, flexibility, privacy, reliability and comfort of use, private cars are preferred over public transport (Hiscock *et al.*, 2002). Private cars have been a popular mode of personalised urban transport over the last 100 years. But, due to its ability to allow only a single-person journey in the morning peak time of the day (ITF, 2015), these journeys can be replaced by on-demand ridesharing services (e.g., taxis, rideshare, carshare) to provide mobility benefits without ownership responsibilities and to avoid associated hassles of parking cost, maintenance.

In a study in South Florida, USA, 27.5% of the surveyed respondents are extremely unlikely, and 26.7% are unlikely to give up their cars in the presence of shared DC in the future (Menon *et al.*, 2018). Even though findings showed 61% of the respondents would accept ridesharing with DC, (Stoiber *et al.*, 2019) reported that altering private car use with a shared DC car is hard to achieve. A similar Australian study reported that 40% of people are willing to use shared DCs for 80% of their trips, and 44% are willing to use them for 50% of their trips (Webb *et al.*, 2019). This study concluded that the remaining 16% would use their private cars for mobility. Haboucha *et al.* (2017) proved that with 100% free service of shared DC, 25% of people will use private DC. Another study from Germany confirmed that private cars would exist parallelly with shared DC use (Pakusch *et al.*, 2018). In Australia, Pettigrew *et al.* (2019) confirmed that despite higher interest in shared DC, 29% of the participants are unwilling to accept any form of DC sharing. Asgari et al. (2018) discussed study findings of a stated preference study in Florida proved that despite a ride-sourcing opportunity, more than 50% of the respondents are willing to use private DC, both in the case of driver and passenger.

Their study to understand the possibility of using shared DC with TNCs (Gurumurthy and Kockelman, 2018) found that about 60% /80% of the individual trips will be operated with shared DC when the wait time is less than 5 and 15 – 30 minutes, respectively. This study found that the 60,000 shared DC should cover nearly 50% of Orlando's 2.8 million daily journeys. Another study by Gurumurthy *et al.* (2007) for Austin, Texas, proved that a fleet of 5000 shared DC could cover 65% of all possible car trips in the daytime with an average car occupancy (VO) of around 1.26.

Another study in Chicago applied a stochastic process to simulate mode choice between shared DC and conventional taxis, which found that shared DC could cover 85% of all Chicago trips if the driver's wage is removed from taxi services (Liu *et al.*, 2019). A similar study by (Farhan and Chen, 2018) proved that shared DC could cover 10% of total travel demand, where 100% of respondents are willing to share the ride with DC. In Halifax, Canada (Alam and Habib, 2018), shared DC assignment and simulation results proved that maximum efficiency can be achieved in the morning peak hour (e.g., 0700-0800), when 20% of the total shared DC trips during the peak periods are served.

Besides, several studies proved that better convenience and flexibility might resonate with the system-wide shared DC use and reduction of total travel distance due to the low number of cars (Mourad *et al.*, 2019; Litman, 2017). From the perspective of potential modal share changes in these simulation studies due to shared DC emergence, conventional car use will likely be replaced by shared DC use. But from the studies above, there is no clear indication of the amount, direction, and in what time frame these replacements will occur. However, to measure the success of shared DC use, in the first instance, it is needed to focus on understanding people's willingness to relinquish their present car (Pettigrew *et al.*, 2019).

2.6.2 Possible impacts of DC shared ridership

Travel behaviour

Trip length increase

The application of shared DC likely impacts travel behaviour and how people travel (Webb *et al.*, 2019; Spurlock et al., 2019). Heiliga *et al.* (2017) show an increase in trip length for a pooling shared DC service if travel costs are lower than the conventional car. With an agent-based model, Liu et al. (2017) proved that commuters travelling longer distances will probably choose shared DC, as they can utilise their time. Likewise, some shared DC users are likely to utilise their time onboard to save their overall working hours (Krueger *et al.*, 2016). Shared DC can be a cost-effective solution to reduce parking demand (Zhang *et al.*, 2015) and high waiting times for users (Shen and Lopes, 2017).

Vehicle miles travel/Vehicle kilometre travel (VMT/VKT)

It's been anticipated that shared DCs increase the VMT/VKT compared to private DC while running empty when repositioning themselves (Alam and Habib, 2018; Bischoff and Maciejewski, 2016; Chen, Kockelman and Hanna, 2016; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014; ITF, 2015; Moreno *et al.*, 2018; Zhang and Guhathakurta, 2018). However, Lokhandwala and Cai (2018) proved that when shared DC operates with ridesharing options, they can replace the current taxi system with a substantially reduced VMT/VKT. Bischoff et al. (2017) observed that ridesharing with the DC system would result in lower VMT/VKT than carsharing with DC (with only one passenger). Similar findings are also found by Soteropoulos, Berger and Ciari (2019) and (Vosooghi *et al.*, 2019). Heiliga *et al.* (2017) simulated ridesharing with shared DC during the night and observed the VMT/VKT reduction. In the case of public service integration with shared DC, one study by Y. Shen *et al.*(2018) shows that in low-demand areas, the shared DC system replaces the PT system with a reduction in VMT/VKT.

A few research studies reported that a higher amount of VMT generation with shared DC is linked with lower travel costs and a higher time value reduction. VMT increase for shared DC operation was also linked with those studies that anticipated the shared DC modal share from private DCs under a competitive market scenario (Fagnant *et al.*, 2015b; Chen and Kockelman, 2016; ITF, 2015). These studies proved an 8-10% increase in shared DC use, with 1.3–10% of private DC trips being replaced and some empty trips reduced. Moreover, the ITF (2015) study proved that when trips are split between conventional private cars and shared DC options with no public transport provision, the VKT is likely to increase by 90%.

On the contrary, shared DCs are likely to decrease private car travel (about 10 – 25% VKT decrease) when the use of DC rideshare is common among people (Martinez and Viegas, 2017; Heiliga *et al.*, 2017). Similarly, another study proved that if shared DC replaces all the home-based private travels, VKT might decrease by 11 – 24% with an increased travel time of 30 - 50% (Burghout *et al.*, 2015). Using a mode and trip choice model for Seattle, USA, Childress *et al.* (2015) proved that VMT might be reduced by 35% when costs per mile are $1.65 for shared DC and that it is likely to replace all private DC.

Car replacement

Carsharing can relieve this kind of nuisance of car ownership, as it is estimated that one car share can replace four to eight personal cars (Momo, 2010). Regarding household car use, (Sivak and Schoettle, 2015) estimated that when the members of a residence share a single car, they can reduce car ownership by 43%. Following the same, shared DC can reduce the cost burden of on-demand taxis and help reduce car ownership.

Car replacement refers to the number of private cars one shared DC can replace, which ranges from a couple of cars to several cars. Milakis *et al.* (2017) reviewed the literature and confirmed that shared DC use could replace 67% to 90% of conventional cars. Based upon the sensitivity analysis of 26 scenarios with agent-based simulation, Fagnant & Kockelman (2014) showed that 10 conventional cars could be replaced. In the case of Austin, this replacement rate is 11 (Fagnant and Kockelman, 2018). Alongside, Zhang *et al.* (2015) and Bösch *et al.* (2017) proved that (in Zurich, Switzerland) every shared DC could replace around ten and fourteen conventional cars, respectively. However, according to Chen et al. (2016), in the case of electric car charging, the replacement rate drops between 3.7 and 6.8. According to the ITF (2015) report, shared DC could deliver 89.6% (65% at peak hours) of conventional cars and manage fewer cars on the streets with high-quality public transport. A simulation exercise in Singapore (Spieser *et al.*, 2014) proved that a shared DC fleet equivalent to one-third of the existing car fleets could meet the existing demand. Although there is still ambiguity about the exact car to shared DC replacement value, under decisive policy intervention, shared DC systems have the potential to reduce car ownership.

Modal share

Considering lower operating costs and higher value of time (VOT) reduction than conventional private DC, shared DC could reduce the need for public transport use, as indicated by Chen & Kockelman (2016). In the case of the mode-choice model for shared DC, with 54% reduced VOT, Bösch *et al.* (2017) indicated a reduction in public transport share from 16% to 12%, a decrease in slow modes share from 26% to 20% and a decrease in private car share from 48% to 36%. Heiliga et al. (2017) indicated the possibility of a higher share of public transport and slow modes for short trips. For instance, with a 45% reduction in shared DC operating cost and no private DC option, Heiliga et al. (2017) used a combined destination and mode-choice model that reported increases in public transport (from 13% to 17%) and walking share (from 22% to 31%).

Energy and environment

In literature, the environmental impact of shared DCs is not elaborated on because DC use is not widespread, and there is a lack of competing mechanisms (e.g., alternative fuel source and its emission capability, the correct number of existing cars that shared DC can replace, congestion amount per DC in measuring the environmental and climate change parameters (Malik, 2017; Jones and Leibowicz, 2019). As anticipated in literature, shared DC use can reduce greenhouse gas (GHG) emissions by efficient driving (decrease fuel use, no fuel use), reduce congestion by platooning, control car demand with efficient DC fleets, decrease parking demand by dynamic ridesharing, and can mitigate other negative transport aspects by intelligent speed adaptation on the road (Greenblatt and Shaheen, 2015; Merlin, 2017; Wadud *et al.*, 2016). Moreover, potentially shared DC can increase GHG gas emission with low-cost travel that might result in extra VKT growth (because of the rebound effect), increased travel demand among non-drivers, and generating empty car repositioning for the next trip (Anderson *et al.*, 2016).

Fagnant & Kockelman (2014) addressed shared DC (shared collective taxis) systems as energy-saving modes that can remove pollutant emissions, help travel patterns, and plan demand distribution at the same level. Studies that utilised complete system replacement by shared DC reported reduced carbon emissions and provided greater accessibility (Lokhandwala & Cai, 2018; Martinez & Viegas, 2017). In a simulation study within Austin, Texas, Liu et al. (2017) predicted shared DCs are 22.4% energy savings and 16.8-42.7% Greenhouse gas emission-saving. Moreover, the fuel efficiency in DC is 3% compared to manual transmission (Mersky and Samaras, 2016).

A few other studies investigated the impact of driverless taxis, which can be added to the prevailing traffic modal shares. By applying the provision of first/last mile transit services, (Moorthy *et al.*, 2017) reported a 37% energy saving that incorporated shared driverless Public Transport.

A simulation study in New York (Bauer *et al.*, 2018) predicted that shared DCs could decrease GHG emissions by 73% and energy consumption by 58% compared to existing taxis using the present power grid, owing to improved car efficiency. With increased VKT produced by shared DC, the GHG per car per mile reduces more than private ownership. As the VKT increases, these cars will continue to reduce GHG emissions (Bauer *et al.*, 2018). In the context of greenhouse gas emission reduction by DC for 2030, shared autonomous electric taxis (SAEV) deployment would reduce per-mile GHG emissions by 87-94% to conventional private cars while 100% reduced fuel consumption (Greenblatt and Saxena, 2015). Research conducted at Rocky Mountain Institute anticipated that 'the marginal cost' of SAEVs' is likely to fall below that of conventional private cars, which can help SAEVs to dominate the mobility market by 2050 (Johnson and Walker, 2016). As a result of these cost savings, overall VMT will grow due to increased demand, which can likely increase emissions. Nevertheless, such negative externalities in transport could be compensated by enhanced efficiencies offered by shared DC due to mobility (Greenblatt and Shaheen, 2015).

The intention of parking near the driver's final destination was observed for 30% of the cases (Shoup, 2006), which identified the fewer-parking facility as a source of emissions. Shared DC could reduce such emissions with low requirements for parking. Besides, Shared DCs can drive more logically and smoothly, positioning themselves in the roadway, thereby reducing the congestion level in the presence of other non-shared DC and conventional cars (KPMG, 2012). Savings in fuel consumption and consequent environmental benefits of using DCs can help reduce environmental impacts if carsharing can simultaneously be implemented with DC (Thomopoulos and Givoni, 2015).

Shared DC could help reduce greenhouse gas emissions by driving more efficiently, eliminating traffic congestion, and accelerating the adoption of alternative fuel vehicles, even though increasing the VMT (Jones and Leibowicz, 2019). This study also claimed that DC implementation is likely better than carbon taxi in decarbonising travel (Loeb and Kockelman, 2019). Therefore, when DCs are the dominant travel feature in the overall mobility ecosystem, using shared DCs could significantly reduce energy consumption and emissions.

Land use

Household Location

The way of life people follow can impact shared DC adoption (Lavieri *et al.*, 2017). People who intend to use shared DC may prefer to live near their workplace downtown and can reduce the parking cost with easy access to their workplace without the need for parking, while people living in the suburbs may need to use private DC, necessitating them to use parking (Moreno *et al.*, 2018). On the other hand, others may think of living in the regions further away from the city centre, considering shared DC could give them the commuting opportunity to work efficiently (Zhang and Guhathakurta, 2018). The study reflects that introducing shared DC can induce urban sprawl and bring older people near the city centre, pushing the young generations away from the city centre. One other location choice study by (Bansal *et al.*, 2016) proved that people from larger households and highly educated individuals would move away from the city centre, while full-time working males, tech-savvy and higher-income individuals would move closer to the centre. Therefore, shared DC's effect on household location choice will affect the future travel demand. This derived demand can help measure the speed-flow relationship of highways and the modal shift from conventional cars to shared DC (Moreno *et al.*, 2018).

Parking demand

The majority of the studies that discussed parking-related land use proved the reduction in parking space requirements by the introduction of shared DC (Fournier *et al.*, 2017; Dia and Javanshour, 2017; Stocker and Shaheen, 2017; Zhang and Guhathakurta, 2017; Zhang *et al.*, 2018). Concerning the cost of parking, Zhang *et al.* (2015) estimated a hypothetical grid-based city parking and reported a reduction in the number of needed parking spaces by 90%, with 2% market penetration by shared DC. Based on two simulation scenarios of passenger waiting time in Melbourne (Australia), Dia and Javanshour (2017) predicted a parking requirement reduction of up to 83% for two types of on-demand DC systems. Also, using simulation-based methods, Zhang and Guhathakurta (2017) suggested a parking land reduction of 4.5% with dispersion for DC at a 5% level, releasing 20 parking spots against one shared DC deployment. Parking space reduction through shared DC would reduce parking demand, significantly releasing high-value urban spaces (Zhou *et al.*, 2019; Zhang *et al.*, 2019). Fagnant and Kockelman (2015) proved the parking budget saving due to the relocation of parking to distant places and ridesharing (Carrese *et al.*, 2019).

However, commuters who adopt shared DCs will likely think about the travel cost because shared DCs can drop off travellers when there is no parking available nearby (Levin and Boyles, 2015) or will head to serve further commuters in the case of operating as public transport service (Tian *et al.*, 2021). Furthermore, Hayes (2011) advocated that shared DCs may economise parking spaces because of their design capability to park inches from each other.

2.7 Methodology Review

2.7.1 Literature to support the theoretical framework

In connection with the proposed research topic, considerable attention has been given to present literature focusing on different aspects of shared DC use, notably on present travel behaviour, perception of automation, willingness-to-pay, awareness and attitudes (Menon *et al.*, 2018; Barbour *et al.*, 2019; Nordhoff *et al.*, 2019; Gkartzonikas and Gkritza, 2019; Sheela and Mannering, 2019) of shared DC use. A few of these studies are choice-based experiments, while a few relate to agent-based modelling and simulation approaches (Spieser *et al.*, 2014; Fagnant and Kockelman, 2014; Firnkorn and Müller, 2015; Martinez and Viegas, 2017). Although the agent-based approach provided a good reflection on shared DC use, it lacked the usefulness of observed variables. Liu *et al.* (2017) presented an agent-based simulation of shared DC with four different fare levels. This experiment compares travel time cost and value to understand the choice between shared DC and conventional cars.

Except for the above, several choice modelling studies were performed in several parts of the world. Steck *et al.* (2018) used the value of travel time savings (VTTS) and commuters' mode choice possibilities to compare private DC and shared DC with other modes by logit model experiments. This study compared In-vehicle time use and cost as essential factors in mode choice, while sociodemographic variables (gender, age and income) have minor importance. The study also suggested that shared DC may reduce the value of travel time by up to 10% for commuting trips. Lavieri *et al.* (2017) analysed private DC and shared DC preferences concerning lifestyle choices. Recently, Stoiber *et al.* (2019) ran a choice experiment among private DC, driverless taxis, and driverless shuttles to unearth the preference for shared DC use, which partially proved that DC would be used on a shared basis. All these studies focus on mode-specific parameters to compare shared DC and conventional cars without emphasising individual-specific parameters.

In contrast to the hypothetical discrete choice modelling method stated above, few studies applied the econometric modelling method with observed behaviour to analyse the propensity for shared DC use in literature. Haboucha *et al.* (2017) estimated a model to analyse the long-term DC choice decisions and identified the taste heterogeneity for shared DC use. They find that gender, age, educational level, and income are significant individual-specific parameters that affect shared DC use. Krueger *et al.* (2016) performed a logit model to understand the propensity to switch to shared DC in light of the recent trip the respondent performed. The outcome of this modelling study indicated the strong influence of age on shared DC choices. Bansal *et al.* (2016) utilised individual-specific parameters to explore shared DC use with different pricing scenarios. This study found that gender and age significantly affect shared DC use.

Menon *et al. (*2019) assessed the possibility of reducing car use by shared DC use propensity with individual-specific travel data (e.g., commuting time, travel frequency, trip duration) related to present car use. This modelling exercise suggested that a bachelor's degree-holding male millennial who faced a car crash earlier is primarily interested in shared DC, while higher commuting time and parking search time are significant determinants of shared DC use. Similarly, Barbour *et al.* (2019) applied the binary logit model to delineate the shared DC use propensity with seven DC usage types. This research indicates that larger households influence shared DC use while driving alone for commuting trips, and commuting distance is negatively associated with shared DC use. Similarly, Lavieri and Bhat (2019) compared solo and shared DC use by applying a generalised heterogeneous data framework with respondent-specific socioeconomic and attitudinal variables.

Assessing the likelihood of shared DC use has been an active area of research in the present literature, where the experimental design approach has been applied to selected population groups (e.g. young people, elderly, students, and employees of an association) and limited spatial settings (e.g. campus settings, office location, part of the city) (Merge Greenwich Consortium, 2018; Nordhoff *et al.*, 2018; Menon *et al.*, 2019). Only a few of these studies discussed the regular and occasional sharing variations and compared the sharing propensity with strangers and family members.

The pros and cons of the shared DC studies from different viewpoints were followed. Therefore, the guiding principles in the variable nature of the theoretical framework for these studies depend on the variables they consider. Table 2-3 listed survey variables to investigate shared DC choice within the present literature as discussed.

Table 2-3: Reviewed studies, variables they considered and their effects on shared DC preference

Study references	Number of respondents	Target Population	Variables (positive: +, not significant: *)
Steck et al. (2018)	172	Commuters	Cost, Trave-time, Gender*, age*, income*
Haboucha et al. (2017)	721	Individuals living across Israel and North America	Gender (male+), age (younger+), income (higher+), educational level (higher+)
Krueger *et al.* (2016)	435	Residents of major metropolitan areas of Australia	Age (younger+)
Bansal *et al.* (2016)	347	Residents of Austin, Texas	Gender (male+), age (younger+)
Menon *et al.* (2019)	1214	Faculty, students, and staff from the University of South Florida; and the members of the American Automobile	Gender (male+), age (younger+), educational level (higher+); carownership (multi car owner)

		Association (AAA) Foundation of the Southeastern United States	
(Barbour *et al.*, 2019)	782	Members of the American Automobile Association Foundation from 12 US states	Educational level (bachelor's degree+); car ownership (at least one car owner+); One driver household (at least one driver -)
(Lavieri and Bhat, 2019)	1607	A web-based survey on mailing lists held by multiple entities	Gender (female+), age (younger+), educational level (higher+); car availability (>1 car owner-); income (higher+); employment type (part-time worker+)

Based on these studies, the most common variables influencing shared DC use are gender, age, income and educational level. However, few of these studies included attitudinal and behavioural considerations. Therefore, it can be said that there is a growing literature related to DC sharing, adoption and the impacts of this disruptive technology. However, the basic features of these studies concern discussions on how the market is prepared for DC and their general adoption pattern. Alongside this, the demand for shared DC ownership among several households is yet to be tested. In this respect, the present research developed a behavioural framework to provide the analytical understanding and extend the respondents' present carsharing and ridesharing behaviour within transformative DC modes: a) shared ownership and b) shared ridership to improve this gap. Based on the research questions, the proposed behavioural framework for this research can be categorised into two broad headings: 1) features of scenarios concerning shared ownership and ridership, and b) explanatory factors to explain the propensities of DC shared ownership and ridership scenarios. The association of present sharing behaviour, personality, and social-norm attitudes with DC shared ownership and ridership preferences was examined.

Further, data was collected on trip purposes and in-vehicle activity preferences, which are essential determinants of choices relating to shared rides (Merat *et al.*, 2017). Also the data on a respondent's personality and social-norm variables through some statements were collected.

2.7.2 Literature on Data Collection Points

Likert scale is a psychometric rating scale that can help understand people's attitudes or perceptions of future behaviour. The Likert scale is used as a five- or seven-point scale to understand how a person agrees or disagrees with a given statement relating to behaviour or future project prospects.

In transport research, the Likert scale has been used to assess the acceptance level of a particular statement relating to discrete choice analysis. In DC research, Likert-scale use is mainly directed to measure the discrete perception of different types of DC use (Menon *et al.*, 2018; Steck *et al.*, 2018; Barbour *et al.*, 2020).

Likert Scales allows the respondent to answer flexibly with quantitative and no opinions. Therefore, the data obtained is numeric, meaning that the data can be analysed with descriptive statistics and used as choices for a discrete choice modelling perspective.

2.7.3 Data collection administration methods

Postal survey

The postal survey allows a more unbiased selection of respondents and gives the respondents the time to answer the questions. Despite these benefits, the drawback of possible lower response rates is crucial for not considering this data collection technique. This technique can include free post envelopes and incentives to ensure a higher response rate. Both measures were out of the question due to budget issues. This technique can be further enhanced with anonymous participation by providing an online link to the questionnaire. The requirement of trained professionals to distribute the paper questionnaire makes it a cost-intensive approach. Besides, printed paper questionnaires are a considerable waste of resources if not disposed of properly.

Intercept survey

On the contrary, the intercept survey technique allows the interviewer to interact with the respondent. However, this method risks generating biased samples due to the lack of control over the respondent selection. With limited human resources, the intercept survey requires a long time to achieve the required responses. For a lengthy questionnaire (like the proposed one), answers can be affected by the respondent's limited time availability.

Online survey

Considering the drawbacks of postal and intercept surveys, online questionnaire surveys conducted for DC studies proved helpful for collecting large samples in recent studies. Respondents should be recruited using commercial services unless the researcher has a rich email contact list. In this case, only an online survey would require a large budget to recruit respondents and specialist personnel to make these arrangements. The online questionnaire's added advantage is that it can demonstrate a video featuring DC sharing and thus disseminate driverless mobility benefits.

Survey method for this research

Regarding the budget and time issues of the proposed research project (e.g., to understand whether and how people will share the use of fully driverless cars), a self-completion online questionnaire was chosen as the most helpful tool to collect data. This method can satisfy Napier University's paperless questionnaire policy and offer a robust data sampling technique within the City of Edinburgh (EH1 –EH17). This method is a valuable tool to control the respondents' spatial and social variations by complying with policy issues. This method can cut the budget by offering zero questionnaire printing and postal delivery costs. The postal delivery cost of conventional postal data collection was converted by online hosting cost in the online data collection technique, which is considerably cheaper.

2.7.4 Data sampling methods

Previous study analysis

The sample sizes of relevant studies concerning DC were considered to get the initial idea of the required sample size (Rayle *et al.*, 2016; Nordhoff *et al.*, 2018; Shaheen *et al.*, 2016; Menon *et al.*, 2018; Lavieri *et al.*, 2017; Krueger *et al.*, 2016; Haboucha *et al.*, 2017; Burkhardt and Millard-Ball, 2006; Jiang *et al.*, 2018). Almost half of these studies used paper-based data collection. Evidence from the number of responses among these studies showed much higher responses from online surveys than paper-based ones. Even though many responses were recorded (Martin, Shaheen and Lidicker, 2010; Dias *et al.*, 2017) by online data collection, the average sample size among these studies was 873. The list of these studies is given in Table 2-4.

Table 2-4: Selected study to observe sample sizes

Study Reference	Number of samples	Area	Administration
Nordhoff *et al.* (2018)	384	Berlin	User’s interview after the use of driverless vehicle
Rayle *et al.* (2016)	380	Sun Francisco	Intercept survey
Shaheen *et al.* (2018)	25	North America	Face-to-face expert interview
Greenwich (2018)	324	London	User’s Interview after the use of driverless vehicle

Menon *et al.* (2018)	1214	Florida	Survey of Universality students and staff of the professional organisation
Lavieri *et al.* (2017)	1832	Puget Sound Regional	Puget Sound regional travel study (census data)
(Krueger *et al.*, 2016)	435	Australia	Online survey
(Haboucha *et al.*, 2017)	721	Israel and North America	Online survey
Dias *et al.* (2017)	2789	Puget Sound Regional	Puget Sound regional travel study (census data)
Burkhardt and Millard-ball (2006)	1340	Carsharing programme members US and Canada	Online survey
(Shaheen *et al.*, 2012)	34	Personal carsharing operators, traditional car-sharing operators, insurance providers, and public policy authorities in the US	Semi-structured questionnaire for Expert interview
Jiang *et al.* (2018)	1002	Major Cities in Japan	SP questions with three levels of three modes

Sample-to-variable ratio

Some authors suggest that the sample-to-variable ratio should be 15:1 or 30:1 (Osborne, 2001) for multiple regression analysis. Considering this, the final model expects 24 explanatory variables, for which the sample size should be between 360 and 720.

The central limit theorem (CLT) for stratified random sampling

Using the central limit theorem (CLT), the minimum sample size was calculated required to include sufficient respondents from each population stratum described in Table 2-5. Population percentages of various population strata can be applied with the CLT approach to estimate the sample size within each stratum. A few strata (sampling criteria) were selected from various Scottish statistics for this research, as shown in Table 2-5. The following equations can give the standard error estimates of the population proportion p, sample size n with the population size N.

$$SE = \sqrt{\frac{(N-n).\,p(1-p)}{N.\ n}}$$

Within a 95% confidence level and a relative error of 5% (it can be understood that this relative error refers to the percentage of having a characteristic or the percentage of not having a characteristic), the SE would be:

$$SE = \frac{5}{(1.96)} = 2.55$$

Applying this SE, the standard sample size can be calculated using the following formula.

$$\text{Standard sample size, n=} \frac{p(1-p)}{(SE)^2}$$

Based on this calculation, different sample sizes were calculated for each discrete stratum of the population, as stated in Table 2-5.

Table 2-5: Sample size estimation for various population strata

Scottish population stratum	Population Percentage	Calculated Sample size	Source for the Population Percentage
Percentage of 17 years old or more who drive at least once a day in Scotland	41.40	373	(Scotland, 2018)
Percentage of driving license holders over 17 years old in Scotland	70	323	(Scotland, 2018)
Percentage of the male population in Edinburgh	48.81	384	(National Record of Scotland, 2022)
Percentage of (16 - 64 aged) working-age people in Edinburgh	69.6	325	(National Record of Scotland, 2022)
Percentage of households with at least one Car available for private use in Scotland	71.00	316	(Scotland, 2018)

Table 2-5 shows that each stratum's sample size did not vary significantly. Therefore, it is recommended that any figure larger than 344 (approximately 350) would be suitable to record population variation within the study area.

2.7.5 Cluster Analysis Method

Cluster analysis (CA) is an exploratory data analysis technique based on grouping the familiar characteristics of variables. CA is widely used to classify data in a structured and meaningful way (Tan *et al.*, 2014). Its primary objective is to divide data into groups with a high degree of association among themselves. SPSS data analysis software was used to perform the CA. For this research, three types of CA methods were used by SPSS software. The types of CA that followed in SPSS are:

1. K-means clustering
2. Hierarchical clustering
3. Two-step clustering

K-means cluster method quickly clusters a large amount of data based on some prior values of clusters. This method helps test different CA models with different cluster sets. K-means and Fuzzy C-means algorithms are used in this research. After assigning specific points, the K-means algorithm applies successive iterations to find the closest centroids for every data point until the centroids do not change. This method is a non-hierarchical and complex clustering method (Bathaee *et al.*, 2018).

The Hierarchical cluster analysis deals with variables and creates clusters in the same way as factor analysis. This type of CA can handle nominal, ordinal, and scale variables. The hierarchical clustering method follows the three analytical steps: 1) calculate the distances among the clusters, 2) link the clusters, and 3) choose a solution by selecting the correct number of clusters. This analysis is relatively slower because the Hierarchical Cluster runs on numerous variables.

The Two-step CA combines both hierarchical and k-means algorithms, where no prior specification values are needed. In the first step, hierarchical logic was applied to the base data source, and then the k-means algorithm was applied to the second stage.

2.7.6 Literature for Cluster Analysis

The cluster analysis technique has been employed in transportation literature over the last fifty years (Govender and Sivakumar, 2020). One cluster analysis exercise recently was done to group blue-tooth sensor data concerning transportation mode choice from a simulated intersection (Bathaee *et al.*, 2018).

One study relating to London’s public transport network used the cluster analysis procedure to research the heterogeneity of commuters and to assess the diversity of urban residents by applying the k-means method with the variations of residents' temporal attributes within days and sequences of activities (Goulet Langlois *et al.*, 2016).

In identifying public transport usage variations, the cluster analysis method was used to group passengers in terms of the public transport level of service quality by De Oña, De Oña and López (2015). This research paper applied the decision tree methodology to compare the customer satisfaction data to distinguish these groups (De Oña *et al.*, 2012).

Guo, Peeta and Mannering (2016) used cluster analysis to establish the link between truck freight carriers' operational characteristics and the factors of users' unwillingness to collaborate with freight shippers. A two-step cluster analysis was applied here to identify relevant groups of freight shippers with similar collaboration perceptions. This study applied categorical and continuous data related to users' perceptions and choices and hence applied a two-step cluster analysis that can efficiently predict the exact number of clusters within the data sample (Chiu *et al.*, 2001).

Traditionally, in transport behaviour research, Cluster Analysis was applied with pre-defined socio-economic variables to be used as the input for the predictive regression analysis. In this essence, Anable (2005) applied cluster analysis to distinguish travellers by their empirical and theoretical psychological variables from the travel behaviour perspective. The k-means clustering method was used here to group car ownership data with some socio-economic attitudes. Later, these clusters were utilised to make the travellers' profiles and delineate them by their travel behaviour and mode choices.

In contrast to the studies mentioned above, cluster analysis applications are limited in DC research. A recent Danish travel demand study on DC divided data samples into three clusters based on attitudes towards DC and conventional car driving: Sceptics (38%); Indifferent stressed drivers (37%), and Enthusiasts (25%)(Nielsen and Haustein, 2018). This research applied the k-means algorithm, where factor analysis results defined the primary cluster sizes.

One recent study used a two-step cluster analysis method to identify variations and grouping of travellers to prefer mobile applications. This study tried to determine preferences for Mobility options as services among the travellers of Slovakia (UNIZA) and the Czech Republic (OLTIS) (Mašek *et al.*, 2023).

2.8 Chapter Conclusion

Based on the overall literature review and discussion in Section 2.7.1, a research method was introduced by highlighting the following gaps in the present literature:

1. Several stated preference choice experiments on shared DC were conducted in different parts of the world. Several agent-based simulations analysed hypothetical shared DC market scenarios with area-wide implementation. Although applicable to define the benefits of shared DC use, these studies underestimated the assessment of observed variables. Therefore, a discrete choice experiment method was followed with hypothetical DC choices to address these gaps.

2. A few of these studies applied a segmentation approach in defining DC sharing options or used only one form of DC to investigate the rideshare possibilities without a comparative approach between regular and occasional car sharing and sharing propensity with strangers and family members. Therefore, regular and occasional travel behaviours were used in this research.

3. Few studies used present travel behaviour (e.g., commuting distance, one-way distance to the grocery) to understand present travel behaviour (Barbour *et al.*, 2019; Nazari *et al.*, 2018). In

contrast, my research used current commuting frequency (regular, occasional travel) as a determinant of adopting shared and non-shared DC use. To this aim, three groups of respondents were identified with present carsharing behaviour and two groups of ridesharing behaviour.

4. In the current shared DC research arena, little research evidence concerns personality traits' effects on the likelihood of shared DC use (Kyriakidis *et al.*, 2015). This study seeks to unveil the relationship between personality characteristics (represented by the big five personality traits) (Gosling *et al.*, 2003) with the likelihood of accepting non-shared and shared use of DC.

5. Besides, my study is the first of its kind to account for the impact of subjective social norms relating to sharing, preserving the environment and seeking a better quality of life (Bamberga *et al.*, 2007);

6. Despite jointly focusing on carsharing and ridesharing preferences for DC (Nazari *et al.*, 2018; Barbour *et al.*, 2019; Menon *et al.*, 2018), the private DC were discussed in these studies for the public interest and lacked the data to understand DC shared ownership in household interest.

7. The idea of flexible ownership models (Masoud and Jayakrishnan, 2017) is shared with a preference for shared costs and liabilities (Jaynes, 2016). To this end, my research analysed the household data to unearth the DC sharing propensities with other household members and advance the discussion of shared ownership of DC within 3 – 4 users who are not from the same household.

In contrast to these research gaps, the idea of flexible DC ownership to reduce household car usage was propelled by transport service providers' (e.g., Uber, Lyft) decisions to include DC in their fleets by 2025 (Kosoff, 2016).

3.Chapter 3: Research Methodology

3.1 Introduction

This Chapter presents the theoretical framework, data collection method and data analysis techniques implemented for this study. This study discussed the determinants of DC shared ownership and ridership under various modelling frameworks. At first behavioural framework for this research study is presented, followed by a comprehensive discussion of explanatory variables for the econometric model development. After that, different survey sampling methods and several data collection methods were discussed. An online survey questionnaire was chosen considering the cost and time used. The design considerations for the online questionnaire and its physical dissemination techniques were then discussed. In the last part of this Chapter, data analysis methods and econometric analysis methods were discussed.

3.2 Overall research method

This research provides important insights into how people within a household interact with DC sharing options and how their DC choices are linked to their present sharing behaviour, personality, social norms, and socioeconomic characteristics. The research method is broadly divided into two sequential but interdependent stages, as presented in Figure 3.1. The first stage was the data collection, initiated by a literature review concerning DC sharing behaviour and its explanatory factors. After that, research questions were formed, and an initial data collection plan was made. Semi-structured expert interviews were conducted to explore the factors further to include in the online questionnaire. After the piloting with the initial online questionnaire and necessary amendments, leaflet invitations were sent to participants from selected Edinburgh addresses. The GIS address dataset was collected from the Royal Mai address dataset to plan the leaflet distribution. Surveymonkey.com was used to host the online questionnaire for four consecutive months (from August 2019 to early December 2019) to ensure enough survey participation. The final collected dataset was cross-checked for errors, and data transformation was performed to prepare the data for statistical and econometric analysis.

The data analysis was the second stage of this research study, subdivided into several parts: descriptive statistics, inferential statistics, cluster analysis, and econometric analysis.

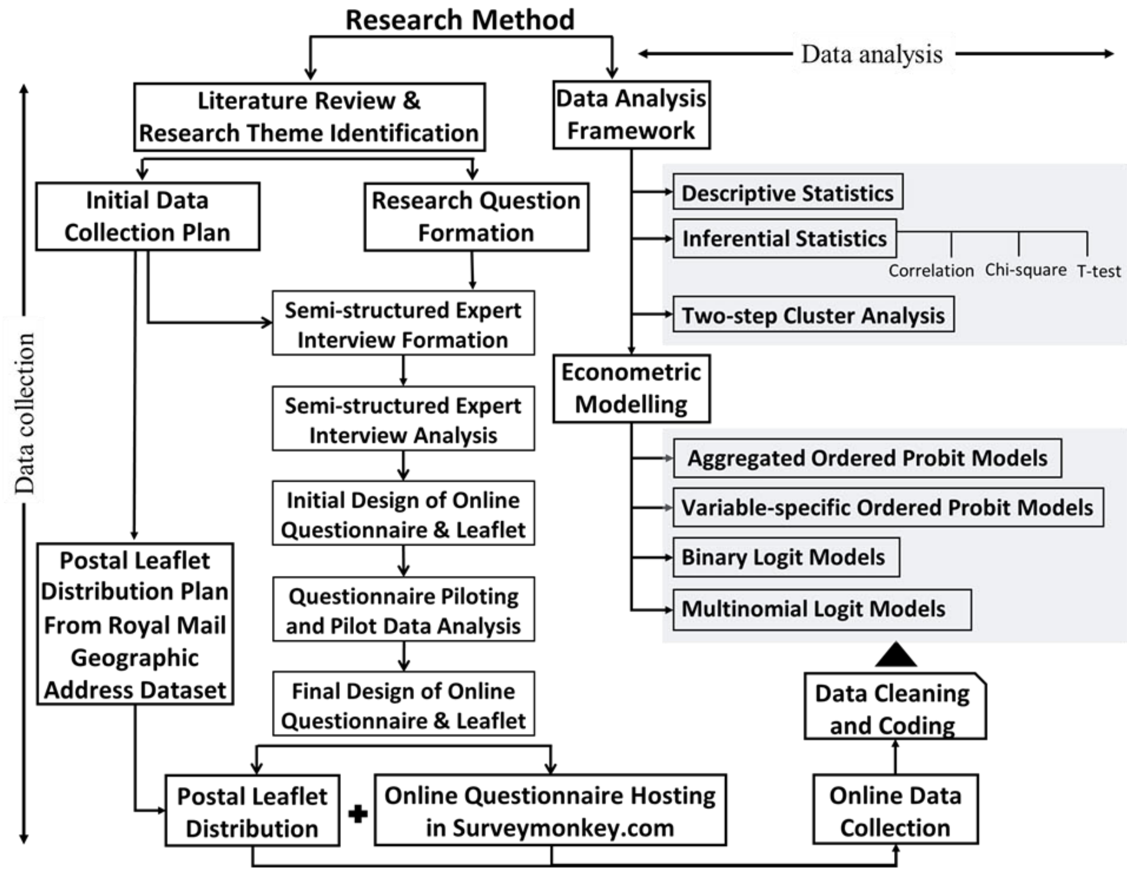


Figure 3.1: Research Methodology

The descriptive analysis deals with the general description of the factors concerning DC use, while inferential analysis identifies the relation among different factors concerning DC usage. Cluster analysis was used to identify respondents with similar behaviour regarding carsharing and ridesharing. These groups were used in the econometric analysis. The demographic, socioeconomic, personality and social-norm data variables are transformed into binary variables for econometric analysis. Several econometric analysis methods were applied to unearth the factors determining the intentions about DC shared ownership and ridership. Binary probit, ordered probit, binary-logit, and multinomial-logit are the econometric methods used in this research experiment. The data analysis framework section describes the purpose and data used for these methods (Section 3.8). All other stages presented in Figure 3.1 are described in the following sections.

3.3 Theoretical framework concerning shared ownership and ridership of DC

The theoretical framework is the structure of a research proposal linked with synthesising a spectrum of established research in the chosen field of study and applying these theories to the proposed research in solving the research questions (Kivunja, 2018). The theoretical framework investigates how the proposed research topic is discussed in the existing literature and if any suggestion can be gained from them to interpret the research findings. A theoretical literature framework was attached in Section 2.7.1 of this research to understand the behavioural determinants concerning shared ownership and ridership of DC.

3.4 Choice set generation for DC shared ownership and ridership

Parallel to the shared mobility classification proposed by Shaheen and Chan (2016), it was envisaged that the future of DC sharing behaviour is divided into two types: 1) Shared ownership and 2) Shared ridership. The classification followed by Shaheen and Chan (2016) was related to the functional use of carsharing, while in this research, the future DC usages were classified in terms of different options of shared ownership and ridership.

The present market for shared mobility helped shape the future DC sharing options. To remove the barrier of shared mobility, DC offers numerous opportunities to share a car or a ride. Three primary DC shared ownership choices were envisaged considering ownership liabilities (e.g., purchase cost, maintenance, insurance, taxes). These three base options were tested for regular and regular travel by asking respondents about their intentions to use these DC options on a five-point Likert scale (e.g., very unlikely – very likely). The types of DC shared ownership options are described below:

1. Private DC (Ow_Pr_Re): This option is similar to a regular privately owned car. The owner will have 24-hour access to DC. The owner must pay all the associated costs (e.g., purchase, tax, insurance, fuel, maintenance). Parking cost/time may not be a significant problem since the DC can drop off the owner at the destination and park itself in a parking zone (office, home). This DC can store personal belongings (luggage, baby buggy, personal stereo, etc.), and the owner utilises or enjoys their time inside the DC.

2. Shared or shared ownership of DC (Ow_Fr_Re): In this DC ownership option, 3-4 persons share the ownership of DC and bear the liabilities together. The owners should ideally divide their usage time for shared DC and sign up for a web platform to maintain that schedule. They can call the shared DC from their mobile devices. If the shared DC is unavailable when needed, the owner must wait for the schedule, arrange a different travel option, or drop the journey altogether. Due to the shared use, some restrictions on long-distance travel and long-time use may clash with another owner of shared DC. Unlike private DC, overnight storage of

belongings may be impossible with shared DC. The owners can still use shared DC to enjoy their time or utilise time while riding.

3. Driverless Taxi (DT) (Ow_Ta_Re): Unlike traditional taxi services, this option may respond to web-enable on-demand calling features from the users at any time, with or without any sharing partner. Subscriptions to Uber-type services by DC may be available, where the user has to pay a monthly/annual subscription fee. This DT may or may not be for exclusive use, and the user has to share the ride with others, at least for part of the journey. For this option, the user is free from the one-time purchase, tax, insurance, and maintenance costs and may lower trip-based costs than the other two options above. However, there may be some wait time for being picked up. For pooled use, DT may take some de-tour and, therefore, will take longer to reach the destination. The pick-up and drop-off point may be far from the user's home location to save time during a pooled ride.

DC shared ridership options are chosen parallelly with DC shared ownership options but unrelated to shared ownership. Thus, the cost and liabilities of DC ownership options are replaced by one-time DC ridership costs. As mentioned below, different DC shared ridership options are considered for this research. For each option, travel alone or with other family members was considered along with the respondent. Shared ridership with DC is not like rented or hired DC and not like current taxi services.

1. Ride alone (Ri_ReNF_A and Ri_ReWF_A): in this ridership option, the rider uses a DC without or with family members and not with others. The rider will likely be flexible enough to carry his belongings when using the DC.

2. Ride with known people (Ri_ReNF_K and Ri_ReWF_K): in this option, the user will share the DC ride with at least one of their close contacts. Unlike riding alone, the rider can carry limited staff as the space inside the car is limited and shared by other riders. It is very likely that in this sharing option, ridesharers are destined to the same place. Considering the self-parking capability of DC, for exclusive use, DC can park itself to wait for a single passenger or multiple passengers when they are related.

3. Ride with a stranger (Ri_ReNF_S and Ri_ReWF_S): this option refers to sharing the ride with a person from the rider's close contacts or family members. Among the DC sharing options, this option allows limited luggage space and scope for privacy. There is little chance that the destination will be the same for the ride sharers who are not tied in any relations. The rider

has the flexibility to utilise their time onboard. When sharing the ride with strangers, when passengers are not related, the DC can drop off one and immediately move to drop off the other. In this case, the parking time and space provision are less relevant.

DC ridesharing options were envisaged for regular and occasional trips with a known person or a stranger. People were asked to rate their preferences for these DC shared ridership options on a five-point Likert scale (e.g., very unlikely – very likely). The detailed picture of DC sharing options envisaged for this research is depicted in Figure 3.2.

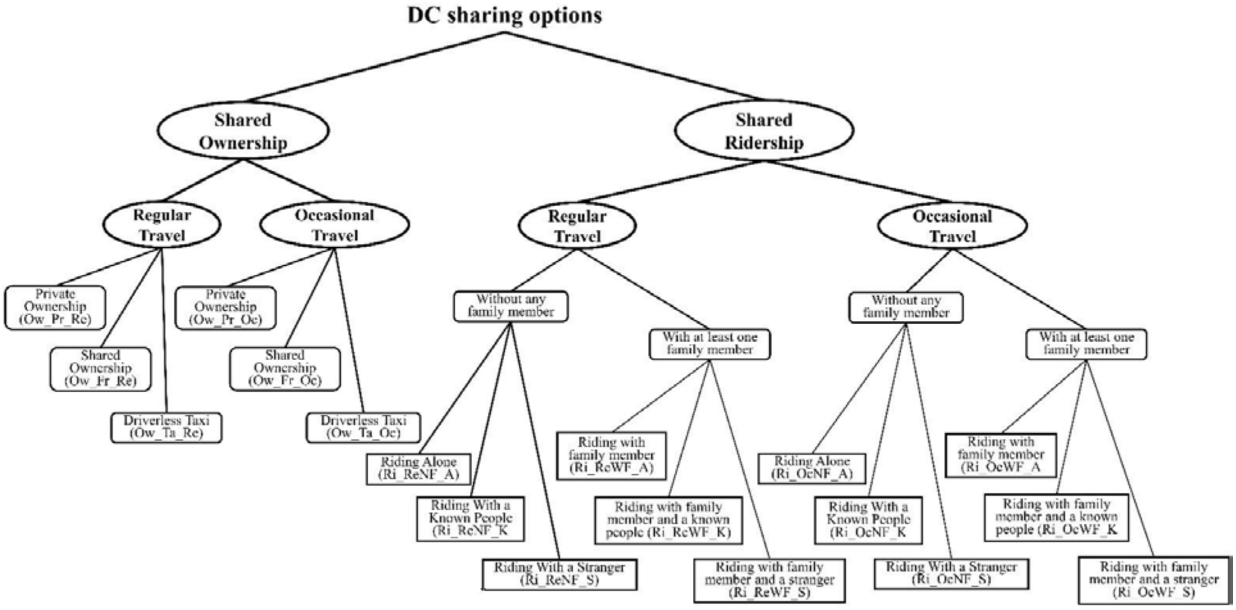


Figure 3.2: DC sharing options used in this research

3.5 Semi-structured expert interview

3.5.1 The objective of the Semi-structured Expert Interview

The expert interview method deals with the qualitative approach of survey responses at the early questionnaire development stage. This interview collects the subject's facts, insights, attitudes, experiences, processes, behaviours, or predictions. An expert interview aims to evaluate and improve the survey instruments (e.g., survey questions and written materials) (Rowley, 2014). As defined by Beatty and Willis (2007), the Expert interview involves: "the administration of draft survey questions while collecting additional verbal information about the survey responses, which is used to evaluate the quality of the response or to help determine whether the question is generating the information that its author intends." The most common cognitive interview technique is conducting a 'semi-structured interview' with 6 - 20 flexible questions among experts in a particular field. The cognitive interview is separate from other sociodemographic interviews regarding purpose, sample size, resource need, materials presented, and the method employed. Concerning the present research, the following are the reasons for conducting a semi-structured expert interview:

1. To understand the experiences, opinions, attitudes, values and processes that other researchers have already applied and to find out if something is missing.
2. To fill the literature gap or to compare and validate the current understanding of a particular subject.
3. With this flexible approach to data gathering, the respondent can give a wide range of information related to the interview subject, which might help form the final survey questionnaire.
4. Before the final survey, this type of survey can help identify the proper strategy to collect the final survey data before the final survey.

3.5.2 Semi-structured Expert Interview Design

A panel of 10 experts was selected at the early stage of the research. Among them, vehicle ride service providers, mobility consultants, researchers and public policy practitioners are notable. Among these experts, seven responded, with 5 sharing their opinion in face-to-face interviews. Each interview session was recorded and lasted approximately 40 – 60 minutes long.

Five semi-structured interview questions were selected to incorporate qualitative data from experts' arguments concerning DC shared ownership and ridership. Each question comprises sub-questions relating to the topic of the research. The form of each interview session was flexible to allow experts to discuss further. Literature sources and web-based data were reviewed concerning DC sharing to identify the expert interview questions.

The researcher conducted five expert interviews from November 2018 – January 2019. The expert panel included three mobility service providers, one consultant, and one researcher. Expert interview questions were developed to address critical issues with DC adoption, such as travel-time use patterns, carsharing and ridesharing with DC and possibilities to perform in-vehicle activities. Besides, respondents' familiarity with any relevant DC project was asked in a separate question. The questionnaire was supplied before the interview so that experts could formulate answers before being interviewed.

In understanding the ridesharing services in North America (Shaheen and Cohen, 2018) and personal vehicle-sharing services (Shaheen *et al.*, 2012), this kind of interview method was applied earlier.

3.5.3 Semi-structured Expert Interview Questions

A questionnaire was conducted in the Semi-structured Expert interview, the details of which are given in Appendix A.

Before the Semi-structured Expert interview was started, an Ethical Approval form was issued, attached to Appendix C.

3.5.4 Key outcomes from the semi-structured interview

The findings from the semi-structured expert interview suggested that travel cost and travel time are two prime factors to consider in shared DC ownership and ridership, while convenience, service familiarity, and in-vehicle privacy are the least essential factors. Almost all of the experts are concerned about the cost of shared ownership. The convenience of DC shared ownership and service familiarity is viewed for DC by most experts, while a few are interested in in-vehicle privacy. Concerning the shared ridership with DC, convenience and service familiarity are less important, while in-vehicle privacy concerns are most important. Compared to the DC shared ownership, this expert interview emphasised the in-vehicle privacy factor for DC shared ridership. Convenience and service familiarity are not essential factors for DC shared ridership. Based on the discussion with these experts, the researcher got in touch with a few of the shared DC projects, as mentioned in Chapter 2: Literature Review (Merge Greenwich Consortium, 2018; Paddeu, Tsouros and Polydoropoulou, 2021; TRL, 2018). Ideas derived from these research projects helped shape the shared DC scenarios of this research. Detailed suggestions from the industry experts, collected through the semi-structured Expert interviews, are given in Appendix B.

3.6 Explanatory factors to explain the propensities of DC share ownership and ridership

Based on the outcome of the Semi-structured Expert interviews, some explanatory variables were selected to explain DC usage. Explanatory variables (determinants) selected were applied in the model formation and were classified into the following categories: current sharing pattern, reasons for carsharing and ridesharing, personality traits, social norm behaviour, and demographic and socioeconomic characteristics. As dependent variables, the possible DC sharing types are associated with future sharing behaviour with DC sharing options measured on a five-point Likert scale (e.g., very unlikely – very likely). The interaction of present and future behaviour and their link in choosing DC sharing are given in Figure 3.3.

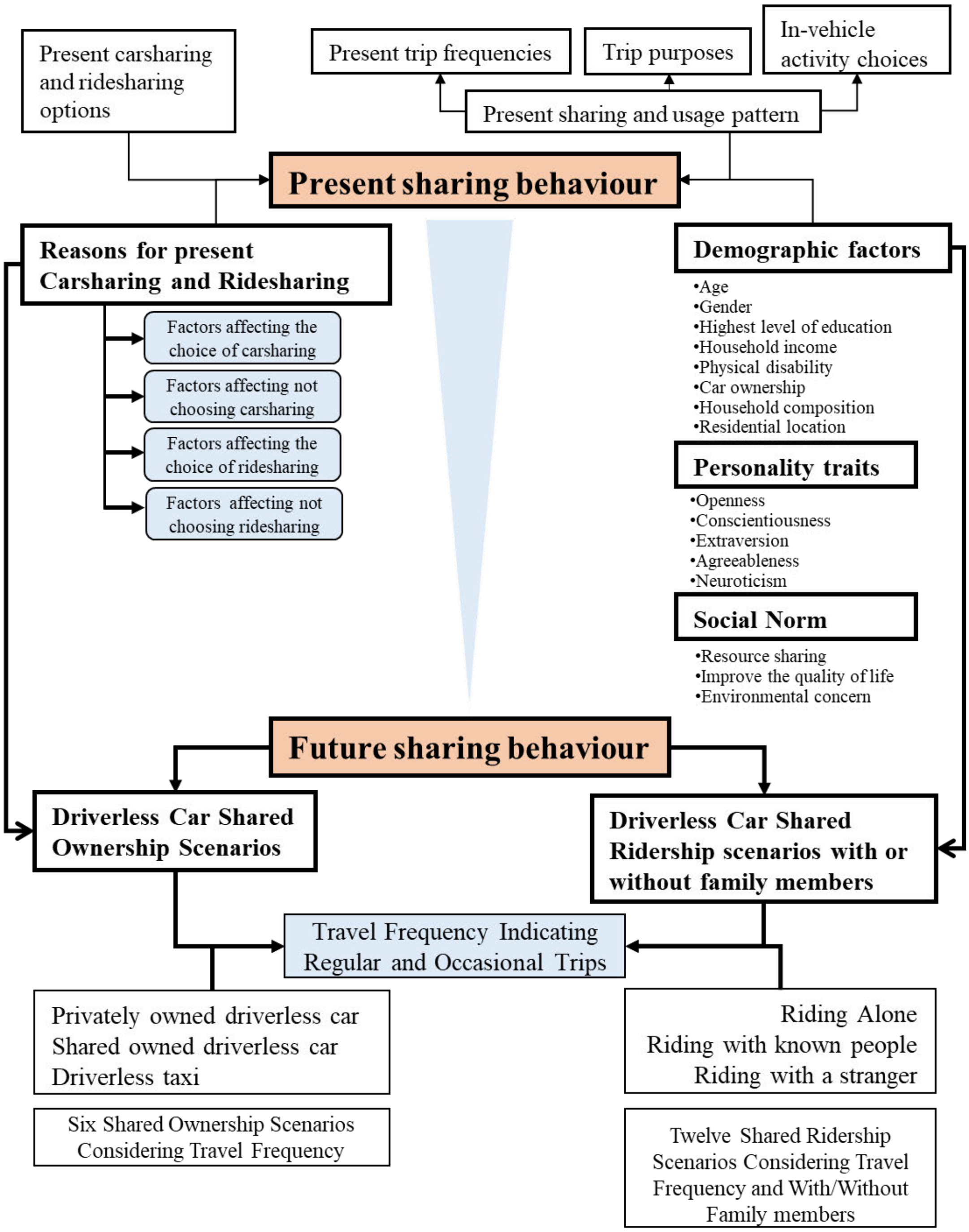


Figure 3.3: Explanatory factors (determinants) concerning shared ownership and ridership with DC

3.6.1 Present travel-sharing behaviour

The concept of present travel-sharing behaviour (e.g., frequency, trip purpose, modes) is described in this Chapter, where carsharing and ridesharing modes are different in type. Concerning the research proposal, a person's probability of sharing a car or a ride depends on personal attitudes towards his frequency of travel, trip purpose, travel mode choice, and in-vehicle activity preferences. Data on trip frequency related to 'ridesharing' are collected in scale ordered: 1) several times in a week; 2) a few days in a month; 3) a few times in a year; and 4) never. Six travel modes are associated with these ridesharing frequencies as the following:

1. Drive alone
2. As a driver with people, you know well
3. As a passenger with the people, you know well
4. As a driver with a stranger
5. As a passenger with a stranger
6. In a taxi

Similarly, to understand the carsharing propensity, the same scale of travel frequencies was considered for the following carsharing modes:

1. Household car
2. Car of people you know well (e.g., friends, colleagues)
3. Car of a car club (e.g., Enterprise car club)
4. Car of a car rental company (e.g., European car)
5. Peer-to-peer car rental (e.g., 'hiya-car' in London)

As well as the frequency, trip purpose plays a vital role in choosing travel modes. For instance, to go to a nearby recreation ground, people may prefer walking or cycling to using the car. But riding in a car or taxi may be preferred for a shopping trip within the same distance. In the case of travel to a distant place, the intention to drive a car or choose to ride in someone's car may depend on the preference to share the ride and the willingness to use the time while travelling. These factors for shared ownership or ridership are not exhaustive and can partially reflect behavioural intentions for choosing shared ridership and carsharing. Respondents were asked about the mode choice and choice frequencies for the following trip purposes:

1. Commute to work/ study
2. Commute from work/ study
3. Shopping
4. Leisure (e.g., gym, cinema, restaurant)
5. Personal/family business (e.g., Doctor, Bank, Post office, Government office)

Mode preferences for each activity are considered based on the available travel modes within the transport network for the City of Edinburgh. They are as follows:

1. Car as a passenger

2. Car as a driver
3. Public transport
4. Walking/cycling
5. Mixed modes

For my research, the relations among carsharing and ridesharing modes, frequencies with intended travel purposes, and in-vehicle activities can be expressed in Figure 3.4.

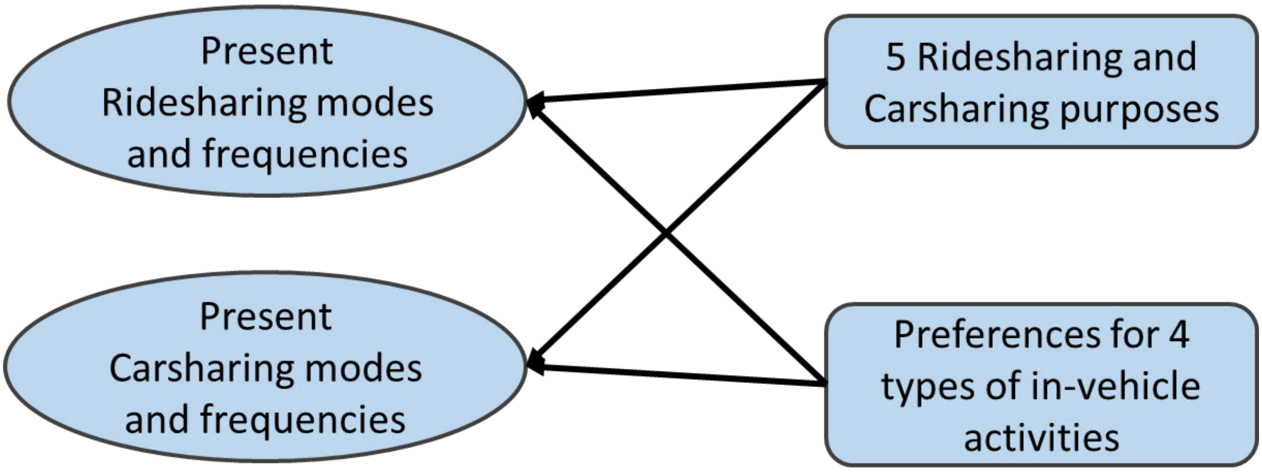


Figure 3.4: Association of present ridesharing and carsharing frequency with their trip purposes and in-vehicle activities

In-vehicle activity preference is related to the revealed disutility or utility while travelling. The idea to include in-vehicle activity preferences in DC sharing is esteemed because travel time with DC can be revealed as travel boredom due to zero driving tasks. Considering the positive aspects of travel time and commitment level while sharing the vehicle or ride, in-vehicle activity preferences can be diverse. Broadly in-vehicle activity preferences are grouped as the following and measured on a five-point Likert scale (e.g., not at all important - extremely important):

1. Work or study-related activities (e.g., calling, email, internet use)
2. Social interaction (e.g., social media, chatting with other passengers, calling friends and family)
3. Relaxing (e.g., music, window gazing, sleeping/snoozing, personal grooming)
4. Enjoy driving

For this research, the preferred frequency of journey makers was the critical factor that helped the respondent decide to own or share the ride with DC unless driving is not his primary activity. For instance, a shared car can take an occasional shopping trip where the passenger can utilise his travel time. Empirically, car share offers easy access to the destination and low-cost travel options for less frequent trip makers and leisure travellers despite having a car in their possession full-time (Litman, 2000). The subsequent sections represent the statistical results related to travel share behaviours collected by the survey.

3.6.2 Demographic variables

The demographic status of the respondent was captured by gender, age and educational background. It has been empirically proved from the studies mentioned in Table 2-3 that age, gender, and education affect the ownership and sharing tendency of DC. Socioeconomic variables are used to account for taste variations in the preferences among groups consisting of household income, household composition, household location, and household cars.

Household income

To capture household income variations, a set of five income categories (e.g., 20k<, 20k-30k,30k-50k,50k-70k,>70k) were observed from the collected data. These income categories are taken from recent Edinburgh Statistics (The City of Edinburgh, 2020), although 30k – 50k and 50k – 70k were used instead of all intermediate categories for simplicity.

Household composition

This variable represents living alone, with or without children, to capture the effect of household composition on carsharing and ridesharing preferences. Children's presence means people might need to own a private car rather than share another car to pursue various trip purposes.

Household location

Household locations for this research are described as living in the city centre, inner suburb, outer suburb and rural. Edinburgh city centre experiences heavy traffic volume, higher parking costs, and higher availability of transit services when inner urban areas can access private cars.

Number of household cars

One would expect automobile ownership to increase with household income, household composition, and the number of family members while all other things are constant. Household car ownership was collected as a count variable for this research, and this collected variable was categorised as 'zero', 'one', 'two' and 'three or more car ownership.

3.6.3 Personality

People's attitudes are aligned with their personalities and are responsible for the diversity of behavioural characteristics, thought patterns, and emotions (Tsao and Chang, 2010). Personality is crucial to determine individuals' social interactions, attitudes, and preferences concerning various life experiences. A personality trait quantifies someone's views by asking direct or indirect questions aligned with personality traits. In judging personality, the widely used method is to conduct the psychometric analysis with the help of a five-dimensional personality scale named the 'Big-five Instrument' (John *et al.*, 2008; Gosling *et al.*, 2003). This 'Big-five instrument' (BFI) is an established classification system of user attitudes linked to 'openness', 'conscientiousness', 'extraversion', 'agreeableness', and 'Neuroticism' (Also known as OCEAN) (John and Srivastava, 1999). Table 3-1 shows the characteristics associated with each 'personality trait'.

Table 3-1: Personality Traits based on the Big five approach and related characteristics

Personality Traits	Characteristics
Openness	Appreciation for novelty, variety of experiences, and diversity of interests
Conscientiousness	Organised, consistent, cautious and dutiful, less creative
Extraversion	Appreciation for environments with a higher level of simulations, high energy, more activity and social life
Agreeableness	Cooperative, adaptable, submissive, tolerant, generous, modest and trusting
Neuroticism	High susceptibility to anger, frustration, insecurity, permission, anxiety and negative emotions

A 44-item short-question inventory introduced in the late 1990s (John and Srivastava, 1999) was used to measure personality. Since then, these 44 items were converted to super-short personality measures to reduce the time required in surveys. Therefore, a self-esteemed BFI index was introduced where the respondent has to answer ten personality statements (Rammstedt and John, 2007) with two statements for each BFI trait. Several statements were condensed to form only two short phrases for each BFI index (Gosling *et al.*, 2003). To get the personality pattern of an individual, each of these phrases is required to be rated on a 5-point Likert scale as shown in Table 3-2 (e.g., '0' stands for Strongly disagree' to '4' for 'Strongly agree'). For the present research, a 5-point scale was used suitably to reduce the task complexity for the respondent. Details of deriving composite personality trait variables are described in Chapter 4.

Table 3-2: Personality traits and 10-item measurement scale (based on Rammstedt and John, 2007)

Personality traits	I see myself as someone who is	Codes used in the questionnaire
Agreeableness	Generally trusting	Gn
Agreeableness	Tends to find fault with others	FO
Conscientiousness	Tends to be lazy	TL
Conscientiousness	Does a thorough job	TJ
Extraversion	Is reserved	Re
Extraversion	is outgoing, sociable	OS
Neuroticism	is relaxed, handles stress well	RHS
Neuroticism	gets nervous easily	Nu
Openness	has few artistic interests	AI
Openness	has an active imagination	Aim

3.6.4 Social norms

Social norms refer to social beliefs about behaviour (McKenzie-Mohr, 2000). In layperson's terms, norms are the expected behaviour of people under normal circumstances. A social norm is a tool to influence the choice to accept one behaviour (e.g., sharing resources) if someone can find others to accept the same (Smith *et al.*, 2012).

As shown in Figure 3.5, social norms are of two types : (a) descriptive and (b) injunctive. Descriptive norms are related to people's usual behaviour (or perceptions) regarding a particular task. Individual actions are guided by the broader societal feelings where their close relationships may or may not be included (e.g., close friends, relatives, family members, and neighbours). Descriptive norms are often confirmed valuable information related to a behavioural agreement (Cialdini *et al.*, 1990).

In layman's terms, the norm indicates a group member's regular activity is called a descriptive norm (e.g., "People of my city do use carsharing") (Cialdini *et al.*, 1990). But when a norm indicates social acceptance or unacceptance within a group, it is referred to as an injunctive norm (e.g., "People of my city approve carsharing") (Cialdini and Trost, 1998). The guiding principle for this type of norm is other people's moral beliefs. The difference between the 'descriptive' and 'injunctive' norms relates to behaviour and morality.

Subjective social norms are part of the injunctive norm, defined as an individual's "perception that most people who are important to him think he should or should not perform/show behaviour in question" (Fishbein and Ajzen, 2009). Subjective social norms are related to some specific social components to signify vital psychosomatic identification (Darnton, 2008). These norms are based on the typical social action of someone to get the highest benefit out of it. A subjective social norm is an essential indication of social stimulus in changing behaviour. Consumers usually follow social norms in supporting shared resources over personal use (Botsman and Rogers, 2011).

[redacted]

Figure 3.5: Norm taxonomy for environmentally responsible behaviour (Thøgersen, 2006)

The crucial difference is between 'what people think other people do' (e.g., descriptive norm) and 'what other people think the person should do' (e.g., subjective social norm). These concepts are related but technically not the same due to their targeted subject. According to Ajzen's (2002) idea, norms designed as descriptive should also be included as the subjective norm. Subjective norms reflect the behavioural intention of close contacts. Responses within close contacts are likely to have minor variations in their behaviour since they usually approve of desirable behaviour and disapprove of undesirable behaviour (Fishbein and Ajzen, 2009). Empirical evidence of a positive correlation between subjective and descriptive social norms is a good reason to include subjective norms in the norm assessment (Cialdini *et al.*, 1990; Larimer *et al.*, 2004).

For this research, the effect of social norms was observed to identify the propensity to accept various DC usages investigated through some statements concerning 1) social expectation for sharing personal resources, 2) social expectation for contribution to a better quality of life, 3) social expectation for preserving the environment. For each of these three latent attitudes, two statements are formed where the first one is related to the descriptive social norm (e.g., what are my close surroundings prefer to do?), and the second one is the injunctive social norm (e.g., what are my close surroundings expect me to do?). Responses for each statement are recorded on a five-point Likert scale (e.g., strongly disagree - strongly agree). Table 3-3 shows the list of social norms to be tested and associated social norm statements used for this research. Detailed analyses of social norm responses are given in Chapter 4.

Table 3-3: Social norm statements used for this research

Social-norms	**Social-norm statements**	Questionnaire Code
The social expectation for sharing personal resources	Most of my acquaintances share or rent their resources (e.g. house or car) when possible	ARS16
	Society expects me to share or rent my resources (e.g. house or car) when possible.	SES16
The social expectation for contribution to a better quality of life	Most of my acquaintances make an effort to improve the quality of life where they live	AEQ16
	Society expects me to make an effort to improve the quality of life where I live.	SEQ16
The social expectation for preserving the environment	Most of my acquaintances make an effort to protect the environment	EPE16
	Society expects me to make an effort to protect the environment	SPE16

Table 3-4 describes the socioeconomic variables used to answer research questions in modelling exercises. The original variables were restructured as dummy variables, where '1' indicates the acceptance of these variables and '0' otherwise.

Table 3-4: Detailed description of all the socioeconomic variables used in this research

Explanation	Code
Male (1 if the respondent is a male, 0 otherwise)	Me
Female (1 if the respondent is a female, 0 otherwise)	Fm
Centennials (1 if the respondent is 0-23 years old, 0 otherwise)	Cen
Millennial (1 if the respondent is 24 – 43 years old, 0 otherwise)	Mille
Generation X (1 if the respondent is 44 – 55 years old, 0 otherwise)	GenX
Baby boomer (1 if the respondent is 56 -74 years old, 0 otherwise)	Bboom
Traditionalist (1 if the respondent is over 74 years old, 0 otherwise)	Trad
Lower education level (1 if respondent have secondary level education, 0 otherwise)	He0
Bachelor's degree holder (1 if respondent holds a bachelor's degree, 0 otherwise)	He1
Masters or higher degree holder (1 if respondent holds a master's degree or higher, 0 otherwise)	He2

Lower-income earner (1 if the respondent earns below £20000 per year, 0 otherwise)	Hi1
Lower-income earner (1 if the respondent earns within £20001 - £30000 per year, 0 otherwise)	Hi2
Higher-income earner (1 if the respondent earns within £30001 - £50000 per year, 0 otherwise)	Hi3
Higher-income earner (1 if the respondent earns within £50001 - £70000 per year, 0 otherwise)	Hi4
Higher-income earner (1 if the respondent earns over £70000 per year, 0 otherwise)	Hi5
Living alone (1 if the respondent is living alone, 0 otherwise)	La
A household without a child (1 if the respondent lives in a household with no children, 0 otherwise)	Hwcn
Household with at least one child (1 if the respondent lives in a household with at least one child, 0 otherwise)	Hcn
Other arrangements (1 if the respondent below to a household with other arrangements, 0 otherwise)	Oa
City centre dwellers (1 if the respondent lives in the city centre, 0 otherwise)	Cc
Inner suburban dwellers (1 if the respondent lives in the inner suburb, 0 otherwise)	Is
Outer suburban dwellers (1 if the respondent lives in the outer suburb, 0 otherwise)	Os
Rural dwellers (1 if the household lives in a rural area, 0 otherwise)	Ru
Zero car ownership (1 if the respondent owns no car, 0 otherwise)	Cown0
One car ownership (1 if the respondent has one car, 0 otherwise)	Cown1
Two car ownership (1 if the respondent has two cars, 0 otherwise)	Cown2
Two or more car ownership (1 if the respondent has more than two cars, 0 otherwise)	Cown3

3.7 Development of the online questionnaire

3.7.1 Choice of the cross-sectional study area

A self-completion online questionnaire was used to collect data. Several methods were explored to collect necessary data for this research, and eventually, the 'online survey with postal leaflet invitation' has been identified as the most suitable one. This method can also satisfy Edinburgh Napier University's paperless questionnaire policy and offer a robust data sampling technique within the City of Edinburgh (EH1 –EH17). The detailed list of explanatory variables is given in Appendix G.

3.7.2 Data Collection Administration

Several data collection techniques were considered before deciding on the online survey method. However, each of these techniques has specific limitations and budget issues. The pros and cons of data from different data collection mechanisms are given in Section 2.7.3 of Chapter 2.

As discussed in Section 2.7.2 of Chapter 2, an innovative data collection method was applied, inviting people to participate in an online survey. DL-sized leaflets were delivered to selected postal addresses of Edinburgh postcode districts (EH1 – EH17) to improve the representativity of the survey sample. These postal addresses were selected following the Scottish Index of Multiple Deprivations (SIMD) criteria (Shaw *et al.*, 2017). SIMD helped to select addresses based on some predefined socioeconomic criteria. A detailed description of SIMD and associated criteria for address selection is mentioned in Section 3.7.6. The researcher targeted these addresses to distribute leaflets to ensure the participation of at least one household member.

3.7.3 Sample size estimation

Data analysis for this research requires discussing factors from a large number of samples. However, the large sample size can reduce the probability of error and maximise the accuracy of the data interpretation (Osborne and Costello, 2004). Besides, large sample sizes incur costs due to acquisition and management issues. On the other hand, a small sample size increases the chance of considerable variation in the estimation result with less reliability (Richardson A J. *et al.*, 2017).

The sample size's adequacy is a trade-off between the study's objective and the resource availability (cost) (Richardson A J. *et al.*, 2017). Stratified random sampling involves selecting units from a population of interest in a study area, and these units represent the population's characteristics to ensure that the study results can be generalised to the whole population. Various sample size estimation procedures (e.g., the sample-to-variable ratio and the central limit theorem) are discussed in Section 2.7.4 of Chapter 2, with the probability of various sample sizes.

Final sample size

Based on the calculated sample size by various sampling approaches described in Section 2.7.4 and experiences from recent studies, it was envisaged that, on average, 450 – 550 samples would be appropriate to capture the population heterogeneity of Edinburgh. Earlier studies were recorded within the world's different geographic and socioeconomic conditions and, therefore, likely to vary. For this reason, they were not taken as examples, and they cannot be fully applicable to my research.

Recent online surveys with a postal invitation can be examples to understand the response rate. In a recent survey in Dublin, leaflets were distributed with a QR code linked to an online questionnaire, and the response rate was 10% (Acheampong and Cugurullo, 2019). So, it was assumed that the expected response rate should be 5% -10% of the distributed leaflet invitations. The lower the response rate for the population, the more the leaflet distribution was considered.

Considering the 5% response rate from distributed leaflets, to achieve 450 – 550 responses, the expected number of target addresses for leaflet distribution should be 10000, a massive number to cover within 4 - 6 months through the effort of the PhD student himself. This was why the target sample size was kept to a minimum.

3.7.4 Questionnaire design

Edinburgh Napier University (ENU) 's research integrity and compliance office processed the 'Ethical approval' for this PhD research. The online survey targeted the people of Edinburgh within the city's 17 postcode districts. The survey platform was designed on surveymonkey.com, and this web platform was subscribed to for six consecutive months to administer the survey. Although the final data collection duration lasted four months, the earlier two months were dedicated to designing and piloting the online questionnaire among the staff of ENU.

Questionnaire piloting

Once these questions were arranged in the SurveyMonkey.com web platform, the questionnaire was planned for a pilot study. The pilot study's main objective was to check the readability of the questions by technical and non-technical participants from different occupations. The average time to complete the online questionnaire was also observed, which helped control the length. The online questionnaire was checked by several ENU employees of the different designations were considered. The participants' details for this pilot study are elaborated in Table 3-5.

Table 3-5: Participants in the questionnaire piloting

Sr. No.	Designation	Time taken (minutes)	Suggestion
1	Lecturer	8	Overall, Ok (Without watching the video)
2	Lecturer	16	Questions 4, 11/12 or 8 should be revised with
3	Lecturer	21	Peer-to-peer meaning; 8 should be revised with
4	PhD student	17	Add a question about driverless acceptance
5	PhD student	18	No issues
6	Research Assistant	15	Introduction is lengthy; Drivers/non-drivers; Regular/Occasional
7	Professor	12	The introduction is lengthy; Question 4
8	Office Assistant	15	Public office meaning (e.g., Doctor, Post office, Bank, Government officer, Pharmacist)

9	Assistant	12	No issues found
	Average time	**15**	

Without any significant issues in the questionnaire design, the outcome of the pilot survey identified a few minor concerns with the questionnaire design and corrected them accordingly.

Final questionnaire design

After the piloting, the final questionnaire was adjusted with 26 questions in four sections to collect data. The following sections describe the structure of the final questionnaire, along with the depiction in Figure 3.6:

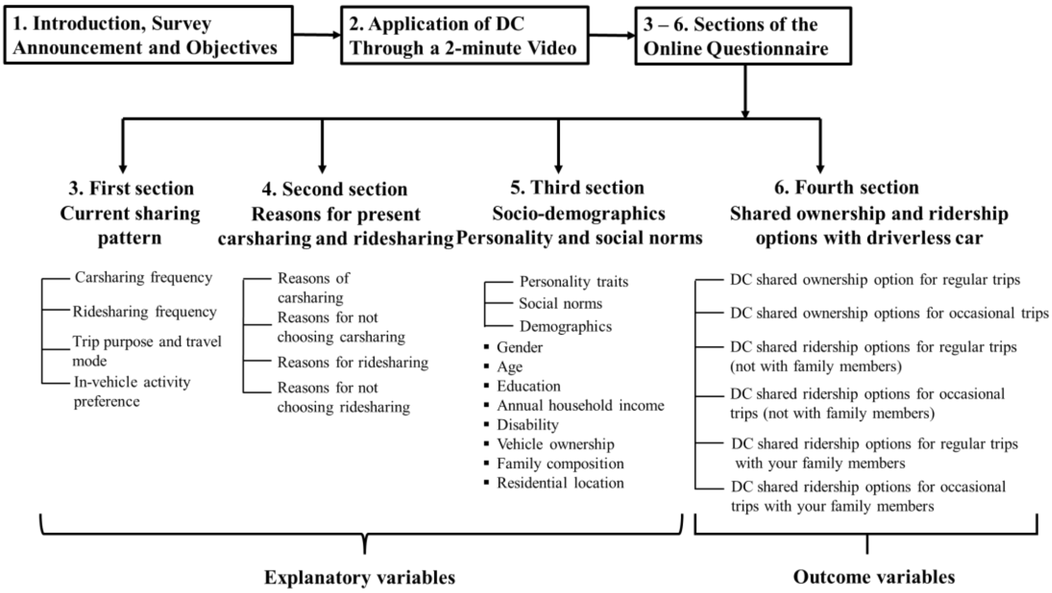


Figure 3.6: Sections of the survey questionnaire with their elements

The introductory section declared general announcements of the survey and its objectives. A short description of the survey was provided with an offer to see the video related to sharing a DC. This section starts with the following phrase to describe the DC:

"Driverless vehicles are vehicles that can drive by themselves without any input from human beings. They are expected to be on our roads in 10 - 15 years. Please watch the video on the next page for more information about how they can be used." At the end of this section, an announcement was made for a prize draw to attract this survey participation. By complying with the rules of the European GDPR described in this section, this questionnaire data will not be shared with any third party and will not be used for any purpose other than this research.

1. The following section describes the application of DC through a 2-minute video related to the shared use of DC. This video was chosen from CDM Smith's website (www.cdmsmith.com), which demonstrated changing the way of travel through the use of

DC sharing (https://www.cdmsmith.com/en/Video/How-will-Driverless-Vehicles-Change-the-Way-We-Travel)

2. The first questionnaire section follows from the announcement and video demonstration and is designed to collect information concerned with present shared ridership (e.g., frequency of driving alone, of travelling as a driver or passenger with known people, a driver or passenger with strangers, in a taxi) and shared ownership (e.g., use of private cars, car clubs, car rentals, and peer-to-peer car rental) behaviour; mode preference (car as a driver, car as a passenger, public transport, walking/cycling, mixed modes) for different trip purposes (commute, shopping, leisure, personal or family business), and importance of different in-vehicle activities (e.g., work or study, social interaction, relaxing, enjoy driving). In-vehicle activities are assessed through their importance levels by a five-point Likert scale (e.g., Not at all important – Extremely important).
3. The second section was designed to ask about respondents' perceptions of factors determining the preferences for present shared ownership and ridership options. Each factor was assessed through a five-point Likert scale (e.g., Not at all important – Extremely important)
4. In the third section, questions were designed to elicit respondents' likelihood of adopting different shared ownership and ridership models of DC under different trip scenarios. The willingness to use different models of DC shared ownership (private DC, shared ownership, taxi service) and shared ridership (travelling alone, with acquaintances, and with strangers) was asked for different urban trip contexts defined by travel regularity (regular and occasional) and presence of family members in the third section. e.g., it was asked, "For your regular personal urban trips made by driverless vehicles, how likely are you to choose driverless vehicles owned by three to four people with possible responses ranging from "Very unlikely" to "Very likely". Shared ridership scenarios were also assessed with travel regularity (e.g., regular, occasional) and concerning family members' presence (e.g., with and without family members). Shared ridership scenarios are 1) ride alone, 2) ride with known people to save the cost, and 3) ride with strangers to save the ride and are assessed through a five-point Likert scale (e.g., Very unlikely – Very likely).
5. The fourth questionnaire section deals with the information about respondents: (a) personality traits, (b) social norms, (c) demographics (e.g., age, gender, educational level), (d) socioeconomic status (household size, annual household income, household location, number of vehicles in the household), (e) disability (yes/no), and (f) personal questions concerning

postcode and email address. These personal questions were asked to identify the respondents if he is one of the winners of the prize draw for three Tablet PCs. The gift was advertised to ensure that many respondents participated in the online questionnaire survey. Figure 3.6 shows four sub-sections of the fourth section of the online questionnaire with the information they are supposed to collect. The final questionnaire for this research survey is attached in Appendix D. The relations of research questions with the final questionnaire are attached in Appendix E.

3.7.5 Postal Leaflet Design

The leaflet used to invite people to participate in the survey was both sides printed DL-sized brochure titled '15-minute survey on driverless vehicle'. The front page described the DC with a short definition and the survey's objective and prize declaration. On this page, a QR code was presented with online links to the questionnaire so respondents could access it from their mobile devices or PCs. The leaflet's back page represented some potentialities of DCs, followed by a graphical comparison of conventional and DCs. Appendix F depicts the final leaflet design for the online survey.

After selecting the number of target addresses, leaflets were distributed to these addresses. The design of this leaflet included a scannable QR code to be scanned by a mobile camera. This QR code connected with the online host allowed the displaying of the questionnaire on the mobile interface. Besides, an online link to the survey appears at the bottom of the leaflet's front page.

3.7.6 Leaflet distribution

Data zones related to the Scottish Index of Multiple Deprivations (SIMD)

To plan the leaflet distribution Scottish Index of Multiple Deprivations (SIMD) was used (Shaw *et al.*, 2017). In SMID 2016, 5.3 million Scottish addresses were divided into 6976 data zones with various deprivation levels. These levels are defined by 38 deprivation indicators from seven broad indicators: income, employment, education, health, access to service, crime, and housing (Figure 3.7). Therefore, SIMD allows population stratification in a simple but meaningful way.

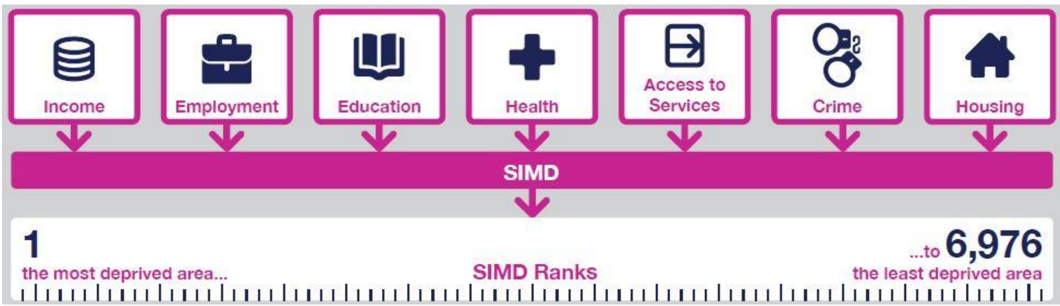


Figure 3.7: SIMD index of deprivation

The questionnaire distribution addresses were selected randomly by combining the SIMD database with the Royal Mail AddressPlus database within the postcode districts of EH1 – EH17. With the expected response rate of 5% - 10%, 10000 leaflets were planned to be distributed in Edinburgh (within the postcode zone of EH1 – EH17). The address selection process is described below in Figure 3.8. Besides, Figure 3.9 shows the GIS map of the City of Edinburgh with SIMD levels and Postcode districts.

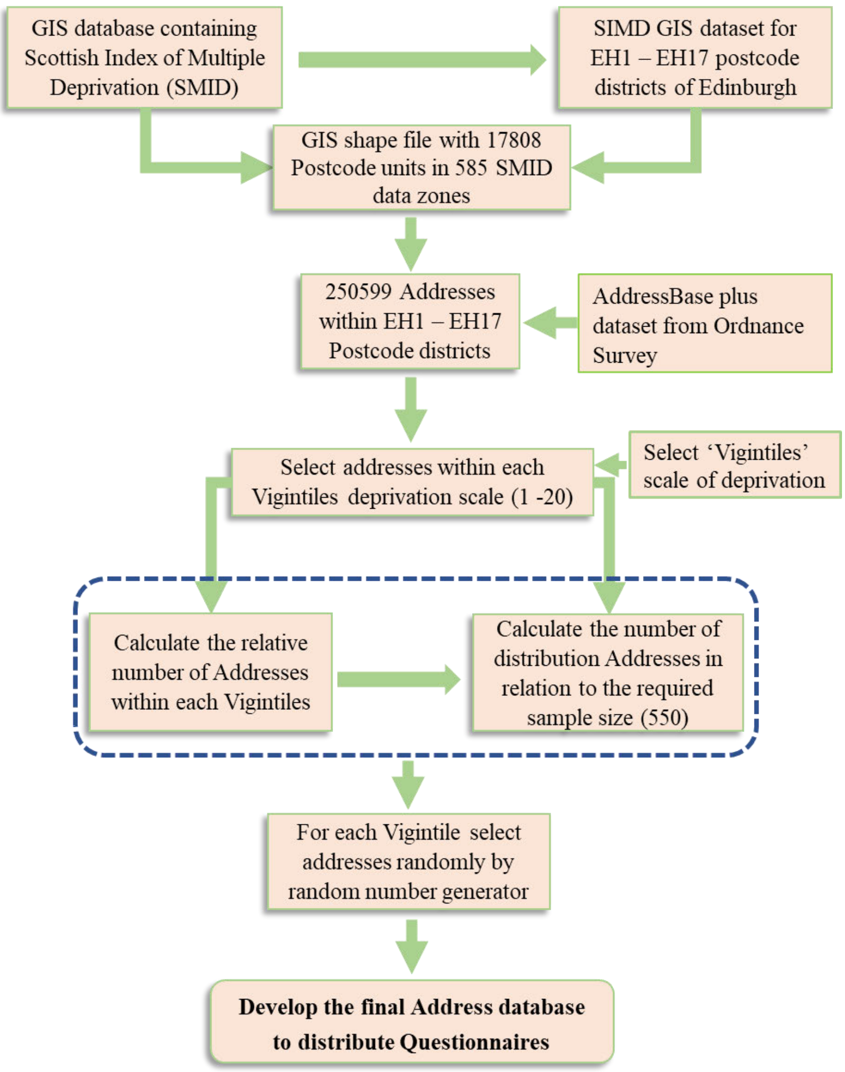


Figure 3.8: Flow chart for Address Selection method

The following flowchart in Figure 3.8 portrays the method of selecting 10000 addresses out of 233584 addresses from within Edinburgh postcode districts (e.g., EH1 – EH17). The steps of this method are the following:

1. After receiving Royal Mail's Address Base Plus GIS dataset and Scottish Index of Multiple Deprivation (SMID) data from Edinburgh Council, the GIS shapefile was prepared to contain the address database encompassing all EH1 – EH17 postcode districts of Edinburgh. The process generated a GIS shapefile with 17808 postcode units and 585 SMID data zones.
2. After this step, these two datasets were combined to form a separate database containing the number of addresses within each SIMD data zone and Edinburgh postcode district, as shown in Table 3-6. A vigintile scale was used for classifying areas according to their SIMD. This process selected 250599 addresses within Edinburgh postcode districts (EH1 – EH20).
3. At the next stage, the address ratio was calculated (by dividing the address number by total Edinburgh addresses) for each postcode district of Table 3-7 and then used these numbers to calculate the target number of addresses within each postcode district to distribute leaflets, as shown in Table 3-7. In total, 10000 leaflets distribution was targeted.
4. Before going to the field, these locations were plotted in Google Maps and loaded in the mobile phone to ease the address search tasks. A typical Google map panel for address search is shown in Figure 3.10.
5. Leaflets were distributed to these addresses within these postcode districts (EH1 – EH17) and the 20 SIMD data zones. The selected number of addresses is shown in Table 3-7.

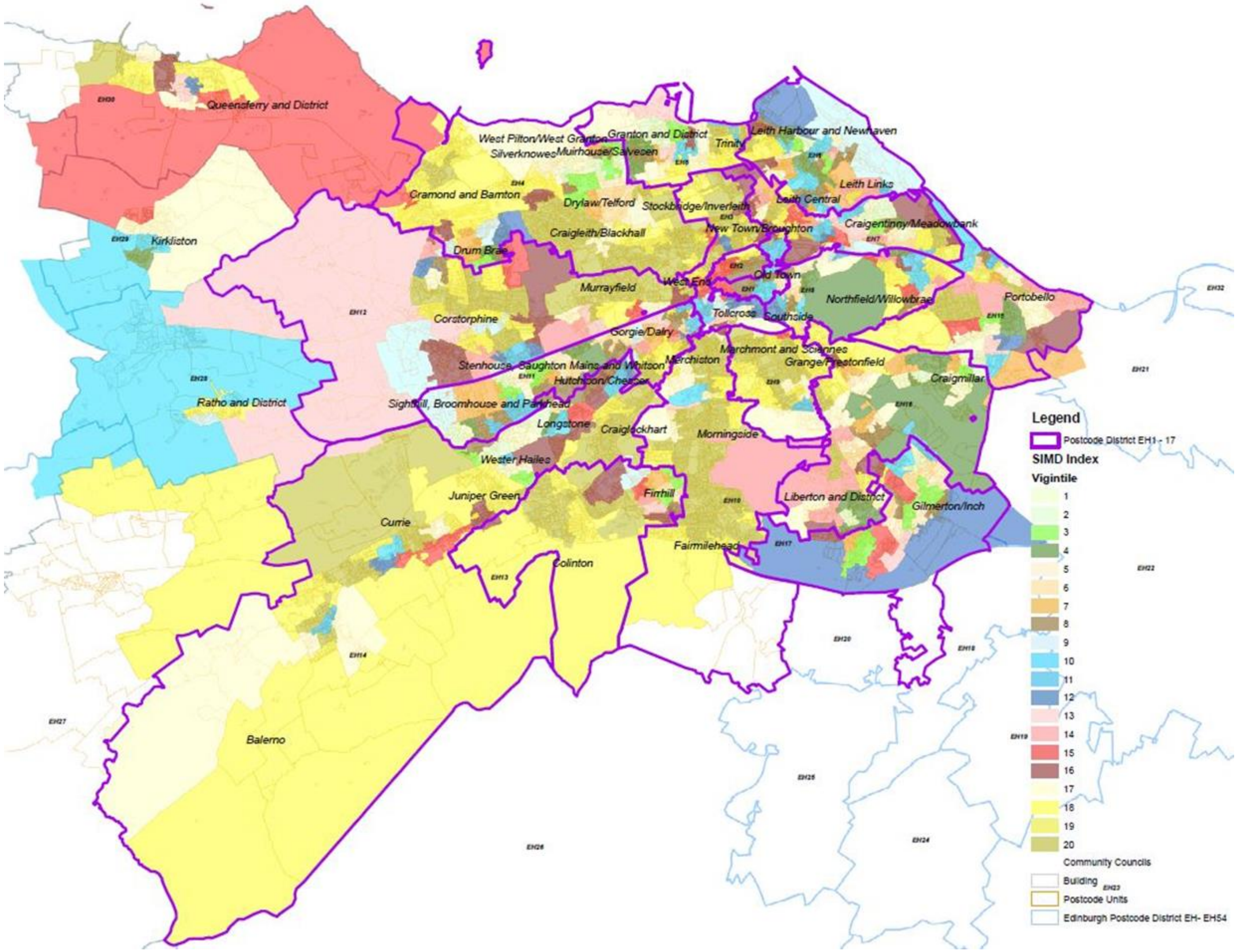


Figure 3.9: Map showing Edinburgh postcode districts (EH1 - EH17) and SIMD data zones

Table 3-6: Overall distribution of addresses within Edinburgh SIMD (e.g., 1 – 20) zones and Postcode districts (e.g., EH1 – EH17)

Postcodel District	**SIMD1**	**SIMD2**	**SIMD3**	**SIMD4**	**SIMD5**	**SIMD6**	**SIMD7**	**SIMD8**	**SIMD9**	**SIMD10**	**SIMD11**	**SIMD12**	**SIMD13**	**SIMD14**	**SIMD15**	**SIMD16**	**SIMD17**	**SIMD18**	**SIMD19**	**SIMD20**	**Total**
EH1	0	0	0	0	129	0	0	651	0	463	348	88	0	0	165	196	0	0	192	113	2345
EH2	0	0	0	0	0	0	0	123	0	0	0	0	0	0	353	0	0	0	148	21	645
EH3	0	0	0	0	0	0	0	0	918	163	500	1825	1008	0	776	942	680	624	1112	4939	13487
EH4	848	1204	2136	471	951	1270	1509	710	684	0	0	420	1	64	624	697	1165	1916	4019	6983	25672
EH5	0	1334	625	1301	125	0	269	363	0	411	390	381	1114	0	0	326	1276	833	473	740	9961
EH6	211	648	976	1548	617	0	2089	3343	751	2179	1179	1875	771	1731	4	844	827	907	743	382	21625
EH7	1406	794	426	390	864	312	1168	370	830	923	1517	549	1173	1513	1674	1708	608	1071	1082	1661	20039
EH8	0	0	0	1201	1267	1105	0	1104	680	1005	896	0	484	0	745	240	652	930	1065	0	11374
EH9	0	0	0	0	0	0	0	0	0	0	374	0	0	0	0	0	1092	0	0	5137	6603
EH10	0	0	0	0	0	0	0	0	0	440	0	0	689	2	0	320	1499	828	1777	9334	14889
EH11	530	860	1162	1233	1043	1859	1312	2480	900	461	2001	483	580	1847	305	260	0	1039	1177	1766	21298
EH12	0	0	0	0	0	0	45	501	1157	0	697	928	1449	1299	745	2419	1045	1803	1284	5158	18530
EH13	0	0	817	0	0	404	421	217	460	0	0	0	356	306	340	661	0	0	967	1767	6716
EH14	1807	797	760	392	259	326	0	941	191	1046	1175	839	6	0	865	1245	931	0	3400	3633	18613
EH15	872	351	313	691	0	349	362	229	0	1197	421	183	380	1147	295	319	1123	0	487	1291	10010
EH16	1601	598	301	2247	1288	497	1542	766	0	0	31	0	62	1855	0	548	961	399	1234	580	14510
EH17	419	429	1748	17	1105	924	276	613	0	348	341	829	387	0	761	556	0	0	46	0	8799
EH27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	83	0	84
EH28	0	0	0	0	0	0	0	0	343	717	0	0	60	0	0	0	0	0	346	0	1466
EH29	0	0	0	351	0	0	0	0	0	561	0	0	0	0	313	0	998	0	0	0	2223
EH30	0	0	0	0	266	0	0	0	0	0	0	298	329	0	1043	469	429	418	1070	373	4695
Total	7694	7015	9264	9842	7914	7046	8993	12411	6914	9914	9870	8698	8849	9764	9008	11750	13287	10768	20705	43878	**233584**

Table 3-7: Distribution of selected 10000 addresses within Edinburgh SIMD (e.g., 1 -20) and Postcode districts (e.g., EH1 - EH17)

Poscode District	**SIMD1**	**SIMD2**	**SIMD3**	**SIMD4**	**SIMD5**	**SIMD6**	**SIMD7**	**SIMD8**	**SIMD9**	**SIMD10**	**SIMD11**	**SIMD12**	**SIMD13**	**SIMD14**	**SIMD15**	**SIMD16**	**SIMD17**	**SIMD18**	**SIMD19**	**SIMD20**	**Total**
EH1	0	0	0	0	6	0	0	28	0	20	15	4	0	0	7	8	0	0	8	5	100
EH2	0	0	0	0	0	0	0	5	0	0	0	0	0	0	15	0	0	0	6	1	28
EH3	0	0	0	0	0	0	0	0	39	7	21	78	43	0	33	40	29	27	48	211	577
EH4	36	52	91	20	41	54	65	30	29	0	0	18	0	3	27	30	50	82	172	299	1099
EH5	0	57	27	56	5	0	12	16	0	18	17	16	48	0	0	14	55	36	20	32	426
EH6	9	28	42	66	26	0	89	143	32	93	50	80	33	74	0	36	35	39	32	16	926
EH7	60	34	18	17	37	13	50	16	36	40	65	24	50	65	72	73	26	46	46	71	858
EH8	0	0	0	51	54	47	0	47	29	43	38	0	21	0	32	10	28	40	46	0	487
EH9	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	47	0	0	220	283
EH10	0	0	0	0	0	0	0	0	0	19	0	0	29	0	0	14	64	35	76	400	637
EH11	23	37	50	53	45	80	56	106	39	20	86	21	25	79	13	11	0	44	50	76	912
EH12	0	0	0	0	0	0	2	21	50	0	30	40	62	56	32	104	45	77	55	221	793
EH13	0	0	35	0	0	17	18	9	20	0	0	0	15	13	15	28	0	0	41	76	288
EH14	77	34	33	17	11	14	0	40	8	45	50	36	0	0	37	53	40	0	146	156	797
EH15	37	15	13	30	0	15	15	10	0	51	18	8	16	49	13	14	48	0	21	55	429
EH16	69	26	13	96	55	21	66	33	0	0	1	0	3	79	0	23	41	17	53	25	621
EH17	18	18	75	1	47	40	12	26	0	15	15	35	17	0	33	24	0	0	2	0	377
EH27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	4
EH28	0	0	0	0	0	0	0	0	15	31	0	0	3	0	0	0	0	0	15	0	63
EH29	0	0	0	15	0	0	0	0	0	24	0	0	0	0	13	0	43	0	0	0	95
EH30	0	0	0	0	11	0	0	0	0	0	0	13	14	0	45	20	18	18	46	16	201
Total	329	300	397	421	339	302	385	531	296	424	422	372	379	418	386	503	569	461	886	1878	10000

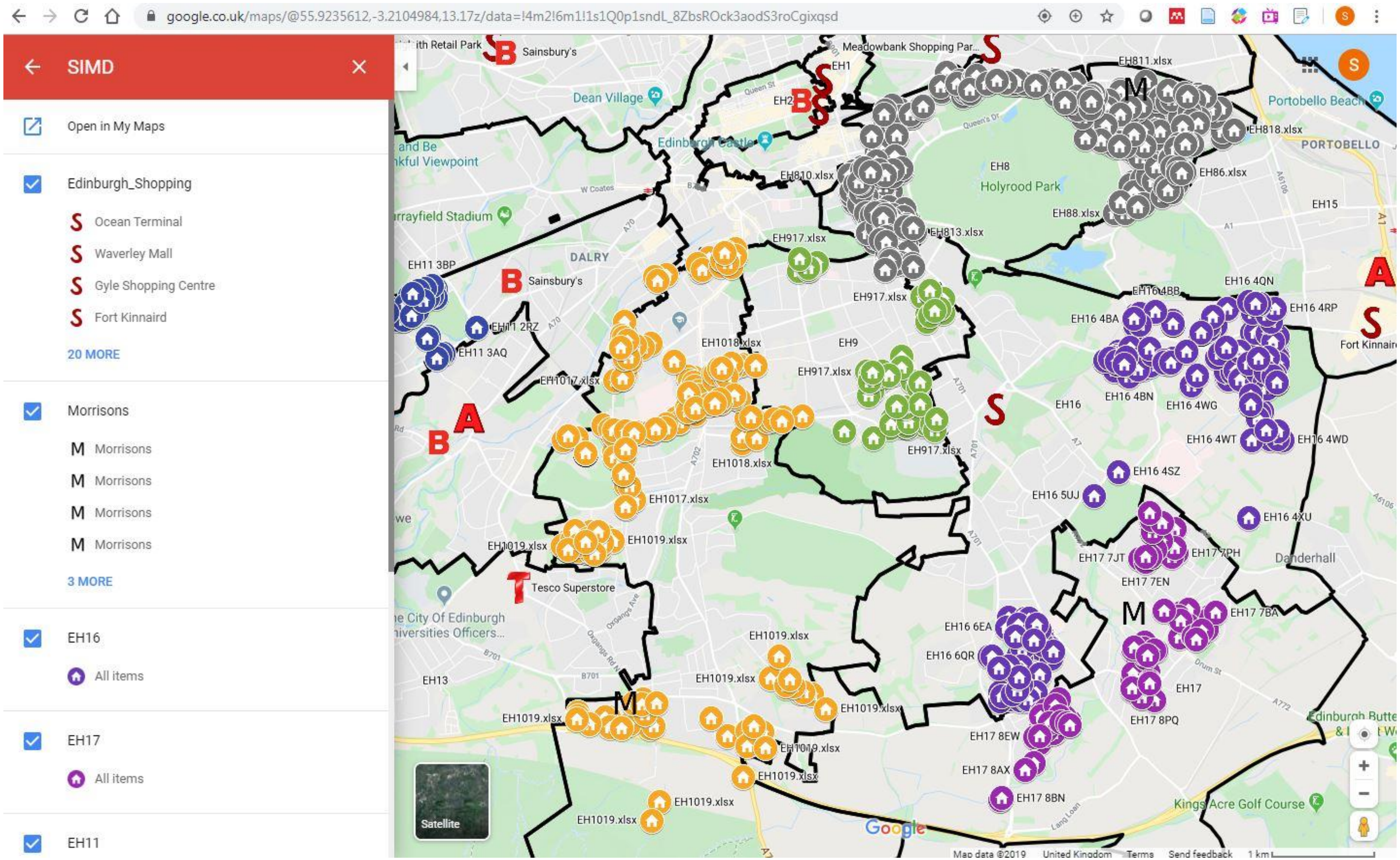


Figure 3.10: Google map screen that used to follow while leaflet distribution (google map)

3.7.7 Challenges and complexities in data collection

While surveying in Edinburgh, the researcher faced some challenges in collecting data, which are reasons for the low number of survey participants and the overall quality of response data. These challenges are listed below:

6. It was observed that responses are lower in highly deprived areas. Even after distributing more leaflets with door-to-door demonstrations, the overall number of responses was lower compared to other areas.
7. People's reluctance to participate in any survey is primarily responsible for the low number of samples, making this effort challenging.
8. It was also observed that some aged people are aware of DC but lack familiarity with DC functions and technology, and this lack of knowledge made them think negatively about DC.
9. While distributing the leaflets, the researcher came across a few other researchers who mentioned that by the time DC came into function, most middle-aged participants might become ageing seniors, making them reluctant to think about DC implementation. This reluctance was the reason for not participating in the survey when the researcher approached several people.

3.7.8 Data Collection Outcome

Five hundred responses were recorded from the main part of the survey. However, not all these responses were of good quality. It was found that there were no 100% incomplete responses. Only 5% of the overall responses are completed partially for at least one questionnaire question. These responses were recorded as missing values and not considered in the model estimation. Out of 7500 distributed leaflets, 500 responses were recorded with a response rate of 7.14%. The survey responses were checked for any errors and misspecifications of the data. No further sanity checks were carried out, considering the missing values will be omitted in the modelling process.

3.8 Data analysis framework

A four-stage modelling procedure was followed to enhance the understanding of various driverless car usage scenarios based on the respondent's present sharing behaviour, personality, social norm behaviour and sociodemographic characteristics. The overall research method for this research is depicted in Figure 3.11. As described in the following sections, several statistical and econometric procedures were followed to capture the influence of multiple determinants that may affect respondents' DC shared ownership and ridership behaviour.

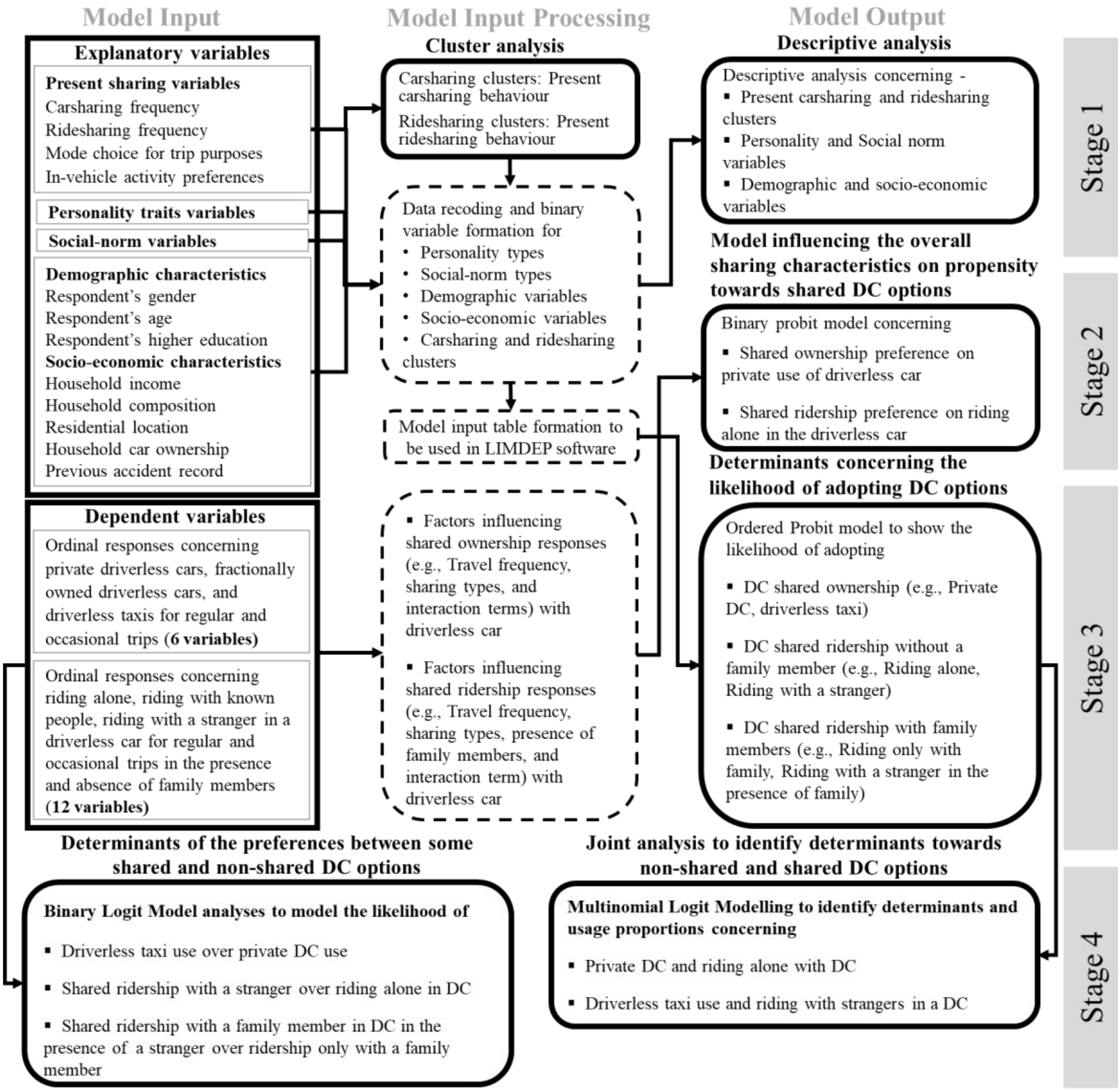


Figure 3.11: Methodology for model development

3.8.1 Stage 1: Descriptive statistics and Cluster analysis

In the first data analysis stage, the descriptive summaries (e.g., mean, median, standard deviation, frequency) dealt with variables used in the model development. This data analysis stage also aimed to produce inferential statistics (e.g., mean, standard deviation) to compare the model variables with the populations and establish links among variables for this survey sample. Chapter 4 describes the survey results, while Chapter 5 describes the cluster analysis, describing carsharing and ridesharing clusters as outcomes. The cross-tabulation method establishes relationships between clusters and socioeconomic variables; these calculations are presented graphically (e.g., bar chart, pie, histogram). The statistical procedures used in the first stage are depicted in Table 3-8. Details of the descriptive statistics are given in Section 4.2, and Cluster analysis descriptions and findings are given in Chapter 5.

Table 3-8: Statistical and analytical procedures followed

Statistical procedures	Purposes	Variables
Descriptive statistics	General data description and variations	All the response variables, including travel behaviour, demographic, socioeconomic, personality and social norms
Cluster analysis	Classify the survey sample based on the frequency and carsharing-ridesharing mode types.	Frequency types, carsharing and ridesharing mode types
Chi-square analysis and cross-tabulation	To perform the cross-classification analysis and to understand the association among variables.	Car ownership, age and income variations, DC preference variations with present carsharing and ridesharing types
t-test	To identify the difference between the survey sample and the population	Generation, income, car ownership, personality, social norms, and travel behaviour

3.8.2 Stage 2: Modelling the influences of sharing characteristics on the overall propensity towards shared DC options.

The second data analysis stage focused on understanding the influences of sharing characteristics. At first, two binary dependent variables were developed:

- JSHOP (Joint SHared Ownership Propensity), which captures the preference for a shared ownership option (shared-owned DC or driverless taxi) over the private ownership of a DC.
- JSHARP (Joint SHAred Ridership Propensity), which captures the preference for sharing a trip on a DC over riding alone.

JSHOP has been explained in terms of trip frequency and shared ownership type, JSHARP in terms of trip frequency, riding sharing types (with a stranger, a known person), and family members' presence (with or without). More details can be found in 6.2.

The binary probit model is used to analyse binary dependent variables (Jin *et al.*, 2006). Binary probit models were developed within the framework of the discrete choice modelling. According to the formulation of the binary probit model, the observed dependent variable Y can take a value equal to 1 if the underlying latent variable Y^* takes on a positive value

(Washington *et al.*, 2011), as shown in the following equation:

$$Y = \begin{cases} 1, \ if \ Y^* > 0 \\ 0, \text{otherwise} \end{cases} \text{.......} (1)$$

where $$Y^* = \boldsymbol{\beta}\mathbf{X}_i + \epsilon_i, \epsilon \sim N(0,1) \text{.......} (2)$$

where Y^* denotes the latent variable corresponding to the observed dependent variable, $\boldsymbol{\beta}$ is a vector of estimable parameters for this latent variable Y^*, $\mathbf{X}_\mathrm{i}$ is the vector of explanatory factors for each observation *i*, and ϵ_i is an error term following a standard normal distribution with zero mean and a variance of one. For this research, binary probit models were developed to identify the factors determining the likelihood of shared DC use (i.e., shared-owned DC, shared ridership of DC), as expressed by the variables JSHOP and JSHARP. By denoting these two outcomes as 0 and 1, the cumulative probability function of occurring 1 from n observations can be written as follows:

$$P_n(1) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(\boldsymbol{\beta}_1\mathbf{X}_{1n} - \boldsymbol{\beta}_0\mathbf{X}_{0n})/\sigma} Exp\left[-\frac{1}{2}w^2\right] dw \text{.......} (3)$$

where σ is the standard deviation used to rescale the normally distributed random variables into the standard normal distribution. By symbolising the cumulative distribution function of the standard normal distribution as $\boldsymbol{\Phi}$(.), the cumulative probability for the Binary Probit model can be written as the following:

$$P_n(1) = \boldsymbol{\Phi}((\boldsymbol{\beta}_1\mathbf{X}_{1n} - \boldsymbol{\beta}_0\mathbf{X}_{0n})/\sigma) \text{.......} (4)$$

The parameter vector β should be estimated using the maximum likelihood methods to fit the Binary Probit model. Without loss of generality, the log-likelihood function can be used in the estimation, as the log transformation does not affect the ordering. For the Binary Probit model, the log-likelihood can be defined as:

$$LL(\boldsymbol{\beta}) = \sum_{n=1}^{N} (\delta_{1n} LN\boldsymbol{\Phi}((\boldsymbol{\beta}_1\mathbf{X}_{1n} - \boldsymbol{\beta}_0\mathbf{X}_{0n})/\sigma) + (1-\delta_{1n})\, LN\boldsymbol{\Phi}((\boldsymbol{\beta}_1\mathbf{X}_{1n} - \boldsymbol{\beta}_0\mathbf{X}_{0n})/\sigma) \text{...} (5)$$

Where N is the total number of observations, δ_{1n} is equal to 1 if the observed discrete outcome for observation *n* is *i*, and 0 otherwise. A chi-square test was conducted through the differences between the final (i.e., with independent variables) and the base (i.e., without any independent variables, but with constant) model Log-likelihood to evaluate the statistical performance of the binary probit model as follows:

$$\textit{Chi-square}\ [\chi^2(df)] = -2[LL(\boldsymbol{\beta}) - LL(\mathbf{c})] \text{.......} (6)$$

Where χ^2 is the chi-square value, and *df* denotes the degrees of freedom equal to the variables' difference between the final and base models; $LL(\boldsymbol{\beta})$ and $LL(\mathbf{c})$ denote log-likelihood values at convergence (i.e., of the final model with all explanatory variables) and at constant (baseline model), respectively. The significance of this chi-square test and of the individual parameters of the explanatory variables in the model are tested through their p-values. Finally, the model's goodness-of-fit was assessed through the McFadden pseudo-R^2, which is defined as:

$$R^2_{McFadden} = 1 - LL(\boldsymbol{\beta}) / LL(\mathbf{c}) \quad \ldots\ldots (7)$$

McFadden Pseudo R^2 can take values from 0 to 1. The closer to 1 is the R^2 value, the better the statistical fit of the model estimation, which means the model can better explain the data variance. As the number of successful explanatory variables grows, the value $LL(\boldsymbol{\beta})$ reduces, making $R^2_{McFadden}$ away from zero but within the $0 < R^2_{McFadden} < 1$ range.

LIMDEP software (Greene, 2016) was used for the binary probit analysis. Statistically significant variable estimations are assumed to vary across the population. The binary-probit analysis resulted in variable coefficients ($\boldsymbol{\beta}$) values without threshold estimates. LIMDEP model estimation results yielded no threshold values since the model estimates only two (e.g., 1, 0) responses.

3.8.3 Stage 3: Modelling determinants concerning the likelihood of adopting DC shared ownership and ridership options by order probit models

The third stage of the analysis framework deals with modelling the ordered propensity to adopt different DC shared ownership and ridership models for regular urban trips. Ordered probit (OP) models are handy tools for treating categorical ordered responses (e.g., Likert scale). The OP model was introduced in 1975 by McKelvey and Zavoina (Mckelvey and Zavoina, 1975).

OP models were primarily used to analyse categorical transport data recorded in ordinal forms. The ordered probit and logit approaches differ in the assumption regarding the distribution of the error terms. A standard normal distribution (Hensher *et al.*, 2008) is typically used for the OP model. Statistically, OP models generate a robust relationship between explanatory and dependent variables. Fewer data required is another reason to prefer the OP model over other model forms.

The objective of the OP analysis is to estimate the propensity of each DC sharing option as a function of several explanatory variables linked with present sharing behaviour, personality, social norm and socioeconomic characteristics. The detailed methodology followed for the OP model is different to the one mentioned in Section 3.8.2.

The outcome through the OP model in this stage is to elicit the significant explanatory variables (e.g., age, income, household composition, residential location) to understand the propensities of shared DC usage. Most of the explanatory variables are expressed in Binary form, and a detailed list of associated explanatory variables is attached in Appendix G.

In the case of the OP model, equation (2) in section 3.8.3 can still be used to specify a latent variable (Y^*), whose value, together with the values of additional parameters μ_j, defines the predicted outcomes according to the following

$$Y = \begin{cases} 1 \text{ if } Y^* \leq \mu_0 \\ \text{j if } \mu_{j-1} < Y^* \leq \mu_j, j > 1 \\ \text{I if } Y^* \geq \mu_{J-1} \end{cases} \quad \text{.......}(8)$$

where, Y^* is a latent variable defining the ordinal ranking of data associated with DC choices, μ_j denote the thresholds of the ordered probit model, which are also estimable parameters, and J, the number of possible outcomes. Assuming the error terms (ϵ_i) in the latent variables normally distributed as in Equation (2), the probability associated with observed outcome Y is calculated as shown in Equation (9) (Washington *et al.*, 2011):

$$\text{Prob}[Y_i = j \mid \mathbf{X}_i] = \boldsymbol{\Phi}(\mu_j - \boldsymbol{\beta}\mathbf{X}_i) - \boldsymbol{\Phi}(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i) \quad \text{......}(9)$$

where Y_i is the observation for respondent *i*, μ_j and μ_{j-1} are threshold values, with *j* denoting the threshold levels, and $\boldsymbol{\Phi}$ is the cumulative normal distribution. These parameters are then used for the Maximum Likelihood Estimation (MLE) process (Greene and Hensher, 2009). The log-likelihood function (by MLE process) can be written as:

$$LL(\boldsymbol{\beta},\mu) = \sum_i \sum_j Y_{ij} \log[\boldsymbol{\Phi}(\mu_j - \boldsymbol{\beta}\mathbf{X}_i) - \boldsymbol{\Phi}(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i)] \quad \text{......}(10)$$

where Y_{ij} is equal to one if the observed value of the dependent variable is *j* for respondent *i*; otherwise, Y_{ij} is zero. The log-likelihood is maximum on the constraint that μ_j = -∞, μ_0 =0 and μ_{j-1}=+∞. After this process, to check the statistical performance, the *Chi-square* estimation and McFadden pseudo-R^2 estimation are done for the OP model, analogously to what is presented in 3.8.2.

LIMDEP software was also applied for OP model estimation, where significant variables are assumed to vary across the population.

3.8.4 Stage 4: Modelling the determinants of non-shared and shared DC options through Logit analysis

The fourth data analysis stage assessed Binary logit and Multinomial logit model formulations with different shared and non-shared DC usage types (propensities) and variations in their determinants.

Determinants of the preferences between some shared and non-shared DC options with Binary Logistic Regression (BLR) Model

In determining the preferences between shared DC (e.g., Driverless taxi, riding with a stranger, ridesharing with a stranger along with a family member) and non-shared DC (e.g., Private DC, riding alone in DC, riding only with a family member in DC), Binary Logistic Regression (BLR) Model was used. In BLR, effort was made to address the weak propensity of DC shared ridership (e.g., Driverless taxi, riding with a stranger, ridesharing with a stranger and a family member) as a binary dependent variable with some explanatory variables in the model (A list of variables are given in Appendix G). The detailed variable formation stage is described in Chapter 6. The functional form of the BLR model with the estimable statistical structure can be the following:

$$F_{in} = \boldsymbol{\beta}_{\mathbf{i}}\mathbf{X}_{\mathbf{in}} + \epsilon_{in} \qquad (11)$$

Where F_{in} is the function that determines the propensity of respondent n choosing response i, $\boldsymbol{\beta}_{\mathbf{i}}$ is the coefficient of estimable explanatory variables corresponding to discrete response i, $\mathbf{X}_{\mathbf{in}}$ is the vector of explanatory variables that affect the probability of discrete response i for respondent n, ϵ_{in} is the disturbance (error) term. If the disturbance terms are assumed to be generalised extreme-valued distributed, the probability of choosing regular use driverless taxi to private DC can be expressed with a standard binary-logit (McFadden and Train, 2000) form as the following:

$$P_n\,(i) = \frac{Exp\,(\boldsymbol{\beta}_{\mathbf{i}}\mathbf{X}_{\mathbf{in}})}{\sum_{i=0}^{n} Exp\,(\boldsymbol{\beta}_{\mathbf{I}}\mathbf{X}_{\mathbf{In}})} \qquad (12)$$

Here $P_n\,(i)$ is the probability of respondent n giving response i, and n is the number of responses corresponding to relevant explanatory variables in the model formation. The probability in this equation (12) refers to driverless taxi use rather than private DC, ridesharing with a stranger to riding alone in DC, and DC shared ridership with a family member and a stranger than DC shared ridership only with a family member. BLR models are assessed in SPSS software with sequential steps.

Joint analysis to identify determinants towards non-shared and shared DC options through the use of the Multinomial Logit Model

A comparative assessment between non-shared and shared DC use was summarized with such model development. Privately-owned DC (Ow_Pr_Re) and riding alone in a household DC (Ri_ReNF_A) can be identified as non-shared DC, while Driverless taxi use and ridesharing with a stranger in DC are termed as shared DC use. To attain the best model fitness through the multinomial logit model, these models' explanatory variables (determinants) are checked through several iterative model estimation processes.

Due to the discrete nature and variations in the outcome variables, standard multinomial logit (MNL) models (with separate utility functions for each DC usage type) were estimated to identify the variations in individual preferences associated with each DC usage type. Consistent with the random utility maximization approach, the multinomial logit model is applied here with explanatory factors such as sharing behaviour, personality, social norm, and sociodemographic characteristics. Four utility functions were used aligned with four DC usage types considering non-shared and shared variations. Therefore, each survey response should be repeated four times, resulting in 2000 observations from 500 responses. By applying the empirical framework discussed earlier (Train, 2009; McFadden and Train, 2000), the functional form of the utility for each DC usage type can be the following:

$U_{in} = \mathbf{\beta_i X_{in}} + \epsilon_{in} \ \forall N$ ……………………………………………………………………………………………………(13)

Where U_{in} is the utility function that helps determine that respondent *n* choosing response *i* from a number of respondents *N*; $\mathbf{X_{in}}$ is the vector of observed explanatory variables that affect the probability of discrete response *i* for respondent *n*; $\mathbf{\beta_i}$ is the vector for corresponding coefficients for explanatory variables for respondent *i*, ϵ_{in} is the random component to capture all the unobserved attributes concerning the response *i* in the case of respondent *n*. Therefore, to satisfy, respondent *n* chooses a mode usage type *i* over *j*, U_{in} *should be greater than* U_{ij}. Considering four DC types, the utility functions can be written in equation (13) with four values of $\mathbf{X_{in}}$.

The vector of explanatory variables ($\mathbf{X_{in}}$) in equation (13) should consist of variables concerning DC usage types relating to respondents. DC usage types (alternatives) may vary for respondents. It's a norm that $\mathbf{\beta_i}$ contains a vector of alternative specific constants (ASCs) that are obvious for alternatives but were not used in the model formation (analogues to a constant in a simple regression model). Therefore, the explanatory variables concerning a particular respondent *i* are identical for four DC usage types (indicated by equation (13), where $\mathbf{X}_i$ is identical across four DC usages). However, since respondents are not similar, variable values relating to respondents are different. Therefore, the variables' coefficient values and directions will likely be heterogeneous among DC usage types. These variations can also indicate the interaction among a few explanatory variables in the utility functions, which needs further inquiry.

For this model, explanatory variables are described in Appendix G. These variables are assumed to vary with DC usage types, which is essential for decision-making. Some of these socioeconomic variables are similar to contemporary DC models (Saeed *et al.*, 2020; Haboucha, Ishaq and Shiftan, 2017; Jiang *et al.*, 2019; Wadud and Chintakayala, 2021) assessed by multinomial logit models. In these models, the reference case is where $\mathrm{Z_{mi}} = 0\ and\ \mathrm{Y_{mi}}$ = 0, indicating no preference for either non-shared (e.g., private DC or riding alone in DC) or shared (driverless taxi use or riding with a stranger in DC) DC options.

If the random components (ϵ_{in}) are assumed to be independently, identically distributed extreme values of type I, the probability of choices for respondent *n* among a set of respondents *N* can be expressed with a standard multinomial-logit form. This distribution is also called Gumble and type I extreme value. With a set of explanatory variable values of $\mathbf{X}_i$, the conditional probability a respondent *n* choosing a DC usage type *i* can be expressed by the standard logit method:

$$P_{in}\,(\beta_i) = \frac{e^{(\boldsymbol{\beta}_\mathbf{i}\mathbf{X}_\mathbf{in})}}{\sum_n^N e^{(\boldsymbol{\beta}_\mathbf{i}\mathbf{X}_\mathbf{iN})}} \text{...} (14)$$

Here $P_n\,(i)$ is the probability of respondent *n* choosing usage type *i*, out of *j* set of usage types concerning DC (e.g., 0 to 3 in this case), among N respondents. Typically, among respondents $\boldsymbol{\beta}_\mathbf{i}\ is\ the\ same\ (\boldsymbol{\beta}_\mathbf{i} = \boldsymbol{\beta})$, with differences in values for alternatives. But, for the models described here, observed variations used among respondents ($\boldsymbol{\beta}_\mathbf{i} \neq \boldsymbol{\beta}$), repeated for DC usage types (alternatives), which is the opposite of what is typically used for the multinomial logit model estimation. Assuming each decision maker's choice is independent of that of other decision-makers, the probability of choosing an alternative for respondent n from a sample of N respondents can be calculated as shown by the equation (15) in line with Train (2009):

$$L(\boldsymbol{\beta}) = \prod_{n=1}^{N} \prod_i (P_{in})^{y_{in}} \text{...} (15)$$

Here, **β** is the vector of estimable parameters relating to explanatory variables in the model.

Where y_{in} = 1 if the respondent n, chooses *i* and y_{in} = 0 for all other non-chosen alternatives. The log-likelihood function is then expressed as:

$LL(\boldsymbol{\beta}) = \sum_{n=1}^{N} \sum_{i}^{I} Y_{in} ln\ P_{in}$ ....(16)

Where the **β** denotes the estimator that maximizes this function. After this estimation, a chi-square test of the differences between the final (i.e., with explanatory variables) and the base (i.e., without any explanatory variables, but with constant) model was conducted to evaluate the statistical performance of the multinomial logit models by applying equation (17):

Chi-square $[\chi^2(df)] = -2[LL(\boldsymbol{\beta}) - LL(\mathbf{c})]$ ....(17)

χ^2 is the chi-square value, and *df* denotes the degrees of freedom equal to the difference in the number of explanatory variables between the final and the base model; **β** and **c** denote the coefficient of explanatory variables and constant, respectively. The significance of this chi-square test and individual parameters (explanatory variables) in the parameter vector can be tested by a ρ-value between 0 and 1. Finally, the model's goodness-of-fit was assessed through the ρ^2 (Ben-Akiva and Lerman, 2010), which is defined as:

$\rho^2 = 1 - LL(\boldsymbol{\beta}) / LL(\mathbf{c})$ .... (18)

ρ^2 can take values from 0 to 1. The closer to 1 is the ρ^2 value, the better the statistical fit of the model estimation, which means the model can better explain the data variance. As the number of successful explanatory variables grows, the value $LL(\boldsymbol{\beta})$ reduces, taking ρ^2 away from zero (0) within the range of $0 < \rho^2 < 1$. Adjusted ρ^2 can be evaluated using the following formula:

$\rho^2_{adj} = 1 - (LL(\boldsymbol{\beta}) - K)/LL(\mathbf{c})$ ....(19)

Here, *K* is the number of explanatory variables used in the final model estimation, $LL(\boldsymbol{\beta})$ denotes the log-likelihood for the model with explanatory variables, and $LL(\mathbf{c})$ is the log-likelihood with constant. Coefficient values concerning variable Z_{mi}, Y_{mi} , and their t-statistics are stated in Table 6-18 and Table 6-19 of Chapter 6.

3.9 Survey data transformation and coding guidance

The questionnaire concerning shared DC ownership and readership is grouped into the following subsections:

- Question 1 – 4: Current behaviour of carsharing and ridesharing
- Question 5 – 8: Factors concerning present carsharing and ridesharing
- Question 9 – 14: Choice concerning DC shared ownership and ridership

- Question 15: Personality traits
- Question 16: Social norms
- Questions 17 – 24: Demographic and socioeconomic variables
- Questions 25 – 26: Postcode and email address of the respondent

A complete list of variables and their coding guidance are attached in Appendix G. For ease of understanding and to build models, age and car ownership variables entries were transformed and recoded into categorical variables with names, as stated in Table 4-1. Each categorical variable was converted to binary form (where '1' indicated the variable itself and '0' otherwise) to identify its significance and represent its non-linearity concerning the factors it belongs. As indicated in Table 4-1, the following transformations were applied to the initial variables:

- The 'age' of the respondent was transformed into five binary variables representing particular generations and presented in Table 4.1 of Chapter 4
- The number of cars the respondent's household owned was transformed into four car-ownership variables.
- Merging the 'primary' and 'secondary' level education to a single variable defining below bachelor's level education
- In the case of annual household income, responses for 'prefer not to say' were assigned as missing, and they were analyzed as missing values.
- The cluster analysis process was performed based on the responses to questions No.1 and No.2, and generated variables representing current carsharing and ridesharing behaviour are presented in Chapter 5.
- Responses concerning personality statements were transformed into five binary variables representing the five traits' openness', 'conscientiousness', 'extraversion', 'agreeableness', and 'neuroticism'.
- The positive responses (i.e., 'very likely', 'likely', 'neutral') about injunctive social norm statements are converted to variables defined as 'social expectation for preserving the environment, 'social expectation for a better quality of life, and 'social expectation for sharing resources'.
- In-vehicle activities are transformed into binary variables to include them in the regression analysis. In this transformation process, only the positive responses (i.e., likely, very likely) are considered to assess the probability of an in-vehicle activity happen

3.10 Chapter Conclusion

This Chapter presents the methodology for data collection and analysis adopted to answer the research questions for this study. An online questionnaire was hosted to collect data concerning respondents' present travel-sharing behaviour, personality and social norm behaviour, and sociodemographic status. Besides, respondents are asked to rate the likelihood of adopting different forms of shared usage in 6 scenarios for shared ownership and 12 for shared ridership. A total of 500 responses were collected. At the end of this Chapter, detailed methodologies for binary probit, ordered probit, binary logit and multinomial logit model development are described to analyse the abovementioned data. The subsequent chapters elaborate on model findings and discuss their policy implications.

4. Chapter 4: Survey Results

4.1 Introduction

This Chapter presents the outcome of Edinburgh's online data collection effort from August 2019 to December 2019. The data collection techniques and analysis methods were described in Chapter 3, while this Chapter outlines the descriptive analysis of the online survey data. This Chapter investigates the extent of respondents' present ridesharing and carsharing behaviour, factors affecting this behaviour, their socioeconomic, personality and social norm status and their future propensities for DC shared ownership and ridership options. This Chapter starts with a descriptive analysis of the demography and socioeconomic segmentation of the sample. After this, a comparative analysis of the sample with greater Edinburgh and Scottish populations was performed. A descriptive analysis was performed to represent the present sharing behaviour and the reasons for choosing and not choosing carsharing and ridesharing at the next step. Results about personality and social norms are described at the subsequent stages, followed by analysing future propensities concerning DC shared ownership and ridership options. From this dataset described here, cluster analysis and inferential statistics are presented in Chapter 5.

4.2 Demographics and socioeconomic structure of the sample

Descriptive statistical procedures were applied to understand the demographic and socioeconomic distribution of survey responses. From the online survey, 95% of the 500 respondents completed all the questions. Due to the very nature of the DC system and considering the urban people are aware of DC through media, the online survey was controlled within the Edinburgh postcode districts EH1 – EH17 defining urban areas. Following this, leaflet invitations were distributed according to the SMID data zones in Edinburgh (Shaw *et al.*, 2017). Among those who responded, 96% are from Edinburgh, and the rest, 4%, are outside EH1 – EH17 postcode districts. Therefore, the sample represented the urban population predominantly. Table 4-1 depicts information for the sample distribution resulting from the online survey.

Table 4-1: Sample distribution concerning the online survey conducted in Edinburgh from August 2019 to December 2019

Demographic variables	Variable levels	Valid Percentages	Variable codes
What is your Gender?	Male	67.00%	[Gdm =1]
	Female	33.00%	[Gdfm =2]

What is your age? (Age data was converted to Generation types.)	Centennials (the respondents born between 1996 – 2015)	6.60%	[Gen = 0]
	Millennials (the respondents born between 1977 – 1995)	29.20%	[Gen = 1]
	Generation X (the respondent born between 1965 and 1976)	22.10%	[Gen = 2]
	Baby Boomers (the respondents born between 1946 - 1964)	36.50%	[Gen = 3]
	Traditionalists (the respondent was born in or before 1945)	5.50%	[Gen = 4]
What is your highest educational qualification?	Primary & Secondary	21.30%	[He=0]
	Bachelor	32.90%	[He=1]
	Masters or higher	45.80%	[He=2]
What is your annual average household income?	Less than £20,000	11.8%	[Hi=1]
	£20,000 to £30,000	18.7%	[Hi=2]
	£30,000 to £50,000	26.1%	[Hi=3]
	£50,000 to £70,000	17.9%	[Hi=4]
	Over £70,000	25.5%	[Hi=5]
Please indicate your household composition.	Living alone	13.40%	[Hc=0]
	Household with no children	41.80%	[Hc=1]
	Household with children	37.00%	[Hc=2]
	Other arrangements	7.80%	[Hc=3]
How many cars do you have in your household? (This variable was converted to car-ownership types)	No car	18.40%	[Cown = 0]
	One car	50.20%	[Cown = 1]
	Two cars	26.20%	[Cown = 2]
	Three or more cars	5.20%	[Cown = 3]
Which of the following best describes the type of your residential location?	City centre	33.80%	[Rl=0]
	Inner suburb	44.30%	[Rl=1]
	Outer suburb	20.60%	[Rl=2]
	Rural	1.30%	[Rl=3]

The findings from the descriptive analysis shown in Table 4-1 showed the sample variations in age, Gender, education level, income level, household composition, car ownership levels and household location types. This process helped code these socioeconomic segments into binary forms, as used for the econometric analysis described in Chapter 6. Percentages for all these segments are calculated based on valid responses (e.g., without the missing values).

This survey data elicited that 67% of the respondents are male, while 33% are female. The age data was converted into generation categories following the types the Centre for Generational Kinetics described based on the respondents' birth year (CGK, 2021). Descriptive analysis proved that millennials (i.e., age range 25 – 43 years) are roughly one-third (29.20%) of the respondents, while 36.50% are baby boomers (i.e., age range 56 – 74 years). Traditionalists (i.e., the age range of more than 75 years) are 5.5% of the respondents. Centennials (i.e., age range less than 22 years) and Generation Xs (i.e., 44 – 55 years) are 6.6% and 22.10%, respectively.

Education-wise, 45.80% of the respondents are postgraduate degree holders, while 32.90% are bachelor's degree holders. So, the data reflected that most respondents (78.70%) are higher educated, with 21.30% being primary and secondary educated.

From Table 4-1, it can be revealed that 26.1% of the respondents belonged to households with an annual income between £30k to £50k, 17.9% of the respondents earned in the range of £50k to £70k, and 35.5% of the respondents' hold annual income of more than £70k. These results revealed that 30.5% of the respondents belong to households with lower income levels (i.e., less than £30k).

Regarding household composition, this survey results reflect that 41.80% of the respondents belonged to households with no children, while 37.0% had no children. Except for these, 13.4% of these respondents live alone.

The majority (51.1%) of the respondents belonged to households with at least one car, 26.20% with two cars, and 5.20% with three or more cars, respectively. Car ownership data revealed that 18.40% of the respondents had no access to cars.

Regarding household composition, this survey results reflect that 41.80% of the respondents belonged to households with no children, while 37.0% had no children. Except for these, 13.4% of these respondents live alone.

4.3 Sample representativeness

Ideally, the sample should represent the population proportionately to various population segments such as Gender, age, household composition, car-ownership status, etc. The online survey yielded biased estimates when the survey is not disseminated through proper advertisements within all the population segments of the study area in question. Earlier studies on DC reflected that online surveys attracted more responses than pen-and-paper surveys, which reflects that participation is proportional to internet usage for online surveys (Shaheen *et al.*, 2016; Nordhoff et al., 2019). The survey result resonates with the empirical findings that showed females are less inclined and young people are more inclined to DC use (Rice and Winter, 2019; Li *et al.*, 2022). Considering demographic factors are typically more important than psychological factors in any society (Tang *et al.*, 2023), people who are psychologically tech-savvy and aware of recent technological developments are most likely inclined to respond to online surveys concerning DC use. The outcome of these phenomena can produce a skewed population representation if not appropriately controlled. Therefore, checking the sample skewness against the population statistics is essential before going to the core part of the data analysis. The online survey results were compared with the population of Edinburgh (National Record of Scotland, 2022) statistics to establish the representativeness of the survey sample. The data analysis to investigate survey representativeness includes all the responses, including those containing at least one missing value in any field.

Gender

Figure 4.1 shows that the survey sample belongs to 67% male respondents' data, which is higher than the male population percentage for Edinburgh and the Scottish population, as reflected in 2019 statistics (National Record of Scotland, 2022). This result reflects the higher internet usage behaviour within the male population in the UK and the subsequent higher concern for DC use (Internet users, 2019).

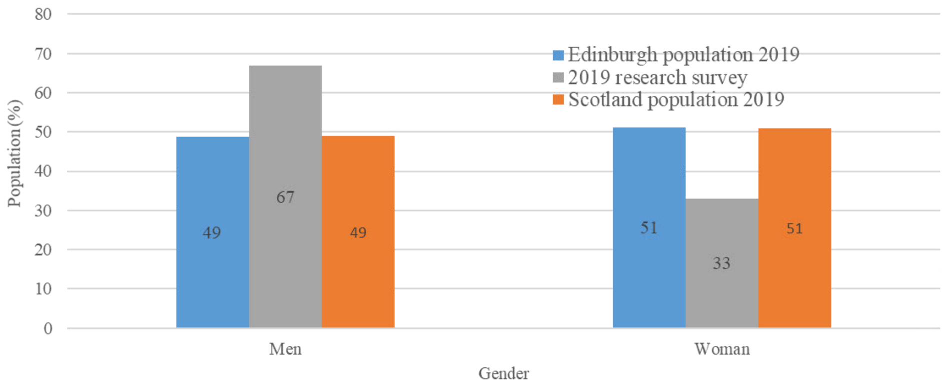


Figure 4.1: Representativeness of the 2019 online survey data by Gender

Age

In terms of age, the participation of 16 – 24 years is relatively lower (7%) than the population percentages of the same age group in Edinburgh (12%) and Scotland (11%) (Figure 4.2). This discrepancy is linked to the fact that collected responses were only from respondents over 18 years old, which made the percentage different from those calculated considering all age groups. The percentage of respondents (31%) in the online survey for the 25 – 44 years age group is almost proportionate to the Edinburgh population (34%). However, the Scottish population percentage for the same age group is almost proportionate (26%). A relatively higher proportion (39%) of people within the age range of 45 – 64 years participated in the survey compared to the Edinburgh (23%) and Scottish (28%) population proportion of the same age group. A similar participation trend was observed for the age range of 65 -74 years. In addition, the 74-year-old participants are fewer (6%) in number, which reflected that older people are less frequent internet users and less aware of DC technology. The majority of survey participants (70%) are within the age range of 16 - 64 years, which is almost proportionate to Edinburgh (77%) and Scotland (64%) populations in the same age range.

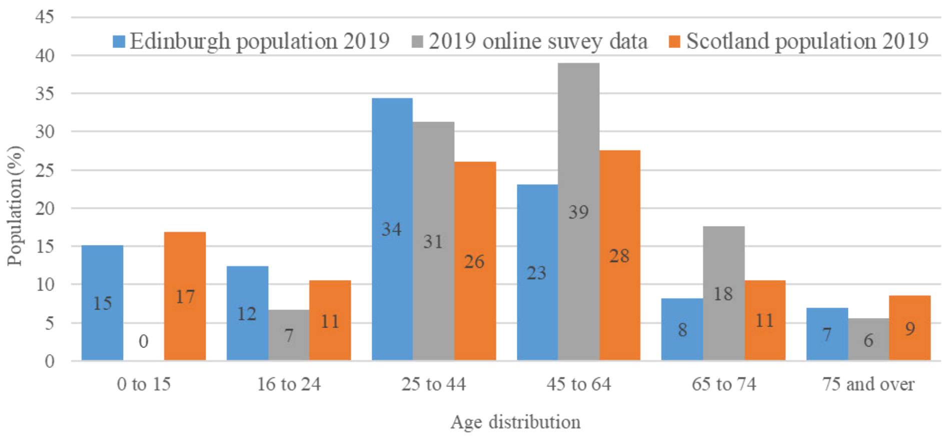


Figure 4.2: Representativeness of the 2019 online survey data 2019 by Age categories

Household composition

Figure 4.3 compares participant ratios among the household types within the 2019 research survey, 2019 Edinburgh (City of Edinburgh Council, 2018) and 2019 Scottish population (National Record of Scotland, 2022). Compared to 2019, Edinburgh and Scottish population proportions of 'live alone, fewer people (13%) of the same household type responded to the 2019 research survey. The proportion of respondents (42%) from households with no children is similar to Edinburgh and Scottish populations. On the contrary, the 2019 research survey showed more participation from households with at least one child than in Edinburgh and Scotland.

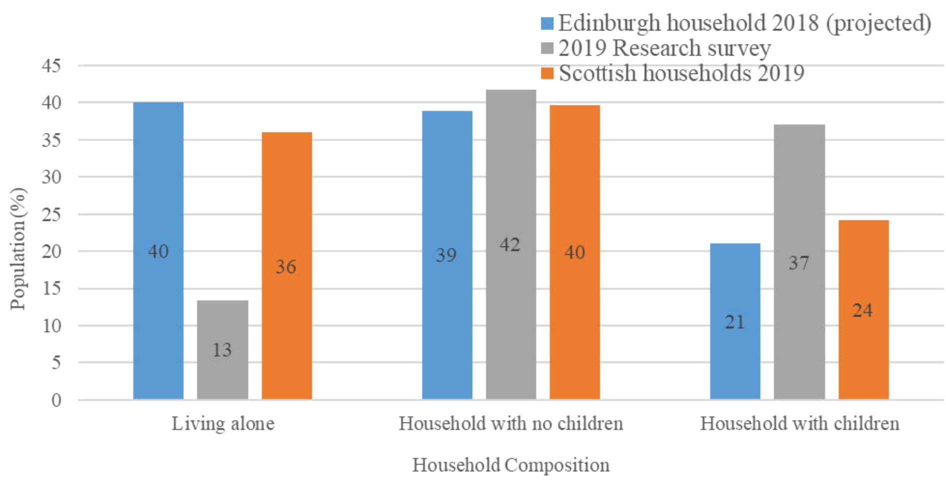


Figure 4.3: Representativeness of the online survey data 2019 by types of household composition

Present car-ownership

As shown in Figure 4.4, the proportions of respondents from various car-owning groups are compared with the 2018 proportions of Edinburgh car-ownership types (City of Edinburgh Council, 2018). 2019 survey participants with no cars are fewer (18%) than the population proportion (28%) of the same type. 50% of the 2019 survey participants are one-car owners, which is higher than the population proportion of the same car ownership group. The proportion of participants with two cars (26%) is close enough to its population proportion, as shown in the Scottish Transport Statistics 2018. The proportion of 2019 research survey participants with three car owners is similar to the 2018 population proportion.

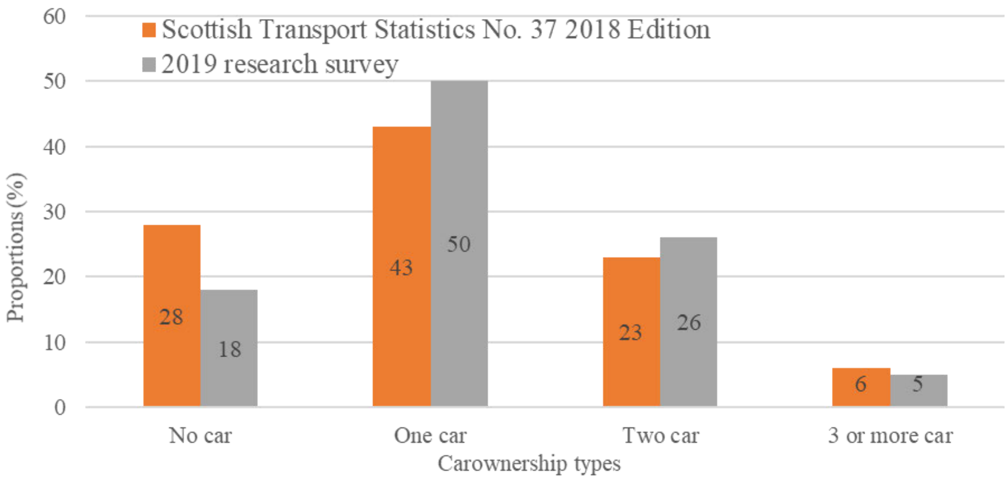


Figure 4.4: Representativeness of the 2019 online survey data by types of car ownership

Commuting mode preferences

Lastly, the Scottish Household Survey (2019) findings are compared to the commuting mode type proportions in the 2019 online survey, as shown in Figure 4.5. The percentage of respondents choosing walking and cycling from the 2019 online survey (34%) is almost double the same as the Scotland household survey in 2019 (14.7%). Regarding car commuting, the percentage of travellers (68%) is double for the Scottish Household Survey (2019) compared to the 2019 online survey results (31%). So, compared to Scotland's population, this survey sample underrepresented the number of car users and their opinions about DC use. Besides, in the 2019 online survey, fewer people responded as public transport users in Scotland (15.4%) compared to 2019 survey findings (23%).

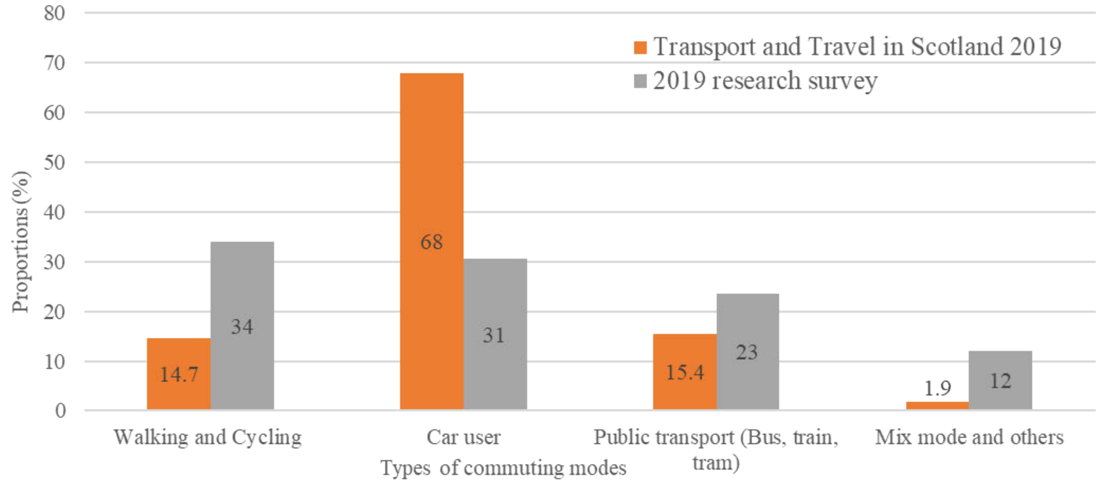


Figure 4.5: Representativeness of the online survey data 2019 by types of commuting modes

4.4 Current travel behaviour

4.4.1 Present ridesharing frequency

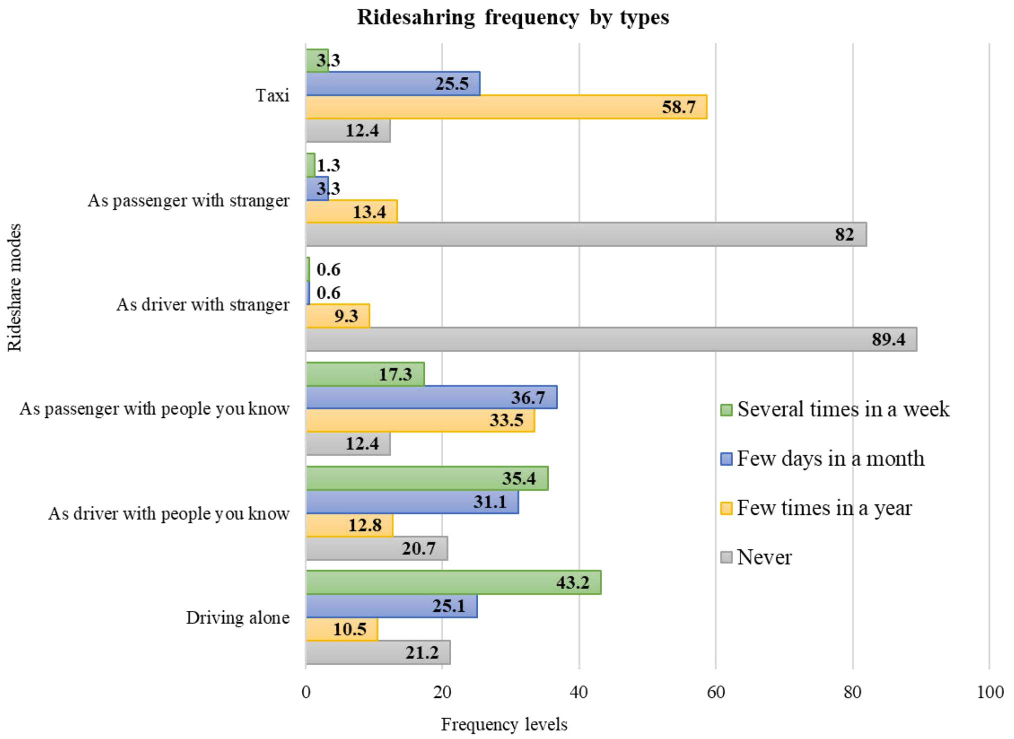


Figure 4.6: Ridesharing frequencies by ridesharing types

Figure 4.6 depicts the information related to respondents' ridesharing frequency by type. In the case of the usage frequency of 'several times in a week', the majority (43.2%) of the respondents preferred to ride alone, even though a substantial amount (35.4%) liked to drive with known people. A few respondents (17.2%) like to share their rides as passengers with known people at the same frequency level. Very few riders liked sharing their ride with strangers as drivers or passengers for their weekly travel needs. Only 3.3% of the respondents preferred to ride in a taxi several times a week.

For the usage category of 'few days in a month, ' respondents showed a higher propensity to ride with their close contacts (36.2%) than driving with known people (31.1%) and riding alone (25.1%). Despite very few people (25.5%) riding in a taxi for their monthly travel needs, ridesharing propensity as drivers or passengers with strangers was considerably lower than other sharing options. Regarding yearly travel, 33.5% of the respondents like to share their ride as a passenger with close contacts. Besides, 12.8% of respondents ride as drivers, and 10.5% drive alone in this frequency category. Of respondents for whom travel demand is yearly, 9.3% are interested in travelling with strangers when they share their rides as drivers. (13.4%). Respondents show higher interest (58.7%) in sharing their rides with a taxi when their yearly travel pattern is limited to a few times a year.

Compared to the travel frequency categories mentioned above, the number of respondents who never travel through ridesharing services is also very high. For instance, 89.4% and 82% of respondents said they never shared their ride with a stranger as a driver and passenger. Rideshare tendency with the taxi was also very low (12.4%) compared to travel with a stranger. Respondents from 'never' frequency were also very low in case they 'drive alone' (21.2%), drive with known people (20.7%) and ride as a passenger with a known driver (12.4%).

Overall, respondents were inclined primarily to drive alone when their travel demand was weekly. For those respondents for whom travel is a monthly occurrence, a higher percentage of respondents were inclined to share their rides with known people, either as drivers or passengers. Similar types of tendencies were observed in the case of travel demand yearly. But in the case of weekly travel demand, fewer respondents are attached to sharing the ride with known people. Frequent taxi-sharing tendencies were observed when respondents' travel demand was yearly. Generally, respondents were reluctant to share their ride with a stranger within all the frequency types.

4.4.2 Present carsharing frequencies

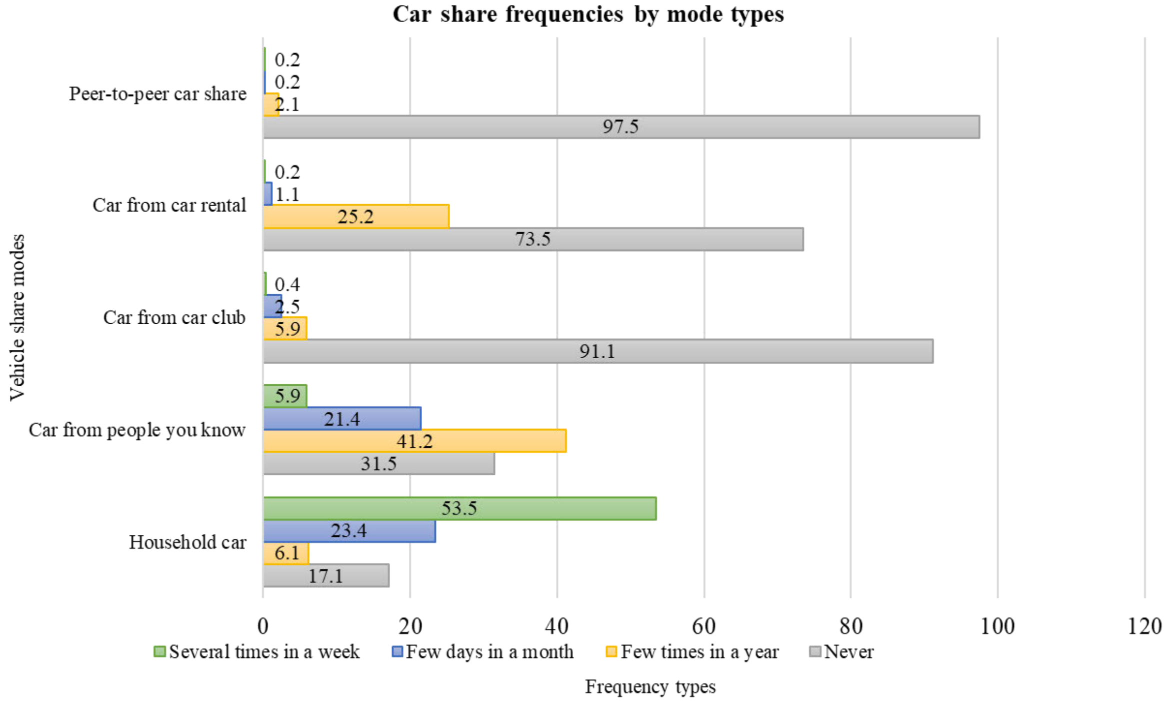


Figure 4.7: Carsharing frequencies by carsharing types

As observed from Figure 4.7, household car usage was the preferred option (53.5%) for those respondents who travel several times a week. On the contrary, a few respondents (5.9%) were inclined to share the car with their close contacts for the same usage frequency. Respondents were not unwilling to share cars from a car club, car rents and peer-to-peer services to meet their travel needs several times a week. If the travel demand is several times a month, respondents preferred 'household car' (23.4%) over 'car from their close contacts' (21.4%). Aside from this, cars from car clubs (2.5%) and car rentals (1.1%) are the least important when respondents' shared ownership patterns were limited to a few times a month. When respondents' travel demand is limited to a few times within a year, they were more willing to share a car than close contacts (41.2%). Besides this behaviour, people preferred to share cars (25.2%) from car rentals rather than to use their household cars (6.1%) and hire cars from car clubs (5.9%).

Survey findings suggested that respondents who never travel (or don't travel as such) were very interested in using peer-to-peer (97.5%), car rental (73.5%) and car club (91.1%) services. Besides, a few respondents in this usage category were inclined to use their household car (17.1%) and car from their close contacts (31.5%). Overall findings suggested that respondents were inclined to use their household car over all other forms of car sharing in case of travel several times a week. When the travel occurs a few times a month, respondents are most willing to share a car with close contacts, let alone use their household cars. Besides the weekly or monthly travel pattern, respondents were highly likely to share a car with close contacts and car rentals when the travel occurs yearly. For those respondents who never travel, peer-to-peer sharing is a popular option, along with car rental and cars from car clubs.

4.4.3 Present in-vehicle activity preferences

In addition to frequency, current in-vehicle time usage preferences were elicited by Question 4, as depicted in Figure 4.8. Respondents were asked for their preferences for in-vehicle activities with a five-point Likert scale ranging from not at all important to extremely important. By unwrapping these preferences, the potential of in-vehicle activities in DC travel was understood clearly.

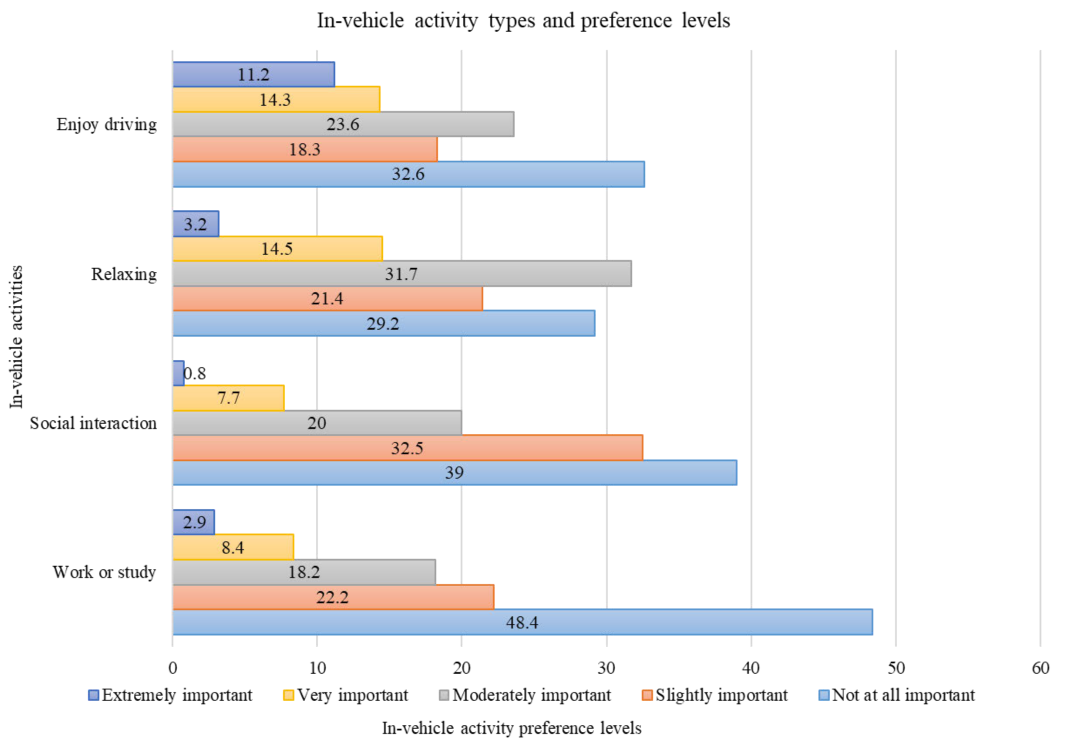


Figure 4.8: In-vehicle activity types and their preference levels

Utility related to in-vehicle activity preferences might be important in selecting DC modes because drivers will be freed from the driving activity, which will allow them to do other activities. Therefore, the importance of socialisation may affect the intention to use DC. In this case, DC will benefit those who travel more. The demand for this extra time will be revealed when the activity choices are compared to those who spend less time on travel (Das *et al.*, 2017).

Among the importance levels of in-vehicle activities selected for this research, the enjoyment of driving was extremely important among 11.2% of the respondents. Apart from this, relaxing, social interaction and work or study-related activities were considered extremely important for 3.2%, 0.8% and 2.9% of the respondents. The importance level of enjoying driving and the relaxing category were appreciated by 14.3% and 14.5% of the respondents. Social interaction and work-study-related activities seemed to be very important for 7.7% and 8.4% of the respondents. Relaxing was attained as moderately crucial for 31.7% of the respondents. Work or study-related activities are measured with a top score (48.4%) in 'not at all important implies that this is the least preferred activity while sharing the travel. The second least preferred (39%) activity is 'social interaction'. Besides, 29.2% of respondents selected 'relaxing', and 32.6% selected 'enjoy driving' as not at all important. Driving enjoyment being the most (25.5%) preferred activity to some respondents means there are fewer chances of other activities preference, or these respondents are inclined to share the ride with someone else's car rather than to drive themselves.

Considering the higher level of importance, enjoying driving was the preferred (26%) in-vehicle activity over work-study-related activities (11%). Besides, relaxing was preferred by a significant proportion (17.7%) of respondents as an in-vehicle activity. A correlation between a respondent's higher importance of in-vehicle activities and their positive DC acceptance (e.g., likely, very likely) could indicate how the DC adoption might influence in-vehicle time use when DC will be fully functional. The complex interactions of in-vehicle time and shared travel behaviour with DC are crucial to forecasting the travel demand with DC intervention. Present in-vehicle activity preferences should be judged jointly with shared ownership and ridership models to test the effects of model parameters over activity use patterns (Das *et al.*, 2017).

4.5 Reasons for sharing

4.5.1 Reasons for choosing carsharing

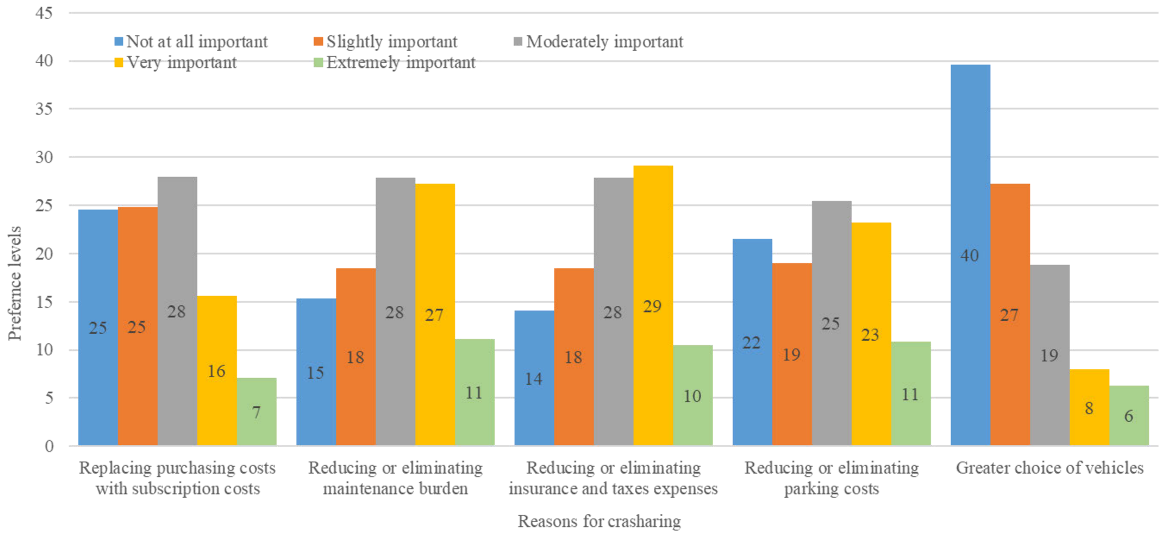


Figure 4.9: Reasons for choosing carsharing and their acceptance levels

This research collected data on carsharing reasons with predefined reason statements using a five-point Likert scale (e.g., not at all important - extremely important). As presented in Figure 4.9, among these reasons, reducing or eliminating insurance and tax expenses are highly important (39%) reasons, while the 'greater choice of cars is the least important (14%) reason for carsharing. Among 38% of the respondents, reducing or eliminating the maintenance burden is an important reason for choosing carsharing, while 34% highlighted reducing or eliminating parking costs as the most important reason for choosing carsharing. Only 23% of the respondents believe they prefer carsharing to replace the purchase costs with subscription costs. Greater choice of cars is the important reason to choose carsharing among only 14% of the respondents.

4.5.2 Reasons for not choosing carsharing

This research identified five reasons that may influence people not to choose carsharing, as mentioned in Figure 4.10. Among these reasons, the availability of carsharing services is the most important (68%), while the lack of familiarity with the shared car is the least (18%) important. Besides, limited convenience (e.g., car condition, luggage space) and the cost of using carsharing constitute the reasons for not giving importance to carsharing for 43% and 33% of the respondents. Due to limited comfort, 28% of the respondents give less importance to car sharing than private cars.

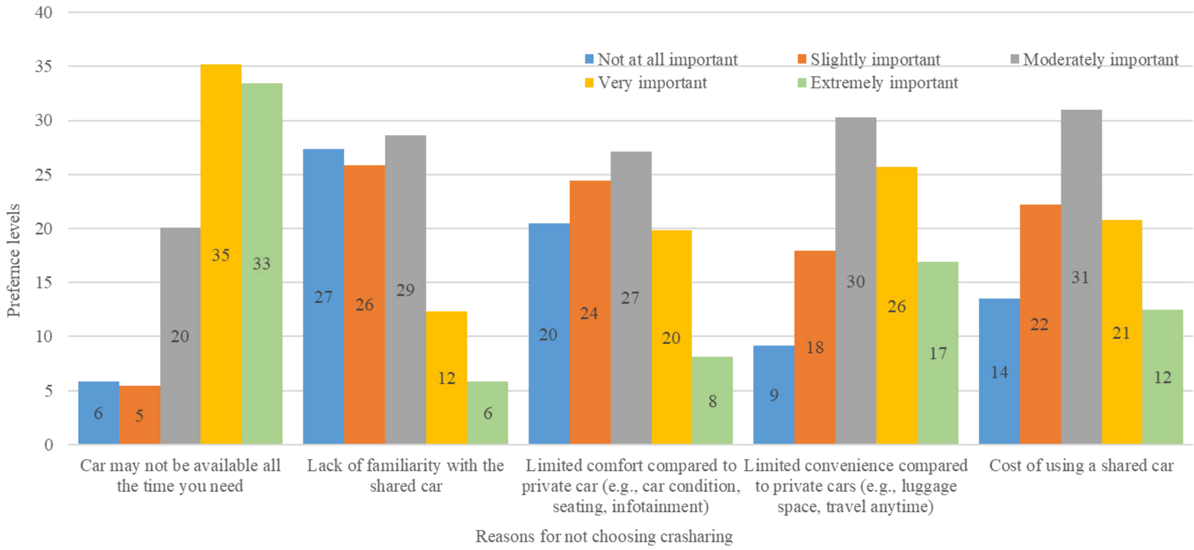


Figure 4.10: Reasons for not choosing carsharing and their acceptance levels

4.5.3 Reasons for choosing ridesharing

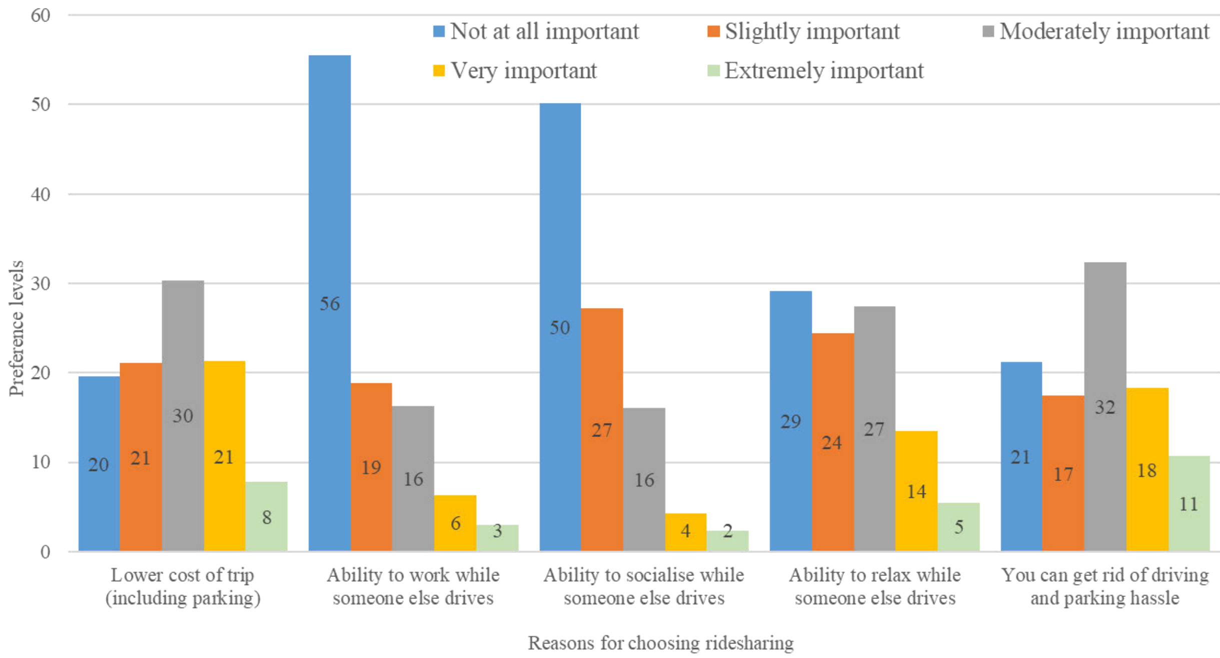


Figure 4.11: Reasons for choosing ridesharing and their acceptance levels

The reasons for choosing ridesharing were assessed through five reason statements measured on a five-point Likert scale (e.g., not at all important - extremely important). As mentioned in Figure 4.11, the two most important reasons for choosing ridesharing are the lower cost of the trip and getting rid of driving and parking hassles (29% of the respondents refer to these two reasons). The ability to work (9%), socialise (6%) and stay relaxed (5%) are the three least important reasons for preferring ridesharing.

4.5.4 Reasons for not choosing ridesharing

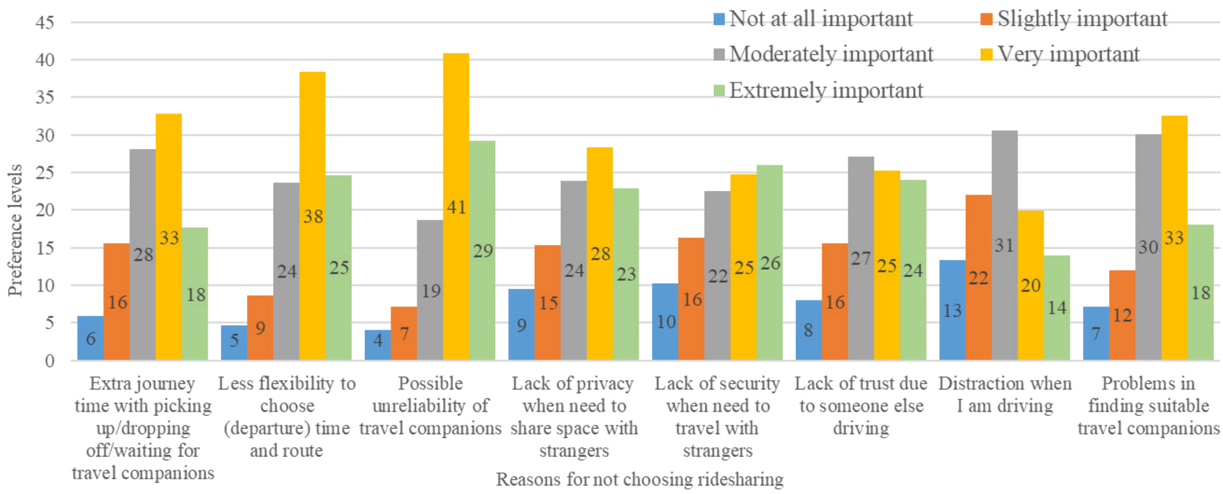


Figure 4.12: Reasons for not choosing ridesharing and their acceptance levels

Compared to the reasons for using ridesharing, reasons for not choosing it also play a vital role in understanding the propensity to accept ridesharing with DC in future, as shown in Figure 4.12. In this view, eight reasons using a five-point Likert scale (e.g., not at all important - extremely important) were assessed. Among these reasons, the unreliability of travel companions (70%) and less flexibility in choosing departure time and route (63%) are the two important reasons behind not preferring car sharing. 51% of the respondents mentioned extra journeys incurred due to picking and dropping off other passengers in-route is vital for not choosing ridesharing. Lack of privacy, security, and trust in sharing the ride with a stranger and problems matching the right sharing companion are the possible vital reasons for almost 51% of the respondents.

4.6 Personality traits of the respondents

Ten personality attributes were assessed for the present research to test each respondent's personality and reduce the respondent's task complexity. Each personality trait is constituted by one positive and one negative statement assessed using a five-point Likert scale (e.g., strongly disagree - strongly agree). The descriptive statistics of the responses concerning personality traits are shown in Table 4-2.

Table 4-2 depicts the five personality traits' acceptance levels. 54% and 5% of the agreeable personality-holding respondents agreed and strongly agreed to be generally trustworthy, while 24% and 10% agreed and strongly agreed to find fault with others. In conscientiousness, 58% and 23% of the respondents can do a tough job, while 14% and 2% reported themselves as lazy—42% of the respondents identified as not lazy. Respondents showing extraversion in their personality are more (50%) outgoing and social, while 45% are identified as reserved. Respondents prone to anger, frustration, and other negative aspects of human behaviour are neurotic. 35% and 10% of these respondents agreed and strongly agreed to relax to handle stress efficiently, while 12% and 39% disagreed and disagreed with getting nervous quickly. The respondents who cherish novelty and have various experiences are positive (67%) to bear active imagination, while the same group expressed fewer (25%) artistic interests.

Regarding trust, sociability, strictness in doing jobs, imagination, and stress management, 59%, 50%, 81%, 67%, and 45% of the respondents show positive attributes, respectively. On the contrary, negative aspects of personality traits are finding faults with others, being lazy, being reserved, getting nervous quickly, and having less artistic interests, for which 25%, 16%, 45%, 25% and 20% of the respondents are responsible, respectively.

Table 4-2: Personality traits and respondents' actions

Big-five personality traits	Personality statement codes	Personality statements	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
Agreeableness	Gn	Generally, trusts	0%	15%	26%	54%	5%
Agreeableness	Fo	Tends to find fault with others	7%	35%	33%	24%	1%
Conscientiousn	Tj	Does a thorough	1%	3%	15%	58%	23%
Conscientiousn	Tl	Tends to be lazy	19%	42%	23%	14%	2%
Extraversion	Os	Is outgoing and sociable	3%	13%	33%	41%	9%
Extraversion	Re	Is reserved	4%	22%	28%	38%	7%
Neuroticism	Hs	Is relaxed and handles stress	3%	18%	35%	35%	10%
Neuroticism	Ne	Gets nervous	12%	39%	24%	22%	3%
Openness	Am	Has an active imagination	2%	7%	25%	48%	19%
Openness	Ai	Has few artistic interests	20%	36%	24%	18%	2%

To characterise the personality of each respondent, one positive and one negative aspect was counted. In doing so, acceptance values (e.g., agree, strongly agree) of the positive statement and unacceptance levels (e.g., neutral, disagree, strongly disagree) of the negative aspect are integrated by conditional logic (stated in the third column of Table 4-3) to form a separate binary variable identifying a particular personality. In both acceptance and unacceptance values, neutral values are included because they also carry some merit as acceptance. The final dataset contains the percentages of positive and negative responses for each personality trait listed in Table 4-3. By counting for the positivity of each personality trait, the personality variables listed in Table 4-3 are transformed into a binary independent variable listed in Appendix G.

Table 4-3: Percentage of responses to satisfy the condition of personality

Big-five personality traits	Personality Variable codes	Conditional logic identifying positive attributes	Positive aspects of this personality	Negative aspects of this personality
Agreeableness	Agr	Gn >=2 AND Fo =< 2	27.7	72.3
Conscientiousness	Cons	Tj >= 2 AND Tl =< 2	53.8	46.2
Extraversion	Extra	Os >= 2 AND Re =< 2	23.3	76.8
Neuroticism	Neu	Hs > =2 AND Ne =< 2	34.6	65.4
Openness	Opn	Am >= 2 AND Ai =< 2	42.5	57.5

Table 4-3 shows that 27.7% of the respondents were highly trusting and less interested in finding fault with others, while 72.3% showed the opposite behaviour. In conscientiousness, 53.8% of the respondents were highly interested in doing a thorough job and were less prone to laziness, while 46.2% showed the opposite behaviour. For the extroverted people, 23.8% of the respondents were highly social-outgoing and less reserved, while 76.8% were the opposite-mannered. Regarding neuroticism, 35% of the respondents can handle stress well but get nervous quickly, while 65.4% of the respondents from the same group showed opposing behaviour. Regarding open-minded personality, 42.5% of the respondents bear few artistic interests with an active imagination, while 57.5% showed opposite personalities.

4.7 Social norms

The three social norms (e.g., the social expectation about sharing personal resources, thriving for a better quality of life, and preserving the environment) described in Table 3-4 (Chapter 3) were tested with two statements each. Among these two statements, the first one is the descriptive social norm (e.g., what do my close contacts prefer to do?), and the second is the injunctive social norm (e.g., what do my close contacts expect me to do?) (Cialdini *et al.*, 1990). Responses for each statement are recorded on a five-point Likert scale (e.g., strongly disagree - strongly agree).

Table 4-4 shows the list of social norm statements and the response values at each level. In terms of descriptive norms from close acquaintances (e.g., descriptive social norm), the majority (68%) of the respondents are unwilling (e.g., strongly disagree, disagree) to share resources. In contrast, for striving for a better quality of life and preserving the environment, most respondents (63% and 61%, respectively) expressed their willingness (e.g., agree, strongly agree). In terms of injunctive norms, most of the respondents were pessimistic about sharing resources (e.g., strongly disagree, disagree) (67.1%), while for the improved quality of life and for preserving the environment, respondents expressed their acceptance (e.g., agree, strongly agree) (50.9% and 70.8%, respectively).

Table 4-4: Social Norm Responses Analysis

Social Norms statements	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
Most of my acquaintances share or rent their resources (e.g., house or car) when possible	23.8%	44.3%	14.4%	9.4%	1.6%
Society expects me to share or rent my resources (e.g., house or car) when possible	20.0%	47.1%	18.0%	7.4%	1.0%
Most of my acquaintances try to improve the quality of life where they live	1.2%	6.2%	23.4%	53.7%	9.0%
Society expects me to try to improve the quality of life where I live	1.8%	12.2%	28.3%	45.9%	5.0%
Most of my acquaintances make an effort to protect the environment	1.4%	7.4%	23.8%	51.9%	9.0%
Society expects me to make an effort to protect the environment	1.2%	5.4%	15.6%	55.6%	15.2%

For this research, only the injunctive norms are considered to understand the significance of social expectations for the likelihood of DC shared ownership and ridership. For this purpose, the three injunctive norm statements are selected as factors of DC choice and turned into three variables, mentioned in Table 4-5. For all the injunctive social norm statements, as stated in Table 4-5, the positive responses (e.g., neutral, agree, strongly agree) for the norm statement were coded as '1', and the negative responses (e.g., strongly disagree, disagree) were coded as '0'.

Table 4-5: Social norm statements used for this research

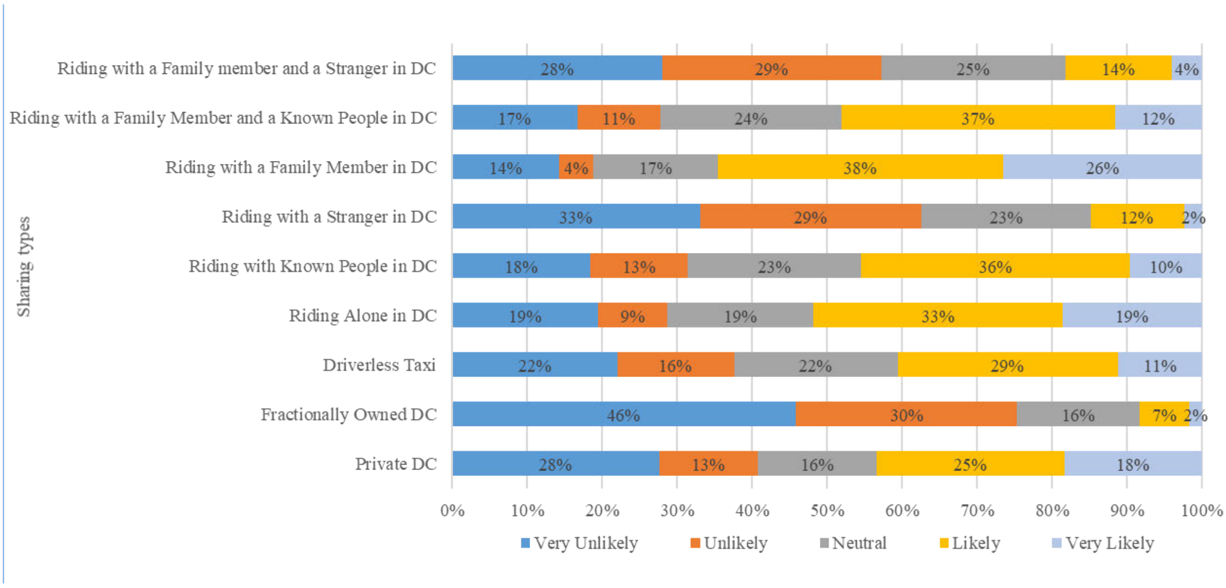
Social-norms	**Social-norm statements**	Questionnaire Code	Positive Responses	Negative Responses
The social expectation for sharing personal resources	Society expects me to share or rent my resources (e.g. house or car) when possible	SES16	26.40%	68.10%
The social expectation for contribution to a better quality of life	Society expects me to make an effort to improve the quality of life where I live	SEQ16	79.20%	14.00%
The social expectation for preserving the environment	Society expects me to make an effort to protect the environment	SPE16	86.40%	6.60%

As mentioned in Table 4-5, after removing the missing values and not considering the 'neutral' responses as acceptances, 26.40% of the respondents expressed their understanding from acquaintances/society about the social expectations for sharing resources. The relevant proportions of social influences for 'better quality of life' and 'to protect the environment' are 79.20% and 86.40%, respectively.

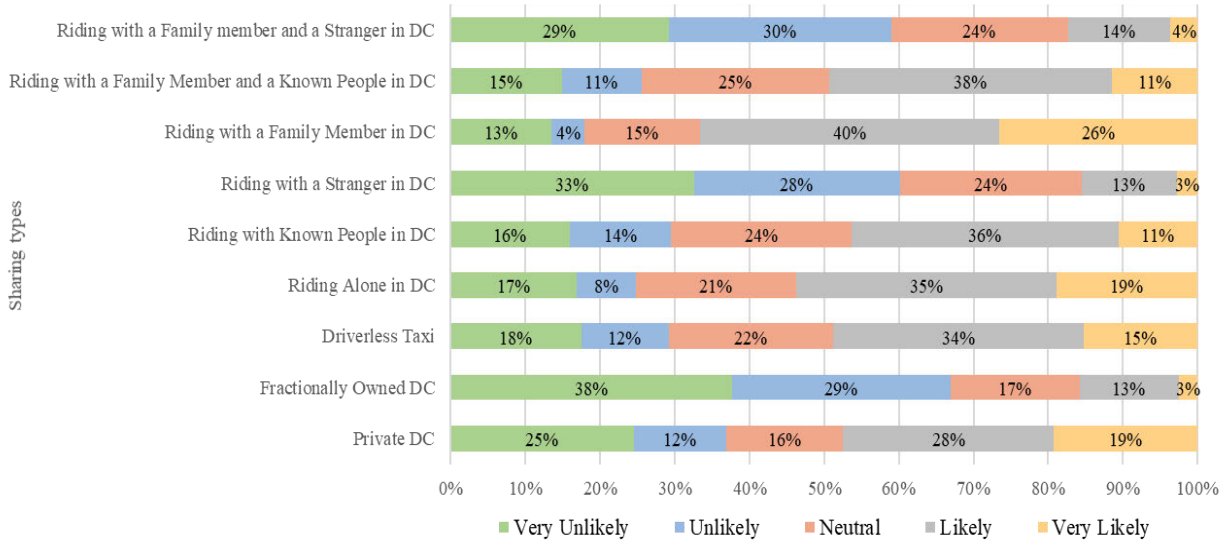
4.8 Attitudes towards shared ownership and ridership with DC

This descriptive assessment was done to understand the preferences for various DC sharing options concerning regular/occasional trips, using shared ridership/ownership, and involving family members/strangers' presence. Figure 4.13 shows the results.

For DC shared ownership, 43% of the respondents are "likely" or "very likely" to use a private DC for regular trips. The corresponding proportion is 8% for a shared-owned DC and 41% for a driverless taxi. Driverless taxis are popular with 49% of the respondents for occasional use. For occasional trips, 47% of the respondents are likely and very likely to accept private DCs, while only 16% are willing to use shared-owned DCs.



(a)



(b)

Figure 4.13: Preference variations for (a) DC sharing options for regular trips, (b) DC sharing options for occasional trips

Regarding DC shared ridership, for regular trips not involving family members, riding alone is "likely" or "very likely" for 52% of the respondents compared to 46% and 15% of riding with known people and riding with a stranger. The attitudes are similar for occasional trips not involving family members.

In the presence of family members in DC shared ridership, the "likely" and "very likely" preferences represent 64%, 49%, and 18% for riding alone, with known people and a stranger, respectively. The attitudes are similar for occasional trips in the presence of family members.

4.9 Chapter Conclusion

This Chapter presents the descriptive analysis of the online survey data. The online survey sample was compared with Edinburgh and Scottish population data. This comparison revealed that my survey sample represents a higher percentage of male respondents than the male Scottish population and moderate variations in younger population percentages compared to the Edinburgh population. Therefore, the results of this survey resonate with earlier study results, which reflected that males appreciate DC surveys more than females (Rice and Winter, 2019). Regarding age, people's perception of DC use varies moderately. Therefore, this survey data may skew model results regarding gender variations compared to age. However, regarding the number of car owners, this survey's results are comparable with Transport Scotland (2019) data, as mentioned below.

Regarding age, 69.54% of the respondents are working age (16 – 64 years), while the (City of Edinburgh, 2020) reported that 69.6% of the City of Edinburgh's population is within this age group. The sample gender ratio (male vs female) was nearly 2:1 compared with the nearly 1:1 ratio reported in the National Records of Scotland (www.nrscotland.gov.uk). Concerning car ownership, 76.5% of the respondents owned one car versus 71% of Scots who own at least one car, according to Transport Scotland (2019).

Descriptive analysis of the survey sample revealed that nearly one-third (29%) of the respondents were millennials, and 44% belonged to higher-income (>£500000) households. 55% of them didn't have any children, and 34% lived within Edinburgh city centre.

The online survey results reveal that eliminating maintenance, tax burden, and parking costs are the primary reasons for choosing carsharing, while car availability, limited convenience, and comfort are the prime reasons for not choosing carsharing. On the contrary, people prefer ridesharing primarily for cheap travel and to avoid driving and parking hassles. People don't prefer to use ridesharing broadly due to the inflexible travel and lack of reliability, security, safety, the trust associated with sharing a ride with strangers.

To the best of the researcher's knowledge, this research is one of the few kinds of research to use behavioural psychology variables, namely 'personality traits' and 'social norm' in DC research. The data analysis segmented respondents' personalities, with 54% showing organised and dutiful behaviour, while 28% bare cooperative sharing attitudes. 43% of the respondents had various experiences and interests, while 35% had negative attitudes in their personalities. Findings suggested that the least amount (23%) of respondents in this survey sample were highly energetic and could feel the environment with a higher level of appreciation.

Social norm behaviour reveals that 76% of respondents were socially influenced to protect the environment, 55% expressed interest in a better quality of life, and only 8.4% expressed sharing resources with others. This research tried to link respondents' ridesharing and carsharing propensities with their sharing intentions revealed by their personality and social norm behaviour. Notwithstanding, only a few respondents shared their social norms and personality intentions.

Overall results indicating respondents' propensity towards DC sharing reveal that respondents highly rely on private DC, with a small portion interested in shared ownership in DC. Driverless taxis are likely to be prevalent for occasional travel. Regarding sharing the ride with DC, respondents are more interested in riding alone and with known people, with only a fraction interested in riding with a stranger.

5. Chapter 5: Characterisation of the current shared mobility behaviour

5.1 Introduction

This chapter statistically investigates the present carsharing and ridesharing characteristics (travel-sharing attitudes) among the sample population. In this vein, this chapter focused on clustering travel-sharing responses by their attitudes (e.g., travel frequency, type), and discussed two dimensions of travel-sharing behaviour related to 1) car share and 2) ride share. A two-step cluster analysis method was followed to categorise travel-sharing variables regarding mode types and usage frequency. The subsequent sections elaborate on the idea of clustering and its implication in identifying the intended adoption of DC. Three broad objectives can be summarised in this chapter as the following:

1. Statistically analyse and identify the clusters within the present travel share dimensions: (a) Carsharing and (b) Ridesharing;

2. Characterisation of the present carsharing and ridesharing clusters concerning demographic, personality and social norm factors;

3. The relationship of various DC scenarios with these clusters

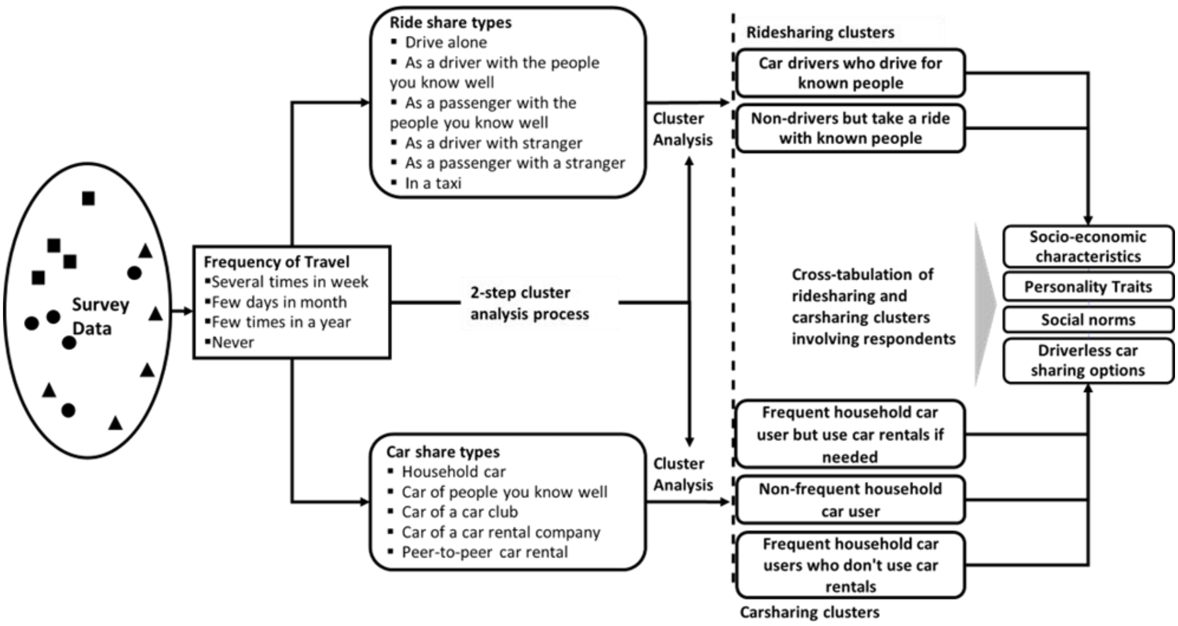


Figure 5.1: The cluster analysis process and association of clusters with other socio-economic variables

The first objective was achieved by conducting a cluster analysis to uncover various groups of similar ridesharing and carsharing attitudes. Figure 5.1 shows the cluster analysis process employed for this research. These clusters are the broad overview of the present travel share attitudes. Econometric models were estimated in Chapter 6 to get some robust behavioural understanding. In this vein, cluster analysis outcomes were used to define present shared car ownership and ridesharing behaviour. These behavioural variables are then modelled with future shared DC ownership and ridesharing choices to explain the propensity of resultant variables (DC choice types) within the framework of ordered probit and logit models.

5.2 Cluster analysis process

This research addressed two dimensions of present sharing behaviour to determine the clusters: 1) present carsharing behaviour and 2) present ridesharing behaviour. Since these two types of sharing behaviour were characterised by categorical variables like frequency types and sharing mode types, it was preferred to use a two-step cluster, as suggested by the literature in Section 2.7.6.

A two-step cluster analysis simultaneously considers categorical and continuous variables. For categorical variables such as frequency, this method is preferred over hierarchical cluster analysis and its capacity to specify the number of clusters in the testing process (Chiu *et al.*, 2001). The two-step cluster analysis is only applicable for complex datasets and when there are no apparent assumptions for the groups in the dataset. So, this method provides a flexible structure within the dataset and uncovers a meaningful insight.

Another PhD study from the University of South Florida utilised the cluster analysis technique to identify four clusters associated with DC's potential benefits and concerns (Menon, 2017): benefit-dominated (19.3%), uncertain (27.5%), well-informed (30.5%), and concern-dominated (22.6%). This research used the two-step cluster analysis procedure based on eleven factors associated with consumer benefits and concerns for DC use. All these variables are categorical; hence, two-step cluster analysis was deemed flexible in identifying the accurate number of consumer segments (clusters).

In the proposed research, the probability of choosing carsharing or ridesharing is related to the frequency of sharing behaviour to serve a trip purpose with some predefined travel modes. Here, the clustering function utilised four types of travel frequency: 1) several times in a week,

2) sew days in a month, 3) a few times in a year, and 4) never. These frequency types are associated with regular urban travel mode preferences.

Based upon the ideas developed in empirical studies relating to consumer behaviour and market research, user groups were segregated with homogenous travel-sharing (frequency) behaviour to form clusters in this research. These clusters were labelled based on the distributions of the variables used to build the clusters within the clusters themselves (De Oña *et al.*, 2015). This way, the significant variables within each cluster were identified for the naming. This significance was tested by the highest probability of the significant variable to show its association within the specific cluster.

The maximum value to the ratio of distance measures followed by Şchiopu (2010) and Trpkova and Tevdovski (2009) was used to find the optimum number of clusters by SPSS26 (IBM SPSS, 2023). The BIC (Bayesian information criterion) and AIC (Akaike information criterion) measure goodness-of-fit to compare different models and select the best one with an optimum number of clusters. Both these measures give similar solutions, but the BIC method was chosen considering the trade-off between model fit and the complexity of the sharing behaviour.

5.3 Cluster analysis application in transport

The cluster analysis applications in transport are discussed in detail in Section 2.7.6.

5.4 Present ridesharing clusters

The first cluster analysis applied the two-step cluster analysis to segment respondents' present ridesharing behaviour. For this, six independent variables were used relating to four levels of sharing frequencies (e.g., several times in a week, few days in a month, few times in a year, never) by ridesharing types, such as 1) driving alone; 2) as a driver, with people they know well; 3) as a passenger, with people they know well; 4) as a driver, with strangers; 5) as a passenger, with strangers, and 6) in a taxi. All these input variables are essential factors in describing ridesharing behaviour because the frequency for ridesharing types is higher than 50%. Independent variables such as 'driving alone' and 'as a driver, with people they know well' bear the most significant impact on ridesharing classification.

Figure 4.6 in Chapter 4 describes all the categorical variables with their importance. Table 5-1 shows the results of the Auto-Clustering process with variations.

Table 5-1: Two-step Cluster Analysis process with ridesharing behaviour

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change	The ratio of BIC Changes	The ratio of Distance Measures
1	5341.279			
2	4731.458	-609.820	1.000	1.817
3	4445.044	-286.414	0.470	1.365
4	4264.636	-180.408	0.296	1.296
5	4150.487	-114.149	0.187	1.176
6	4069.847	-80.640	0.132	1.028
7	3994.461	-75.386	0.124	1.107
8	3936.926	-57.536	0.094	1.071
9	3890.409	-46.517	0.076	1.418
10	3889.893	-0.516	0.001	1.024
11	3891.913	2.019	-0.003	1.085
12	3902.380	10.467	-0.017	1.034
13	3916.108	13.728	-0.023	1.135
14	3941.241	25.133	-0.041	1.099
15	3973.976	32.735	-0.054	1.062

Clusters in Table 5-1 reveal that two clusters are optimal based on the highest ratio of distance measures. In addition to this metric, the BIC, BIC change, and the ratio of BIC changes were demonstrated. Table 5-1 illustrates the BIC values calculated for 15 clusters. In general, a high number of clusters leads to a problematic model. Through SPSS, an analytical approach was applied to adopt an automatic solution based on a negotiation between a large ratio of BIC changes and a large ratio of distance measures. This method derived two optimal numbers of clusters (ratio of BIC changes = 1.00, ratio of distance measures = 1.817). These independent variables divide the sample into clusters identifying specific ridesharing behaviours. Figure 5.3 shows these clusters as,

- Car drivers who drive for known people (75.6%) (Coded as Rs_cd in the final dataset)
- Non-drivers but take a ride with known people (24.4%) (Coded as Rs_nd in the final dataset)

Figure 5.2 demonstrates that the cluster analysis with six independent variables is good/fair because Silhouette's measure of cohesion and separation indicates 0.5 (between the fair and reasonable band) (Crespo Casado *et al.*, 2016). This metric demonstrates the fair zone if Silhouette's measure exceeds 0.2.

Figure 5.2: Model summary and cluster quality based on Silhouette's measure of cohesion and separation

Figure 5.3 summarizes the results of the two-step cluster analysis as the cluster size, the importance of the input variables (see the scale), and the most numerous groups of respondents depending on the selected independent variable. Figure 3 reveals the ranking of the input predictors according to within-group importance in each cluster.

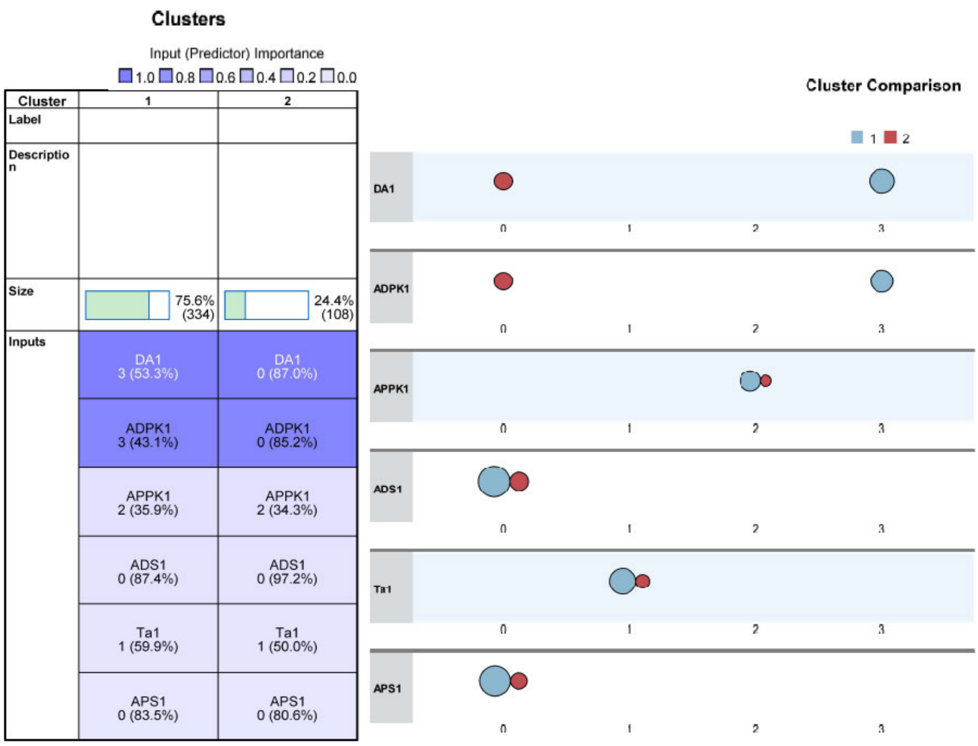


Figure 5.3: Ridesharing clusters analysis and their variations

User types concerning different present ridesharing behaviour are presented in the left pane of Figure 5.3. The first cluster is 'car drivers', comprising 75.6% of the respondents. Respondents in this cluster drive their cars (53.3%) and drive with known people (43.1%) several times a week. Along with regular travellers, 35.9% of car passengers occasionally ride with known drivers (35.9%). Most people in this cluster (59.9%) rarely use taxi services. Rideshare behaviour for most respondents in this cluster neither driving with a stranger (87.4%) nor showing any intention to share the ride with an unknown driver (83.5%).

The second cluster of ridesharing type belongs to non-drivers, comprising 24.4% of the respondents. Respondents in this cluster predominantly share the ride with known people (34.3%) several times a month. A small portion of the respondents (50%) use taxi services a few times a year. Respondents from this cluster didn't show any appreciation for other ridesharing options. The detailed ratios of non-divers with these later types of sharing are listed in Figure 5.3.

5.5 Present carsharing clusters

In the second two-step cluster analysis, present shared car ownership behaviour (e.g., Q2) was applied. For this, five independent variables relating four levels of shared car ownership frequencies (e.g., several times in a week, few days in a month, few times in a year, never) such as 1) Household car (Hcr2); 2) Car of the people you know well (CPK2), 3) Car of a car-club (CCC2), 4) Car of a car rental company (CCR2), 5) Peer-to-peer car rental (P2P2) was applied. These independent variables, such as 'driving a household car' and 'driving with a person they know well', significantly affect shared car ownership behaviour. Figure 4.7 in Chapter 4 describes all the car-sharing categorical variables with their importance. Table 5-2 shows the Auto-Clustering process with shared car ownership variations.

Table 5-2: Two-step Cluster Analysis process with carsharing behaviour

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change	Ratio of BIC Changes	Ratio of Distance Measures
1	3331.601			
2	2937.111	-394.490	1.000	1.043
3	2562.885	-374.227	0.949	2.002
4	2421.966	-140.919	0.357	1.068
5	2295.925	-126.041	0.320	1.081
6	2186.138	-109.787	0.278	1.288
7	2121.441	-64.697	0.164	1.007
8	2057.843	-63.598	0.161	1.144
9	2013.784	-44.059	0.112	1.287
10	2000.103	-13.680	0.035	1.244
11	2007.142	7.039	-0.018	1.087
12	2020.977	13.834	-0.035	1.015

13	2035.990	15.014	-0.038	1.087
14	2057.140	21.149	-0.054	1.200
15	2090.088	32.948	-0.084	1.042

Table 5-2 demonstrates the BIC values calculated for 15 clusters. Through SPSS, BIC ratio changes and the ratio of distance measures were chosen, resulting in 3 optimal cluster numbers (ratio of BIC changes = 0.949, the ratio of distance measures = 2.002). This analysis divides the sample into three clusters, identifying present shared car ownership behaviour. Figure 5.5 shows these clusters as:

1. Frequent household car users but use car rentals if needed (30.2%) (Coded as Vs_fhcr in the final dataset)
2. Non-frequent household car users (33.4%) (Coded as Vs_nhc in the final dataset)
3. Frequent household car users who don't use car rentals (36.4%) (Coded as Vs_fhc in the final dataset)

Figure 5.4 demonstrates that the car-sharing cluster analysis with five independent variables is good/fair because Silhouette's measure of cohesion and separation indicates 0.3 (between the fair and reasonable band). This metric demonstrates the fair zone if Silhouette's measure exceeds or equals 0.3.

Model Summary

Algorithm	TwoStep
Inputs	5
Clusters	3

Cluster Quality

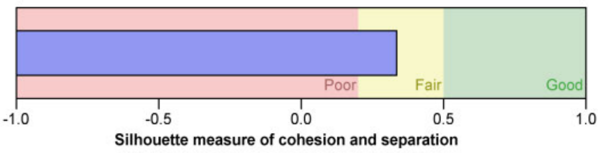


Figure 5.4: Model summary and cluster quality based on Silhouette's measure of cohesion and separation for present shared car ownership

Figure 5.5 summarizes the results of the two-step cluster analysis with present shared car ownership behaviour with cluster size, the importance of the input variables (see the scale), and the most numerous groups of respondents depending on the selected independent variable. Figure 5.5 reveals the ranking of the input predictors according to within-group importance in each cluster.

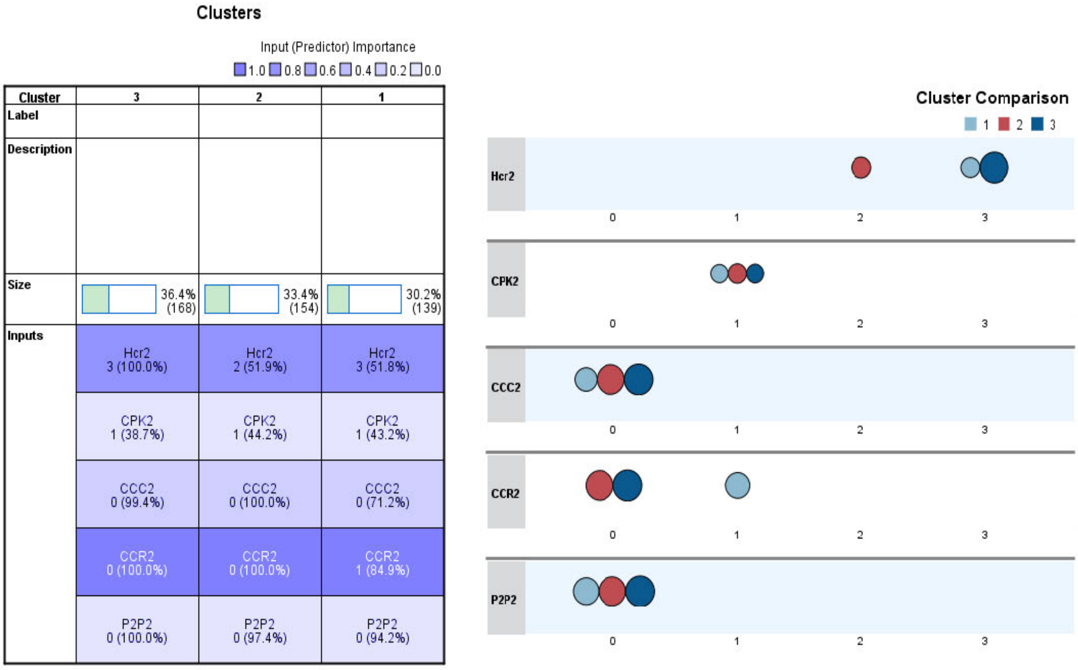


Figure 5.5: Carsharing clusters and their variations

Figure 5.5 shows the shared car ownership cluster analysis results with their variants. The first cluster comprises 30.2% of the respondents. Respondents in this cluster used household cars (51.8%) several times a week. Additionally, respondents who belong to this cluster share cars of their close contacts (43.2%) and rental cars (84.9%) several times a year. However, most of the respondents from this cluster rarely use the car from car club (71.2%) and peer-to-peer car (94.2%) services. Overall, this cluster reflects the moderate approach to carsharing behaviour.

The second cluster is the non-frequent car sharers, comprising 33.4% of the respondents. Respondents in this cluster primarily drive their household car (51.9%) a few times a month. Besides, respondents in this cluster occasionally share a car with their close contacts (44.2%) in a year. All of the respondents (100%) from this cluster showed complete reluctance to use a car from a car club, rental car, and peer-to-peer sharing. (97.1%). This cluster belongs to those car users who are neither regular car users nor share a car frequently.

Respondents in the third cluster mainly depend on their household car for their mobility needs and travel regularly. Although respondents from this cluster showed moderate behaviour toward sharing a car with their close contacts (38.7%), they are entirely reluctant to use a car from a car club (99.4%), car rental (100%) and peer-to-peer car share (100%) service. This cluster can be termed car lovers.

5.6 Characteristics of ridesharing clusters

5.6.1 Influence of demography and socio-economic segments on present ridesharing behaviour

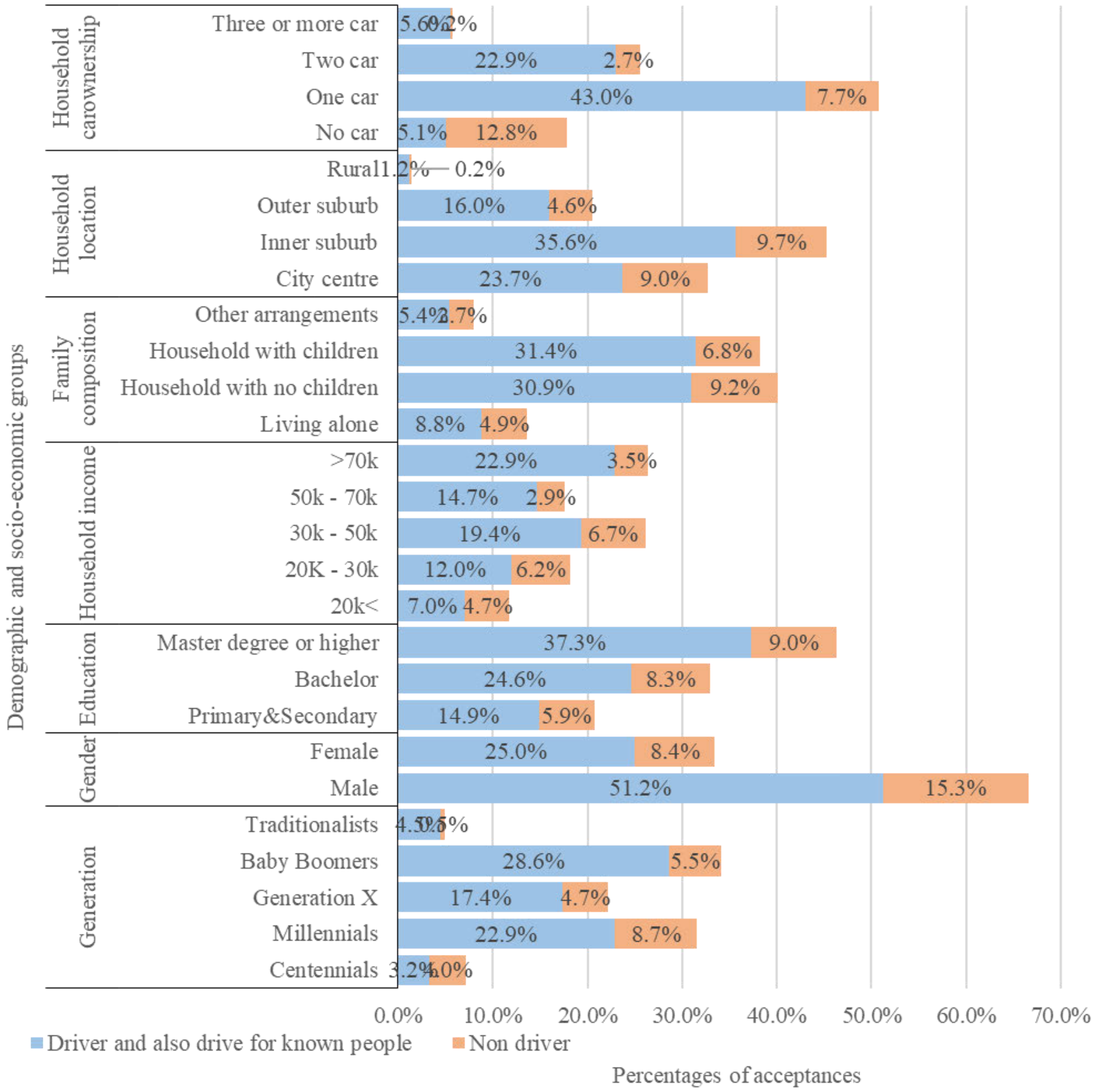


Figure 5.6: Ridesharing clusters and their variations within demographic and socio-economic classes

The cross-classification analysis revealed the age influence of present ridesharing behaviour, as shown in Figure 5.6. Millennials (e,g, aged between 23 – 55 years) and baby boomers (e.g., between 55 - 75 years) are the most influential groups for driving alone and with known people.

More male drivers (51%) are more likely to drive alone and with known people than females (25%). Upper degree-holding car owners are more (37.3%) likely to drive alone and with their acquaintances than bachelor's degree-holding drivers (25%).

Regarding income, higher-income holders are more (19%) likely to drive their car for themselves than lower-income holders. In terms of living status, households with at least one child are more (31.4%) likely to drive alone and with known people than households living without children (31%) and living alone (9%).

Household location affects the present decision to ride alone and with known people. People from inner-suburban living households are more (36%) likely to ride alone and use their car with close contacts than people from outer-suburban living (16%) and city-centre dwelling households (24%). This result also reflects higher responses from the inner suburb locations. The survey findings suggested that driving alone and sharing a car with known people is more prominent (43%) among one car owner than two or more car owners (29%).

5.6.2 Influence of ridesharing reasons on present ridesharing behaviour

Ridesharing reasons are divided between drivers (who also drive for known people) and non-drivers in a split of 76:24, the actual ratio of these two user groups. This data analysis reflects that sharing reasons is less important to non-drivers regarding ridesharing. Among the drivers (who also drive for known people), 'You can get rid of driving and parking hassle', and 'Lower cost of the trip (including parking)' are the two essential reasons. On the other hand, the ability to socialise while someone else drives and the ability to work while someone else drives are the two least important reasons.

Figure 5.7 shows the distribution of ridesharing reasons within ridesharing clusters. 45.2% of the drivers (who also drive for known people) prefer to use DC to eliminate driving and parking hassles, while 44.9% anticipate lower trip costs (and parking) when DC comes into practice. On the contrary, 61.3% of the drivers believe socialising, and 57.8% believe working while riding is not essential in choosing DC ridesharing.

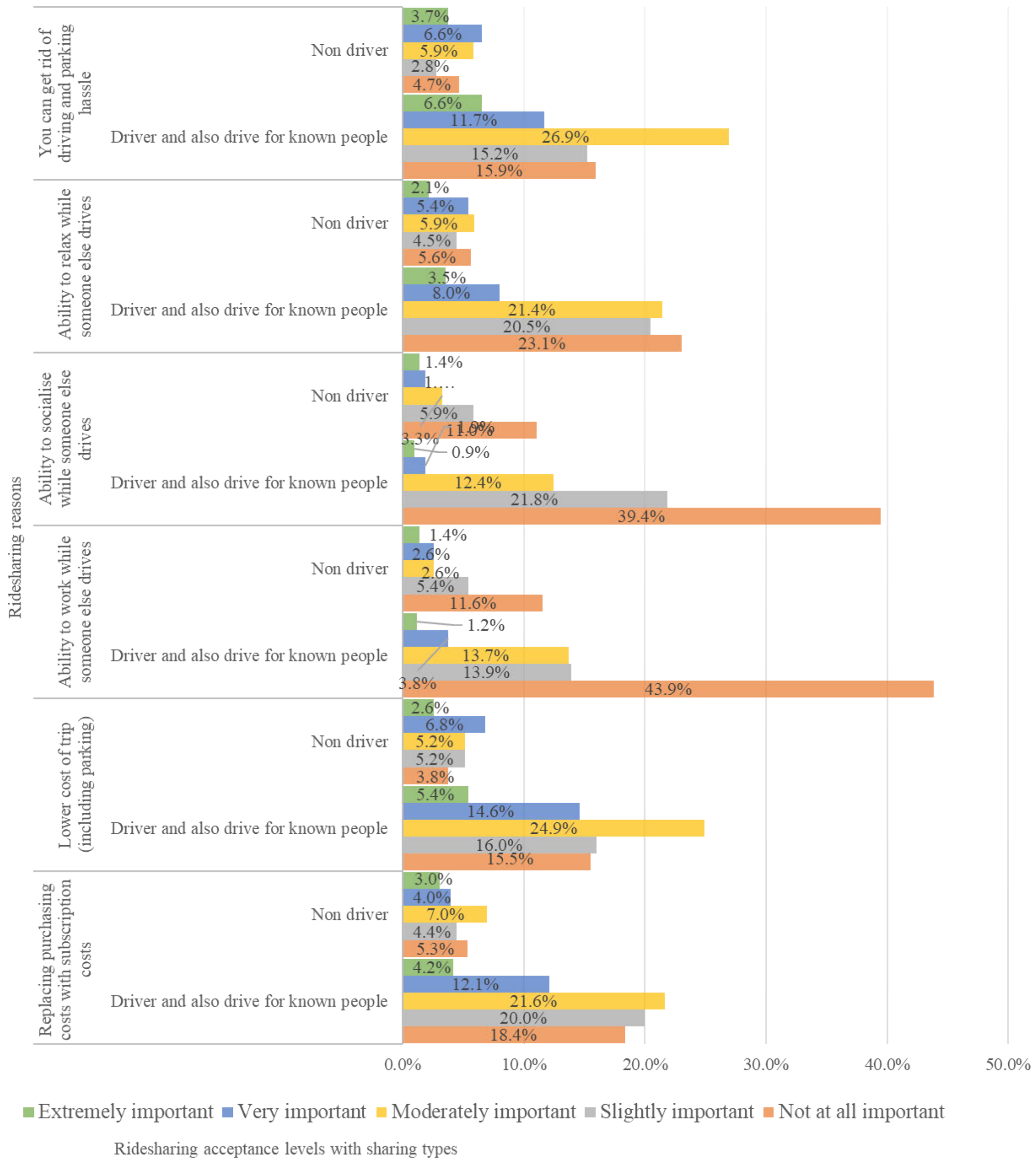


Figure 5.7: Influence of present ridesharing reasons on ridesharing behaviour

5.6.3 Influence of personality traits on present ridesharing behaviour

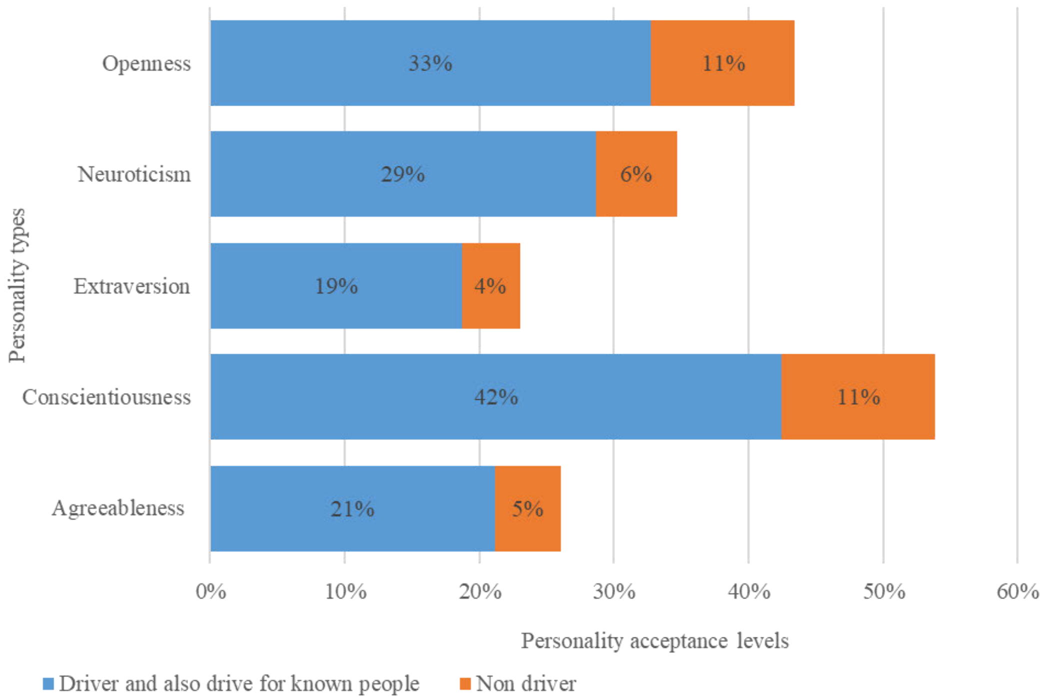


Figure 5.8: Relation of respondents' personality types with present ridesharing behaviour

Regarding personality, respondents vary widely in their ridesharing behaviour based on whether they drive (who also drive for known people) or do not drive, as shown in Figure 5.8. In addressing the personality in influencing DC ridesharing behaviour, positive responses (e.g., agree, strongly agree) of the positive personality statement and negative responses (e.g., neutral, disagree, strongly disagree) of the negative personality statements are coordinated and used as variables defining the respondents' personality.

21% of the respondents who drive cars showed cooperative and generous attitudes towards sharing, while 5% of the non-drivers showed the same personal attitudes. 42% of the drivers showed organised attitudes and were more consistent in their behaviour than 11% of the non-drivers.

19% of the car drivers and 4% of the non-car drivers appreciated the environment and actively enjoyed their social life. Personality-wise, 29% of the divers showed negative attitudes and were susceptible to anger, frustration and anxiety. Among the respondents who drive, 33% were experienced and had positive attitudes toward life, while only 11% were non-drivers with a similar mentality.

The personality distribution with ridesharing types indicated that respondents with organised (42%) attitudes and a lot of personal interests (33%) were more likely to choose ridesharing than cooperative and trusted (21%) respondents.

5.6.4 Influence social norms on present ridesharing behaviour

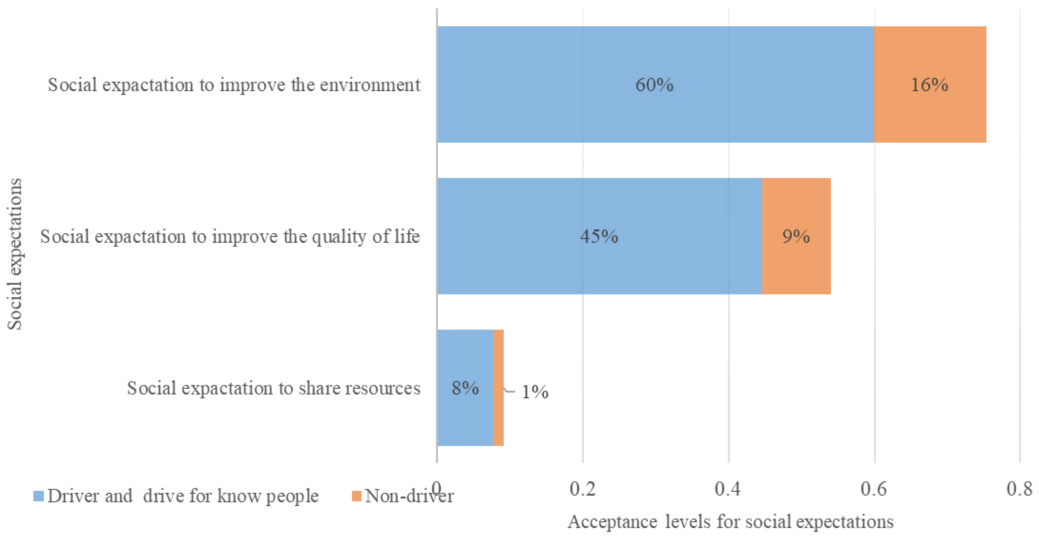


Figure 5.9: Relation of respondents' social norm behaviour with present ridesharing behaviour

Regarding social norms, the expectation of sharing resources is the least essential behaviour among drivers to share their rides with others, as shown in Figure 5.9. Most people who had societal feelings to improve the environment were most likely to drive and share their rides with known people.

45% of the respondents who drive or drive with known people showed feelings for social norms for an improved quality of life. These results revealed that other than the resource-sharing social norm, caring for the environment (60%) and seeking a quality lifestyle (45%) were two prominent social norms influencing people to choose ridesharing.

5.7 Characteristics of Shared Car Ownership Clusters

5.7.1 Influence of demography and socio-economic segments on present carsharing behaviour

Figure 5.10 represents the cross-classification analysis that revealed the age influence of present shared car ownership behaviour. Millennials (e,g, aged between 23 – 43 years) are the most influential age group, with a high number of regular household car users and occasional car renters. On the contrary, baby boomers (e.g. aged 55 - 75 years) are the most frequent household car users with no sharing tendencies (13.8%). More male drivers are household car owners with (22.1%) and without (22.6%) car renting tendencies than females (8.6% and 14.7%, respectively).

Upper degree-holding car owners are more likely to own household cars than bachelor's degree and primary-secondary school degree holders. 16.7% of the respondents with a master's degree background are mostly car owners who don't like renting a car for their use, while 14.3% are not willing to rent cars.

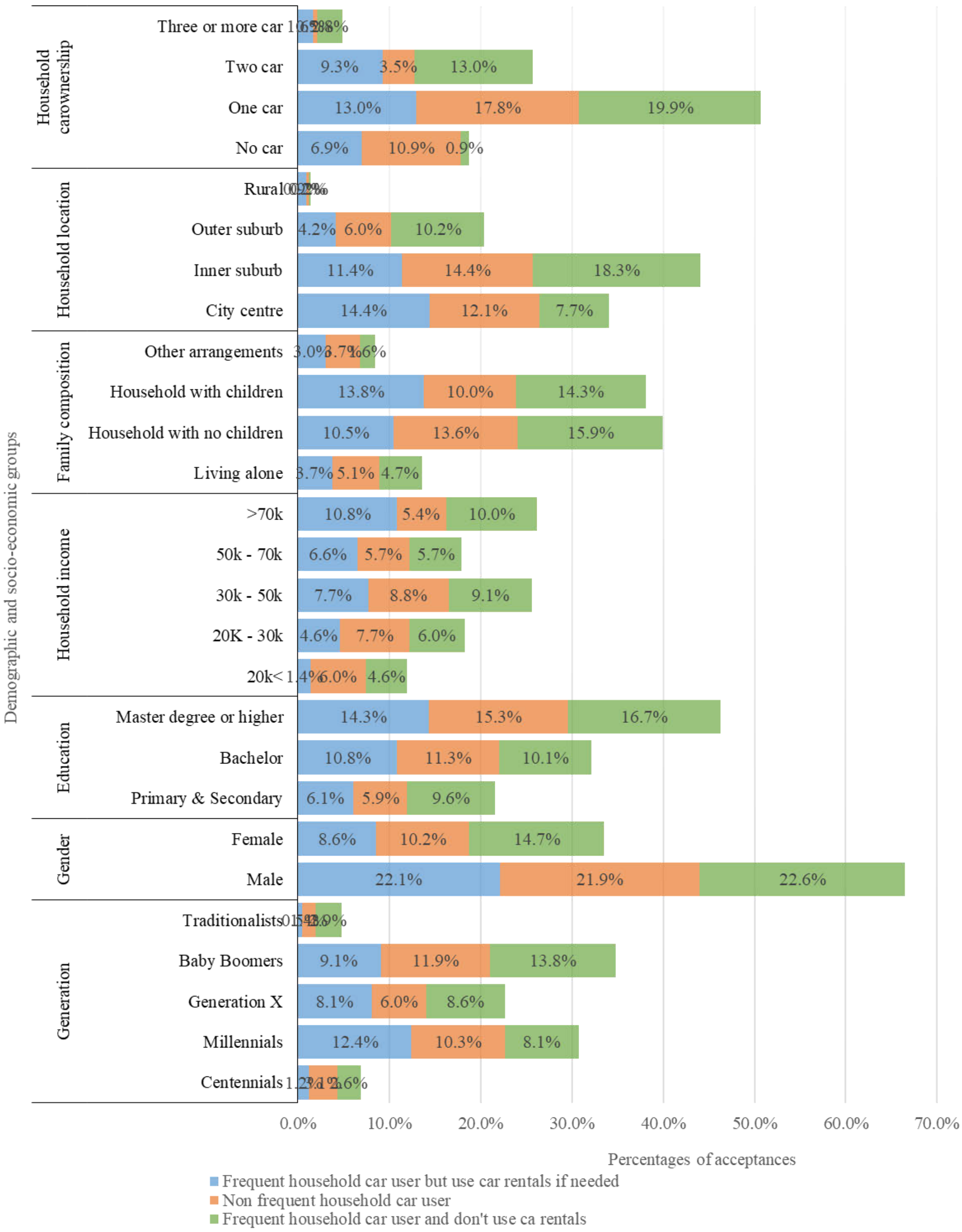


Figure 5.10: Shared car-ownership clusters and their variations within demographic and socio-economic classes

Higher-income holders (>30k yearly income) are more frequent household car owners than lower-income holders; infrequent household car owners are relatively lower.

Considering the household size, households with at least one child are more (13.4%) frequent household car-users than households living without children (10.5%) and living alone (3.7%). However, households without a child are more (15.9%) frequent household car owners when people are unwilling to hire cars.

Household location affects the present decision in choosing shared car ownership. 14.4% of city-centre living households are frequent household car owners without renting tendency than people from inner-suburban (11.4%) and outer-suburban (4.2%) living households. These results also reflect that the respondents from inner suburb locations are mostly (18.3%) household car owners.

The survey findings suggested that frequent household car users with/without the willingness to rent cars are higher (13% and 19.9%, respectively) among one car owner than two or more car owners combined.

5.7.2 Influence of carsharing reasons on present carsharing behaviour

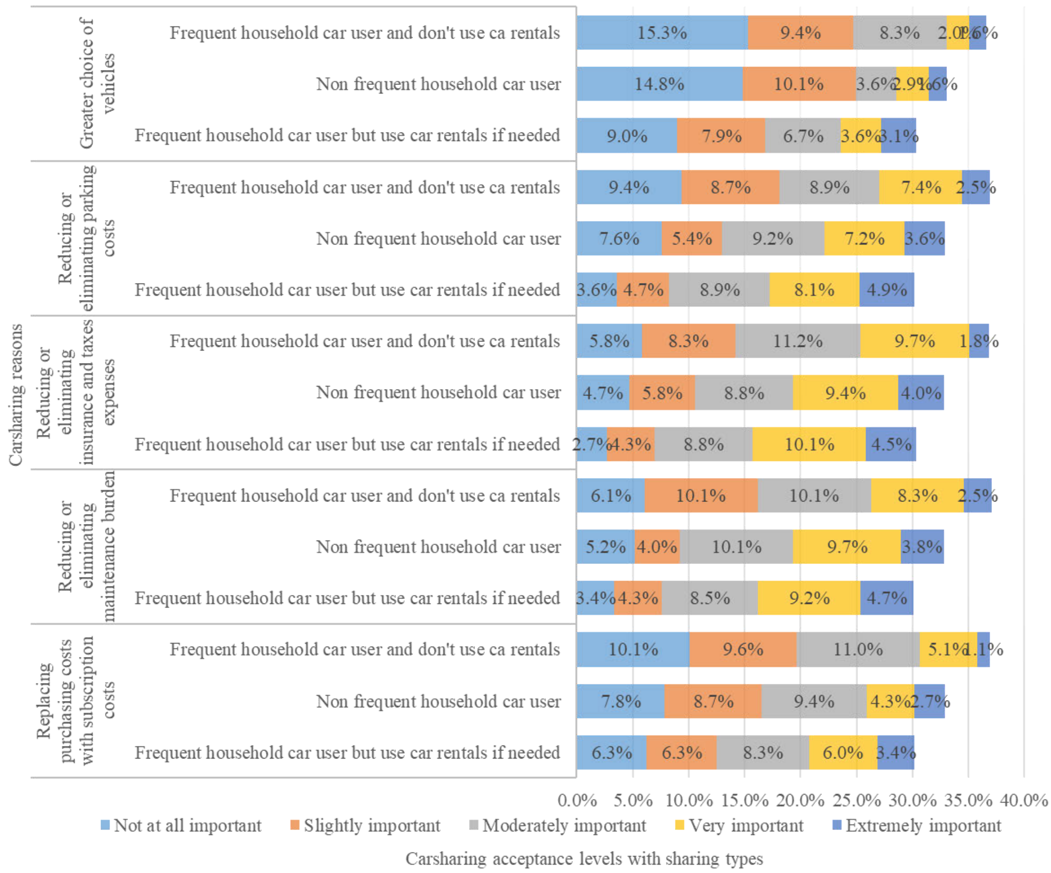


Figure 5.11: Present shared car-ownership behaviour and influence of carsharing reasons

As depicted in Figure 5.11, six car-sharing reasons were observed and divided into three shared car ownership types (frequent household car use with/without the willingness for car rent, non-frequent household car owner). This data analysis reflects that carsharing reasons are more important to frequent household car users with/without the willingness for car hire. Counting the very-important and extremely-important types, 'reducing or eliminating maintenance burden', and 'reducing or eliminating insurance and tax expenses' are the top reasons to help people decide about shared car ownership.

13.9% of the frequent household car users (who also prefer to share a car) like to reduce or eliminate maintenance costs, while 13.5% of the non-frequent household car owners anticipate the same. 14.6% of the frequent household car users prefer to use shared car ownership to reduce or eliminate their insurance and taxes. The results show that 'maintenance costs', 'insurance and taxes', and 'parking cost' reduction are the most important reasons influencing people's preference for shared car ownership.

5.7.3 Influence of personality traits on present carsharing behaviour

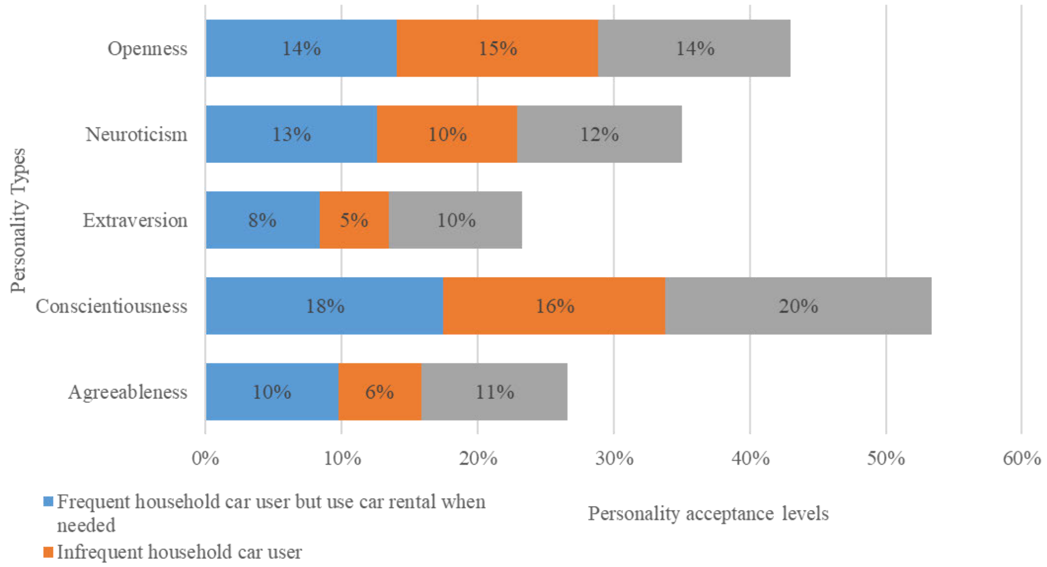


Figure 5.12: Relation of respondents' personality types with present shared car-ownership behaviour

As shown in Figure 5.12, 10% of the frequent household car users who don't use car rentals showed cooperative and generous attitudes towards sharing. In comparison, 11% of the frequent car users with no intention to hire a car showed the same personal attitudes. 18% and 20% of the frequent household car users with and without the intention to hire cars possessed organised attitudes. They were more consistent in their behaviour, and 16% of the non-frequent household car users showed the same attitudes. This result showed that organised people are more inclined to use household cars than carshare or ride.

8% and 10% of the frequent household car users with and without car hire intentions, and 5% of the non-frequent household car drivers appreciated the environment and actively enjoyed their social life. This result reveals that household car users were more socially aware of the environment than non-frequent drivers.

Personality-wise, 13% of the frequent household car drivers with car hiring expectations showed negative attitudes and were susceptible to anger, frustration and anxiety. Among the respondents, 14% are frequent household car users willing to hire cars and experienced positive attitudes toward life, while 15% were non-frequent household car users with a similar mentality.

The personality distribution with carsharing types indicates that respondents with organised behaviour and positive attitudes were more likely to choose shared car ownership than cooperative and trusted respondents.

5.7.4 Influence of social norms on present carsharing behaviour

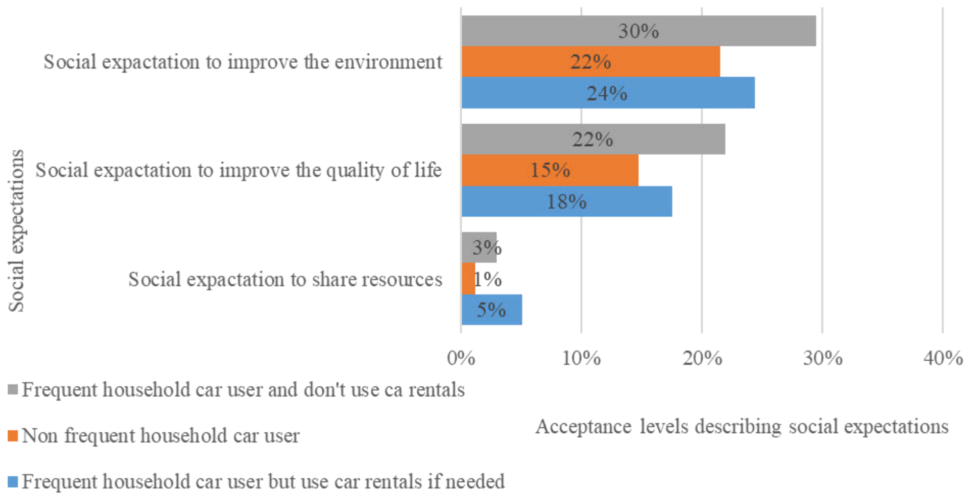


Figure 5.13: Relation of social norm behaviour with present shared car-ownership types

As shown in Figure 5.13, the social expectation of sharing resources is the least essential social norm among frequent household car users who like to rent cars. 24% of the respondents are frequent household car users with car-hiring tendencies and belong to the social norm about improving the environment. 30% of the respondents hold similar social norms but do not intend to hire cars for their use. 18% and 22% of the respondents who are frequent household car users with/without car hire expectations bear the social norm to improve the quality of life. These results reveal that other than resource-sharing behaviour, caring for the environment (54%) and seeking a quality lifestyle (40%) are two prominent social norms influencing people to choose shared car ownership that follow the same findings in choosing ridesharing.

5.8 Influence of current sharing behaviour over sharing behaviour with driverless cars

This section aims to unearth the possible relationships between hypothetical DC sharing options and present ridesharing and shared car ownership behaviour. Only the positive responses in adopting DC (e.g., very important, highly important) sharing options were applied in this analysis.

5.8.1 Ridesharing with DC and present ridesharing behaviour

The statistically significant correlation values between DC sharing options and present sharing clusters were assessed using confidence intervals and hypothesis testing. A 95% confidence level was considered with a p-value of less than 0.05. The signs and magnitudes of correlation coefficients elicited significant relationships between the present shared car ownership behaviour and DC shared ownership propensities regarding DC shared ownership. The correlation analysis did not elicit any significant relationship between DC-shared ridership and present ridesharing behaviour. Therefore, these relations are presented by descriptive statistics, as shown in Figure 5.14.

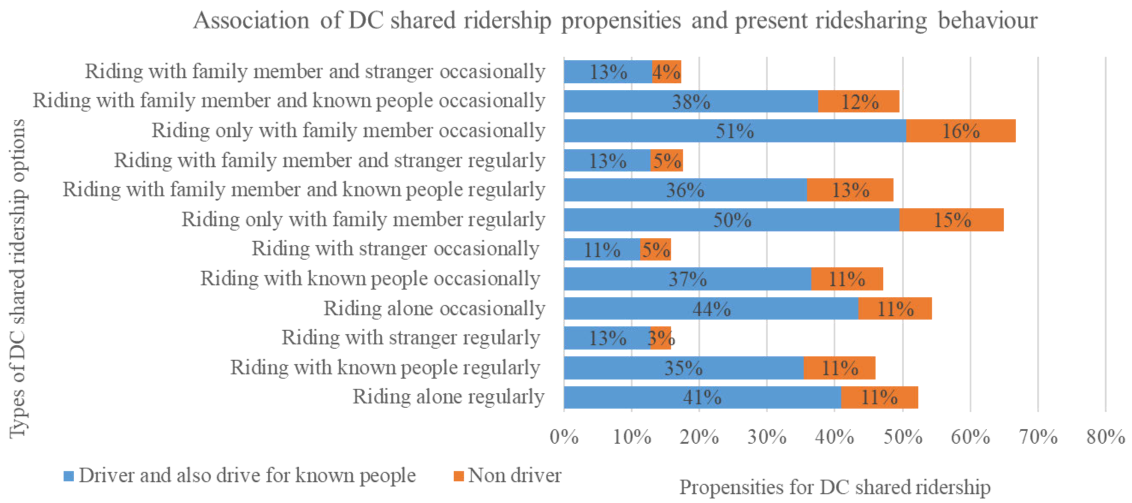


Figure 5.14: Association of DC shared ridership propensities and present ridesharing behaviour

The future propensity of DC shared ridership options is linked with the present ridesharing behaviour, illustrated in Figure 5.14. This figure shows that driving alone or with family is the preferred form of ridesharing with DC, while riding with a stranger is the least. 41% and 44% of the respondents who drive a car are inclined to ride alone with DC regularly and occasionally, compared to 11% of non-drivers who are likely to ride alone. But when their families are accompanied, sharing proportions are likely higher than riding alone (50% and 51%, respectively, for regular and occasional travel). Among non-drivers, the propensities to share the ride with families are 15% and 16% for regular and occasional travel, respectively. These behaviours proved that respondents for this study sample are more interested in sharing their ride in the presence of at least one household member than riding alone. On average, 37% of the car drivers responded to sharing their ride with a known person, compared to only 13% who shared their ride with a stranger. Therefore, the overall scenario suggested that a greater proportion of present car drivers are likely to ride alone and with family members, while non-drivers' proportions in choosing DC are much less.

5.8.2 Carsharing with DC and present carsharing behaviour

Table 5-3 shows the Pearson Correlation results (significance and number of responses - N values) between hypothetical DC-shared ownership choices and respondents' present shared car ownership behaviour. Here, DC-shared ownership choices are recorded on a five-point Likert scale (0-4), and present shared car ownership behaviour is coded in the range of 0-2. In this table, significant findings are shown in red colour.

Table 5-3: Correlation results between present carsharing types and shared ownership preferences with DC

Shared ownership options with DC		Frequent household car user but uses car rental when needed		Infrequent household car user		Frequent household car user but don't use rental cars		N
		Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	
Regular	Private DC	-0.016	.737c	0.191	.000c	-0.172	.000c	430
	Shared ownership DC	-0.037	.435c	0.013	.780c	0.023	.636c	438
	Driverless taxi	-0.151	.002c	0.07	.144c	0.076	.111c	439
Occasional	Private DC	-0.056	.242c	0.201	.000c	-0.143	.003c	435
	Shared ownership DC	-0.077	.109c	-0.025	.598c	0.098	.040c	436
	Driverless taxi	-0.08	.094c	0.055	.249c	0.023	.638c	439

Users who frequently use a household car and do not use car rental services will likely be the least influential for private DC use. The possible reason could be that the propensity to private DC might reduce the tendency to use a conventional car. The magnitude of these negative significance is weak, revealing that this result is based on very few samples, and the change processes may take time. Besides, infrequent household car users' intention for private DC use is significant with a positive magnitude. Due to no driving tasks in DC, many infrequent household car users might be attracted to owning private DC in future. On the contrary, many conventional household car users may give up driving inspired by the on-demand availability of DC. Frequent household car users who like to ride in a rental car may prefer driverless taxis (DT) instead of rental cars, thereby reducing the need for a conventional rental car in the future.

For occasional use, private DC use is most significant among infrequent household car users, while private DC use is least significant among frequent household car users who don't use car rentals. Frequent household car users are attached to their private car use and are unwilling to use private DC. On the other hand, it is more logical for those household car users who drive occasionally and are likely to support private DC use to satisfy their occasional travel needs. Respondents with frequent household car use and not with car rental tendencies correlate significantly for occasional shared DC use, reflecting that people with this type of shared car use behaviour are likely to choose shared DC for their occasional travel.

5.9 Chapter conclusion

This chapter observed the cross-classification analysis with various population segments to comprehensively address the variations in people's perceptions concerning DC preferences and motivations. Behaviour was not necessarily homogenous, and a false homogeneity assumption can lead to biased results.

In order to distinguish between the present shared car ownership and ridesharing groups, a cluster analysis method was applied. The cluster analysis results identified two ridesharing and three shared car ownership groups. These cluster analyses reveal exciting insights into the travel-sharing market based on the frequency and usage types. Aside from representing the current travel share market, they reflect an essential indication of travel-sharing behaviour among the sample of the Edinburgh population. These findings would be equally informative to policymakers, researchers and business providers to better understand the present market challenges to provide alternative ridesharing or carsharing options using DC.

In the subsequent sections, several associations of these clusters were analysed with statistical models to reveal their association with DC adoption options.

Section 5.6 describes the relationships between ridesharing – carsharing clusters and respondents' demography, socio-economic status, ridesharing/carsharing reasons, personality traits and social norms. Socio-demographic (e.g., age, gender, income, household composition, household location, household car ownership) factors, personality, and social norm behaviour are cross-classified with ridesharing and shared car ownership user classes as determinants to identify the users' heterogeneity. The statistical average is considered for each segment, searching the population for heterogeneity.

These one-to-one analyses reflected a linear relationship representing present ridesharing and shared car ownership attitudes. However, this method may not produce effective results in identifying the non-linear effects of the determinants in choosing future ridesharing and shared car ownership behaviour. The effects of these determinants (explanatory variables) in choosing DC shared ownership and ridership differ among respondents according to their user classes. The outcome of this Chapter is given in Table 5-4 showing all three shared car ownership and two shared ridesharing behavioural variables, with their descriptions.

Table 5-4: Variables indicating present travel-sharing characteristics and their proportions

Explanatory Variables	Code	Proportions
Car Driver (1 if the behaviour shows for car driver and who drives with other people, 0 otherwise)	Cd	75.60%
Non-driver (1 if the behaviour shows for a non-driver, 0 otherwise)	Nd	24.40%
Regular car user (1 if the behaviour shows frequent household car user who shares rides sometimes, 0 otherwise)	Vs_fhcr	30.20%
Non-frequent car user (1 if the behaviour is oriented to infrequent household car user, 0 otherwise)	Vs_nhc	33.40%
Frequent household car user (1 if behaviour shows for frequent household car user who doesn't use rideshare, 0 otherwise)	Vs_fhc	36.40%

6. Chapter 6: Modelling shared ownership and ridership with driverless car

6.1 Introduction

This Chapter describes the variables, processes, outputs and discussions of four econometric models associated with answering the research questions. Section 6.2 described the influence of sharing behaviours on the overall propensity towards shared DC options. Section 6.2 models the determinants concerning the likelihood of adopting non-shared and shared DC options through estimating ordered probit models. Section 6.3 described the modelling exercise to identify weak preferences between shared and non-shared uses of DCs. Section 4 described the joint analysis to identify determinants towards non-shared and shared DC options through multinomial logit models. All the facts and figures described in this Chapter are the direct outputs of these discrete choice models with factors determining the shared DC usage possibilities.

6.2 Influence of sharing behaviours on the overall propensity towards shared DC options

Figure 6.1 portrays the complete model development process. The thick-lined rounded rectangles are the main steps for the model development process, along with thin-lined boxes showing the additional steps. The binary-probit model development process is described in Chapter 3. This chapter used the terms 'shared ownership of DC' and 'shared DC ridership' interchangeably.

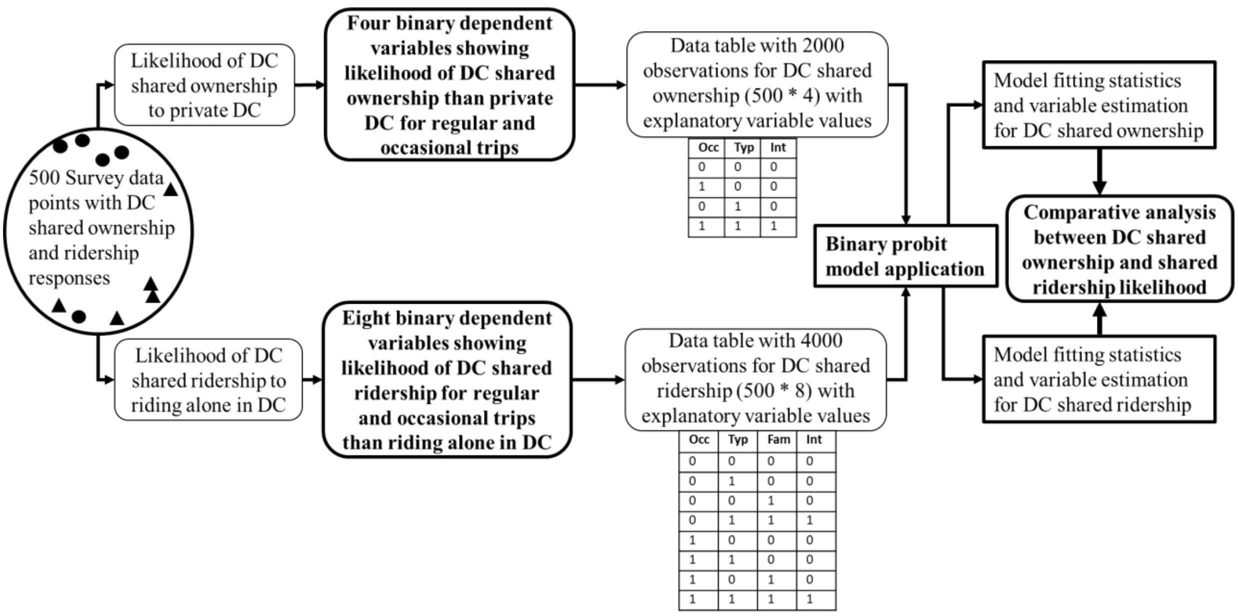


Figure 6.1: JSHOP and JSHARP model development process

Despite some observed correlation between present carsharing and ridesharing behaviour in Chapter 5, factors influencing the future adoption of carsharing and ridesharing with DC use were not addressed. This chapter studies the sharing types (e.g., shared ownership, ridership) and trip frequency (e.g., regular, occasional) to understand respondents' attitudes towards DC shared ownership and ridership in an aggregated way. In line with the research objectives, the aim is to understand how these factors influence DC's shared use intentions (e.g., shared ownership, ridership). Here, aggregation refers to the joint consideration of shared DC use intentions for trips (regular and occasional, with and without family members) and sharing options (private DC, shared owned DC, driverless taxis, riding alone, riding with acquaintances, riding with strangers). A 5-point ordered scale was employed in the main survey questionnaire to measure observed dependent variables concerning the likelihood of accepting DC shared ownership and ridership, as described in Table 6-1 of this chapter.

Two different modelling exercises analysed two binary dependent variables in this chapter. The first variable was built by considering all the responses comparing the likelihood of DC shared ownership (e.g., shared ownership, driverless taxi) to private DC use (Joint Shared Ownership propensity J-SHOP). The second variable compares the likelihood of accepting DC shared readership (e.g., riding with known people, riding with a stranger) and riding alone by DC (Joint Shared Ridership Propensity JSHARP). Overall, in the aggregated models, the binary probit model results were estimated to establish the association of –

- JSHOP, the binary variable (outcome variable) model with DC shared ownership types (*typ*)(e.g., shared owned DC, driverless taxi), trip frequency (*occ*) (e.g., regular, occasional) and interaction terms (*int*) (e.g., driverless taxi use for occasional trips) as explanatory variables
- JSHARP, the binary variable (outcome variable) model with DC shared ridership types (*typ*)(e.g., riding with known people, riding with a stranger), frequency of trip making (*occ*)(e.g., regular, occasional), family members' presence (*fm*)(e.g., with and without family members), and interaction terms (*int*) (e.g., shared ridership with a stranger while a family member is there) as explanatory variables

Both these models use binary probit models with binary explanatory variables to understand each binary explanatory variable's magnitude and direction in explaining respondents' likelihood to accept various DC shared ownership or shared ridership options. Three levels of ownership: (a) private DC (Ow_Pr); (b) shared DC ownership (Ow_Fr); and (c) driverless taxis (Ow_Ta) were considered. Besides, three DC shared ridership options were considered: a) not travelling with anybody else but family members (besides when the trip involves family members) (Ri_A); b) sharing the ride with known people (besides family members, when relevant) ((Ri_K); c) sharing the ride with strangers (and possibly with family members) (Ri_S).

Table 6-1 mentions various DC shared ownership and ridership options along with their acronyms and their acceptance levels from the survey. Respondents' acceptance levels were recorded with a five-point Likert scale (0-4). The normality test was performed to check the skewness of the respondents' acceptance levels for each DC type applying SPSS. Considering some of the levels are skewed more towards '0', the median values were chosen, as they show the perfect middle value for the distribution and can show better reflection of the distribution.

Table 6-1: Data coding for the dependent variables

Dependent variables indicators	Variable name	Minimum (e.g., very unlikely)	Maximum (e.g., very likely)	Median	Standard Deviation
Likelihood of private DC use for regular trips	Ow_Pr_Re	0	4	2.00	1.495
Likelihood of shared-owned DC use for regular trips	Ow_Fr_Re	0	4	1.00	1.003
Likelihood of driverless taxis use for regular trips	Ow_Ta_Re	0	4	2.00	1.331
Likelihood of private DC use for occasional trips	Ow_Pr_Oc	0	4	2.00	1.474
Likelihood of shared-owned DC use for occasional trips	Ow_Fr_Oc	0	4	1.00	1.140
Likelihood of driverless taxis use for occasional trips	Ow_Ta_Oc	0	4	2.00	1.323
Likelihood of riding alone in a DC for regular trips	Ri_ReNF_A	0	4	3.00	1.381
Likelihood of riding with known people in DC for	Ri_ReNF_K	0	4	2.00	1.274
Likelihood of riding with a stranger in DC for regular	Ri_ReNF_S	0	4	1.00	1.108
Likelihood of riding alone in a DC for occasional trips	Ri_OcNF_A	0	4	3.00	1.333
Likelihood of riding with known people in DC for occasional trips	Ri_OcNF_K	0	4	2.00	1.245
Likelihood of riding with a stranger in DC for occasional trips	Ri_OcNF_S	0	4	1.00	1.131

Likelihood of riding in a DC in the presence of a family member for regular trips	Ri_ReWF_A	0	4	3.00	1.314
Likelihood of riding in a DC with known people in the presence of family members	Ri_ReWF_K	0	4	2.00	1.261
Likelihood of riding in a DC with a stranger in the presence of family members	Ri_ReWF_S	0	4	1.00	1.150
Likelihood of riding in a DC in the presence of a family member for occasional trips	Ri_OcWF_A	0	4	3.00	1.289
Likelihood of riding in a DC with known people in the presence of family members	Ri_OcWF_K	0	4	2.00	1.229
Likelihood of riding in a DC with a stranger in the presence of family members	Ri_OcWF_S	0	4	1.00	1.143

Table 6-1 shows that the likelihood of private DC for occasional and regular use is similar, and people showed moderate acceptance levels. The same pattern was observed for the occasional use of shared-owned DC and driverless taxis. By comparing the standard deviation, Table 6.1 reveals that driverless taxis were preferable for occasional use. Despite the least acceptance for the shared-owned DC for regular use, they are more acceptable for occasional use. However, the private DC is preferred over the other two forms of DC. Regarding DC shared ridership, respondents expressed their likelihood to accept riding alone in DC for regular (mean 2.22) and occasional (mean 2.31) trips.

In contrast, people enjoy riding with only family members for regular (mean 2.58) and occasional (2.51) trips. Respondents' feelings about DC ridesharing are negative towards sharing the ride with strangers for regular (mean 1.22) and occasional (mean 1.26) trips. In sharing the ride with known people while family members were present, respondents showed more positive affirmation for regular (mean 2.16) than occasional (mean 2.10) trips. In a stranger's presence, the DC ridesharing behaviour will be almost half what is observed for sharing with known people. So, the responses were skewed towards negative for both regular and occasional trips. These median values of the responses were counted in absolute values based on 500 samples without missing values.

Overall results from Table 6-1 show that besides preferences for riding alone, respondents were more inclined to share their ride in the presence of at least one member of their family or known people. Respondents expressed their negative feelings about riding with a stranger.

6.2.1 The shared ownership propensity model – JSHOP

Variable specification for the JSHOP model

In the first stage, the binary dependent variable JSHOP was built, which refers to the likelihood of accepting the shared use of DC rather than private DC use. In the survey questionnaire, the likelihood of shared DC ownership was assessed on a five-point Likert scale (e.g., Very unlikely to Very likely) by three types of shared DC ownership types, as stated below:

- Private DC (Ow_Pr)
- Shared ownership with DC (Ow_Fr)
- DV taxi service (Ow_Ta)

Each respondent was counted 4 times by 4 entries of the variables by applying equation (1) below to form the JSHOP model estimation variable. By equation (1), the coding principles of the JSHOP binary dependent variable were described.

$$JSHOP_{Ji} = \begin{cases} 1 \; if \; VarSh_{J,i} \geq \; VarPr_{J,i} \\ 0 \; if \; if \; VarSh_{J,i} < \; VarPr_{J,i} \end{cases} \quad \ldots\ldots(1)$$

Where $JSHOP_{Ji}$ is the *j*th entry for the respondent *i* accepting shared DC ownership, $VarSh_{J,i}$ represents the variables concerning the shared ownership options and $VarPr_{J,i}$ to private ownership of DC. For respondent *i*, four pairs of $VarSh_J$ and $VarPr_J$ are considered mentioned by the codes below:

- *J=1:* $VarSh_J$*=OW_Fr_Re,* $VarPr_J$*=OW_Pr_Re*
- *J=2 :* $VarSh_J$*=OW_Ta_Re,* $VarPr_J$*=OW_ Pr _Re*
- *J=3:* $VarSh_J$*=OW_Fr_Occ,* $VarPr_J$*=OW_Pr_Oc*
- *J=4 :* $VarSh_J$*=OW_Ta_Occ,* $VarPr_J$*=OW_ Pr _Oc*

The survey questionnaire collected the potential likelihood of DC shared ownership propensities with a five-point Likert scale (e.g., very unlikely - very likely) as described in Table 6-1. For instance, if the Ow_Ta_Re response was 3 and Ow_Pr_Re response was 2, the acceptance of Ow_Ta_Re than Ow_Pr_Re was coded as ‘1’. All other lower responses for Ow_Ta_Re to Ow_Pr_Re were coded to ‘0’. Therefore, $JSHOP_{Ji}$ expresses the existence of a stronger preference for a shared DC ownership option than for a private DC.

Table 6-2 illustrates the coding approach for the independent variables in the JSHOP model. Therefore, the JSHOP model counts four observations for each participant, corresponding to the likelihood of adopting shared-owned DC (Ow_Fr) use and driverless taxi (OW_Ta) use over private DC (Ow_Pr) use for regular and occasional trips. So, the JSHOP model utilised 2,000 binary observations (4 observations per participant x 500 participants) to the likelihood of DC shared ownership (e.g., shared ownership, driverless taxi) over the private DC use.

Table 6-2: Variable definition for the JSHOP model

Considered alternatives	JSHOP coding	Explanatory variables code		
		Occasional trip: Occ = 1 if an occasional trip, 0 if regular	Ownership type: Typ = 1 if driverless taxi, 0 if fractionally owned DC	Interaction: taxi for occasional trips (Int)
Fractionally owned DC weakly preferred to private DC for regular trips	JSHOP = 1 if Ow_Fr_Re ≥ Ow_Pr_Re, 0 otherwise	0	0	0
Fractionally owned DC weakly preferred to private DC for occasional trips	JSHOP = 1 if Ow_Fr_Oc ≥ Ow_Pr_Oc, 0 otherwise	1	0	0
Driverless taxis weakly preferred to private DC for regular trips	JSHOP = 1 if Ow_Ta_Re ≥ Ow_Ta_Re, 0 otherwise	0	1	0
Driverless taxis weakly preferred to private DC for occasional trips	JHSOP = 1 if Ow_Ta_Oc ≥ Ow_Ta_Oc, 0 otherwise	1	1	1

Dependent variables for the JSHOP model

This JSHOP model has three explanatory variables mentioned in Table 6-3. Variables that define trip characteristics, and the level of sharing are explanatory, while JSHOP is the binary dependent variable.

Table 6-3: Explanatory variables and their descriptions for the JSHOP model

Explanatory variables	Coefficients (β)	Reference value
Occasional travel (1 if occasional travel, 0 regular)	$\boldsymbol{\beta}_{\mathbf{occ}}$	0, regular travel
Shared ownership types (1 if driverless taxi, 0 if shared-owned)	$\boldsymbol{\beta}_{\mathbf{typ}}$	0, fractionally-owned DC use

Taxi use for occasional trips (1 if occasional driverless taxi use, 0 otherwise)	β_{int}	0, other than occasional driverless taxi use

Descriptive statistics of dependent variables concerning the JSHOP model

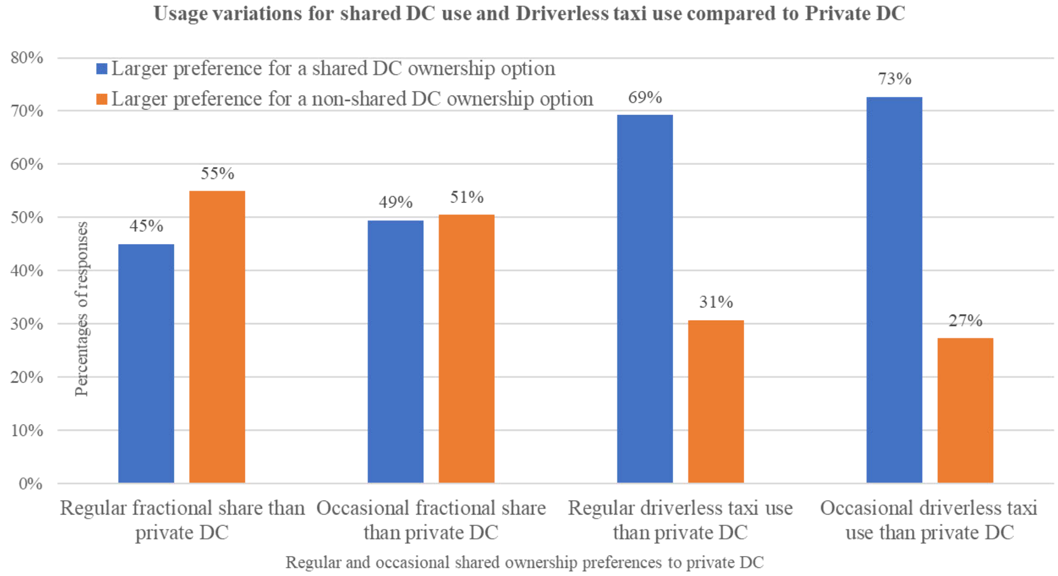


Figure 6.2: Variations in the likelihood of DC shared ownership than DC private ownership

The descriptive representation summarises the likelihood of DC shared ownership adoption to non-shared DC use. 45% of respondents showed the likelihood of preferring shared or shared ownership (Ow_Fr_Re) to private DC (Ow_Pr_Re) for regular urban trips, whereas, in terms of occasional DC use, this percentage is 49%. 69% of the respondents showed a likelihood for the driverless taxi (Ow_Ta_Re) use for regular trips (Ow_Pr_Re) compared to 73% for occasional trips. These findings proved that driverless taxis are more popular than shared owned DC, or people are more familiar with driverless taxis in shared DC. Respondents' likelihood of DC shared ownership is higher for occasional trips than regular trips.

Binary probit model specification and overall method of JSHOP and JSHARP model

For the JSHOP model, the specification of the binary probit model can be expressed as:

$$Y^*_{JSHOP} = \beta_{occ}{*}occ + \beta_{typ}{*}typ + \beta_{int}{*}int + \varepsilon_1 \quad (2)$$

Where Y^*_{JSHOP} is the binary variable with '1' belonging to the likelihood of DC shared ownership to private DC and '0' otherwise for a respondent i and $i = 1, 2, \ldots 500$; occ and β_{occ} are the signs denoting occasional trips variable (occasional, regular) and its coefficient values, respectively; typ and β_{typ} are ±signs to denote shared ownership types (shared ownership and driverless taxi) and their coefficient values, respectively; int and β_{int} are ±signs to denote the interaction types (occasional use of a driverless taxi, others) and their coefficient values, respectively. ε_1 denotes the error term following a standard normal distribution. The complete modelling method of the binary probit model is described in Chapter 3.

Model estimation results for the JSHOP model – Model fitting statistics for the JSHOP model

A likelihood ratio test was performed to test the null hypothesis that all coefficient estimates except the error term are zero. In line with this, the chi-square value is 111.96 [χ^2 *(3) =111.96, p<0.001*], which indicates the null hypothesis can be rejected and the alternative hypothesis can be accepted. The value of *p* significantly improves the final and base models. The model estimation results are shown in Table 6-4.

Table 6-4: Model estimation results for the JSHOP model

JSHOP model variable estimations		
Explanatory variables	Coefficient	t-ratio
ε_1	-0.125	-2.140
Occasional travel (1 if occasional travel, 0 regular)	0.112	1.354
Shared ownership types (1 if driverless taxi, 0 if shared owned)	0.628	7.433
Interaction of occasional taxi use for occasional trips (1 if occasional driverless taxi use, 0 otherwise)	-0.012	-0.101
JSHOP model fitting statistics		
Final model log-likelihood (**β**,μ)	-1195.66	
Base model log-likelihood (**c**,μ)	-1251.64	
Chi-square χ^2	111.96	
Significance, ρ	< 0.001	
$R^2_{Mcfadden}$	0.0447	
Degrees of freedom, df	3	
Number of observations, N	1850	

Discussion on JSHOP model findings

The error term concerning the JSHOP model shown in Table 6-4 is the intercept of the dependent variable. The error term is significant for the JSHOP model, with a negative sign implying a greater inclination of respondents for private DC than shared ownership of DC (e.g., shared ownership, driverless taxi). Trip frequency does not significantly differentiate between shared and private use of DC. But driverless taxi use significantly affects sharing choices, and Driverless taxi preference decreases if the trip is occasional.

As shown in the following paragraphs concerning coefficient estimates for the explanatory variables, a positive significant coefficient is likely to increase the probability of preference levels (e.g., likely, very likely). The opposite effects might be possible for the significantly negative coefficient estimates where values increase for one preference and decrease for the other preference levels.

1. Trip frequency is insignificant in explaining the shared use of DC over private DC.

2. For the interaction variable concerning driverless taxi use for occasional travel, the insignificant result proved the lack of association of this variable in deciding shared ownership with DC to private DC. The negative sign indicated a lack of preference for driverless taxis to private DC for occasional trips in an urban context. Respondents are likely to accept driverless taxis for their regular urban trips.

3. The model results proved that sharing types are essential variables in deciding shared DC use, where the likelihood of driverless taxi use is dominant. This behaviour revealed that driverless taxis would be the likely alternative to the private DC, while shared-owned DC would have the least popular market share. The occasional sharing and occasional driverless taxi use are not significant factors in deciding sharing preferences with DC, and these behavioural associations can predict the demand for regular driverless taxi use compared to private DC use.

6.2.2 Shared ridership propensity model - JSHARP

Variable specification for the JSHARP model

The second variable, JSHARP, corresponds to the greater or indifferent likelihood of accepting DC shared ridership than riding alone by DC and is expressed by eight levels of variations, as stated below. From the survey questionnaire data, DC shared ridership (RS) is assessed by three DC modes with a five-point Likert scale (e.g., very unlikely - very likely), as stated below:

- Ride alone (Ri_A)
- Ride with known people (Ri_K)
- Ride with a stranger (Ri_S)

Each response for DC shared ridership was counted 8 times by 8 response entries applying equation (3) below to form the JSHARP variable. By equation (3), the coding principles of the JSHARP binary dependent variable were described, as mentioned below –

$$JSHARP_{Ji} = \begin{cases} 1 \; if \; VarSh_{J,i} \geq VarRi_{J,i} \\ 0 \; if \; if \; VarSh_{J,i} < VarRi_{J,i} \end{cases} \quad \text{......(3)}$$

Where $JSHARP_{Ji}$ is the *j*-th entry for the respondent *i* accepting shared DC ridership, $VarSh_{J,i} \geq VarRi_{J,i}$ refers to a weak propensity to accept shared ridership of DC than riding alone in DC, as presented by $VarSh_{J}$ $[VarRi_{J,i}]$. Equation (3) translates the outcome of this relation to '1' for the likelihood of accepting DC shared ridership '0' for not accepting. For respondent *i*, eight pairs of $VarSh_{J,i}$ and $VarRi_{J,i}$ are considered mentioned by the codes below:

- J = 1: $VarSh_J$ = Ri_ReNF_K, $VarRi_{J,i}$ = Ri_ReNF_A
- J = 2: $VarSh_J$ = Ri_ReNF_S, $VarRi_{J,i}$ = Ri_ReNF_A
- J = 3: $VarSh_J$ = Ri_ReWF_K,$VarRi_{J,i}$ = Ri_ReWF_A
- J = 4: $VarSh_J$ = Ri_ReWF_S, $VarRi_{J,i}$ = Ri_ReWF_A
- J = 5: $VarSh_J$ = Ri_OcNF_K, $VarRi_{J,i}$ = Ri_OcNF_A
- J = 6: $VarSh_J$ = Ri_OcNF_S, $VarRi_{J,i}$ = Ri_OcNF_A
- J = 7: $VarSh_J$ = Ri_OcWF_K, $VarRi_{J,i}$ = Ri_OcWF_A
- J = 8: $VarSh_J$ = Ri_OcWF_S, $VarRi_{J,i}$ = Ri_OcWF_A

The variable indicates the respondent does not prefer to ride alone to riding with known people (Ri_ReNF_K) and riding with a stranger (e.g., Ri_ReNF_S) than riding alone in a DC. By applying equation (3), these codes were counted in the binary order model shown in Table 6-5. Therefore, the JSHARP model utilised 4,000 observations (8 per participant x 500 participants) to explain the likelihood of accepting shared ridership with DC rather than riding alone.

The survey questionnaire collected the potential likelihood of shared DC ridership with a five-point Likert scale (e.g., very unlikely - very likely). DC shared ridership options were taken pairwise to form 8 binary dependent variables per respondent. Applying the coding principle in equation (7) above, the higher and indifferent responses concerning riding with a known person and riding alone were coded '1' and '0' otherwise. For instance, if the Ri_ReNF_K response was 3 and the Ri_ReNF_A response was 2, the acceptance of Ri_ReNF_K to Ri_ReNF_A was coded as '1'. All other responses were coded as '0'. These data selection and binary coding methods were repeated for all eight shared ridership pairs, as in Table 6-5.

Table 6-5: Dependent variables for the JSHARP models and data coding principles

Considered alternatives	JSHARP coding	Explanatory variables code			
		Occasional trip: occ = 1 if an occasional trip, 0 if regular	Ridership type: typ = 1 if with a stranger, 0 with known people	Presence of a family member: fam = 1 if involving a family member, 0 otherwise	Interaction: int = 1 if sharing with a stranger in the presence of a family member, 0 otherwise
Sharing a ride with known people weakly	JSHARP = 1 if Ri_ReNF_K ≥	0	0	0	0

preferred to travel alone on a regular trip, not including family members	Ri_ReNF_A, 0 otherwise				
Sharing a ride with a stranger weakly preferred to travel alone on a regular trip, not including family members	JSHARP = 1 if Ri_ReNF_S ≥ Ri_ReNF_A, 0 otherwise	0	1	0	0
Sharing a ride with known people weakly preferred to travel alone on a regular trip including family members	JSHARP = 1 if Ri_ReWF_K ≥ Ri_ReWF_A, 0 otherwise	0	0	1	0
Sharing a ride with a stranger weakly preferred to travel alone on a regular trip including family members	JSHARP = 1 if Ri_ReWF_S ≥ Ri_ReWF_A, 0 otherwise	0	1	1	1
Sharing a ride with known people weakly preferred to travel alone on an occasional trip, not including family members	JSHARP = 1 if Ri_OcNF_K ≥ Ri_OcNF_A, 0 otherwise	1	0	0	0
Sharing a ride with a stranger weakly preferred to travel alone on an occasional trip, not including family members	JSHARP = 1 if Ri_OcNF_S ≥ Ri_OcNF_A, 0 otherwise	1	1	0	0
Sharing a ride with known people weakly preferred to travel alone on an occasional trip including family members	1 if Ri_OcWF_K ≥ Ri_OcWF_A, 0 otherwise	1	0	1	0
Sharing a ride with a stranger weakly preferred to travel alone on an occasional trip including family members	JSHARP = 1 if Ri_OcWF_S ≥ Ri_OcWF_A, 0 otherwise	1	1	1	1

Independent variable description for the JSHARP model

Explanatory variables for the JSHARP model were travel frequency, sharing types (with a stranger, a known person), family members' presence (with or without) in sharing, and interaction type (travel with a stranger in the presence of a family member or not) for both regular and occasional trips mentioned in Table 6-6. Variables that define the JSHARP model are binary. This modelling process considers a reference variable for each explanatory variable to adjust the coefficient of variables. The dependent variable in the JSHARP model is the weak preferences for accepting shared ridership than riding alone by DC (coded 1 = likelihood of accepting, 0 = likelihood of not accepting), where the "likelihood of not accepting" is the reference (baseline) category and the "likelihood of accepting" is the target category. Four explanatory variables in the JSHARP model are binary: frequency of travel ('occ', coded 0 = Regular, 1= Occasional travel; rideshare types ('type', coded 1 = riding with a stranger, 0 = riding with known people; 'presence of family members ('fam', coded 1= rideshare with family, 0 = rideshare without family); interaction type to refer sharing with a stranger in the presence of family members ('int', coded 1 = sharing with a stranger in the presence of a family member, 0 = otherwise). The reference category for all these explanatory variables is 0, and a list of reference variables is given in the final column of Table 6-6.

Table 6-6: Explanatory variables for the JSHARP models

Explanatory variables for the JSHARP model	***Coefficients (β)***	***Reference value***
Frequency of travel (Occ) (1 if occasional, 0 regular)	$\boldsymbol{\beta_{occ}}$	0, regular travel
Ridership types (Typ) (1 if choosing to ridesharing with a stranger, 0 if ridesharing with known people)	$\boldsymbol{\beta_{typ}}$	0, ridesharing with known people
Presence of family member (Fam) (1 if with choosing to share the ride with a family member, 0 without a family member)	$\boldsymbol{\beta_{fam}}$	0, rideshare without a family member
Interaction type defining shared ridership with a stranger in the presence of a family member (int) (1 if sharing with a stranger in the presence of a family member, 0 otherwise)	$\boldsymbol{\beta_{int}}$	0, other than sharing the ride with a stranger in the presence of a family member

Table 6-6 shows the relations of JSHARP variables with their explanatory variables. These values form the input dataset for the JSHARP model. Overall, the DC shared ridership model intended to measure three constructs like the following:

1. Travel frequency effects in choosing shared ridership to ride alone with DC
2. The effects of shared ridership types on riding alone with DC
3. The effect of the presence of family members on shared ridership with DC

4. The interaction of shared ridership with DC with a stranger in the presence of a family member

JSHARP model's explanatory variables are assessed against a priory hypothesis. The priory hypothesis helped establish the possible association of the JSHARP variable with its explanatory variables, and Table 6-7 defines these hypotheses.

Table 6-7: Prior hypothesis concerning shared ridership with DC

Explanatory variables for the JSHARP model	Reasons for the hypothesis	Expected relationship of hypothesis with the model outcome
Frequency of travel (1 if occasional, 0 regular)	People who travel regularly are more likely to ride alone in a household car. So, their propensity to share the ride with DC on an occasional basis would be highly likely.	Riding with others in a DC will be higher for occasional trips.
Ridership types (1 if choosing to ridesharing with a stranger, 0 if ridesharing with known people)	The preliminary assumption was to adopt the DC for riding alone. The JSHARP model tried to understand the propensity of sharing the ride in DC with known people and with a stranger.	DC ridesharing is preferred in the presence of known people.
Presence of family members (1 if choosing to share the ride with a family member, 0 without a family member)	People who are willing to share are more inclined to share the ride with their family members.	Ridership of DC is preferred with a family member than without a family member.
Interaction type defining shared ridership with a stranger in the presence of a family member (1 if sharing is preferred with a stranger in the presence of a family member, 0 otherwise)	People are most likely to share the ride with their close contacts while their family members share. Taking this as the base scenario, the JSHARP model tries to understand the interaction for the presence of a stranger in DC ridesharing along with their family members.	People are most likely to share the ride with known people when family members share DC.

Descriptive statistics of dependent variable concerning the JSHOP model

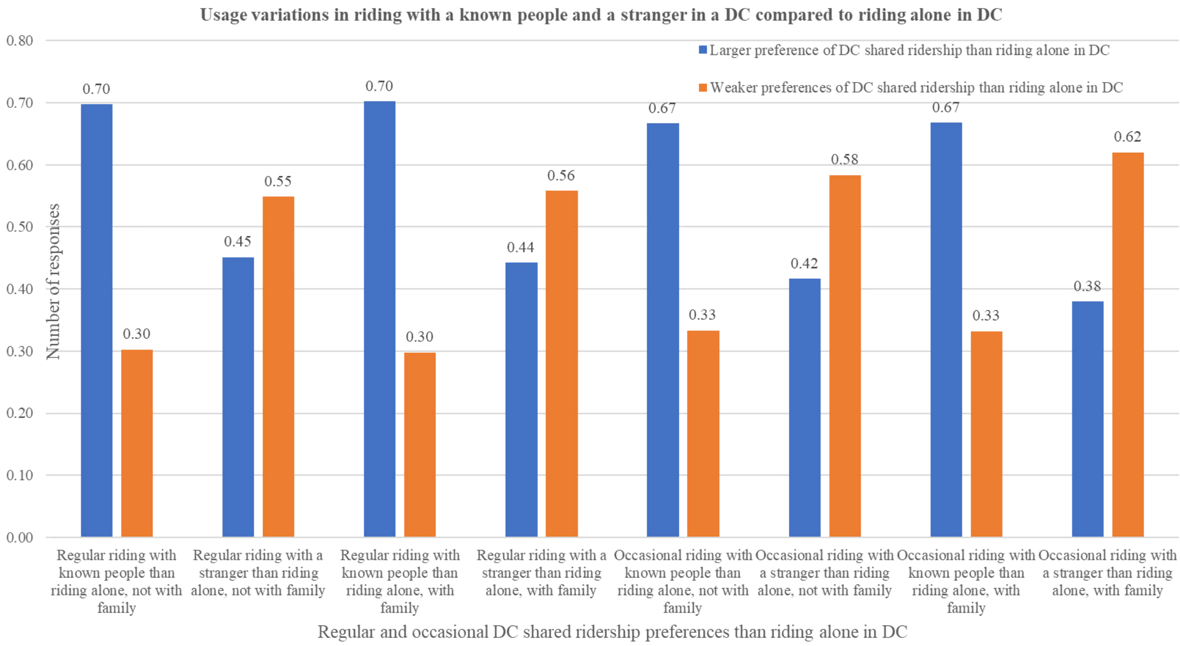


Figure 6.3: Proportions of larger and weaker preferences for shared ridership with known people and with a stranger than riding alone in DC

The JSHARP model has resulted in eight preference cases described in Table 6-3. It is apparent that on average, without a family member present, 68% of respondents expressed their higher and indifferent likelihood for a shared ride with a known people than to ride alone in DC, while 42% of them are higher and indifferently likely to share their ride with a stranger than to ride alone in DC for regular trips. The higher and indifferent likelihood of accepting DC shared ridership than riding alone in DC proved to have the same variations for regular and occasional trips. Riding with a stranger in the family member's presence in DC and shared ridership followed a similar sharing pattern as without a family member.

Binary probit model specification associated with JSHARP

The JSHARP model includes sharing regularity, sharing types, family members' presence, and interaction types as explanatory variables. Mathematically, the JSHARP model can be written by the following equation (4).

$Y^*_{JSHARP} = \boldsymbol{\beta}_{occ} * occ + \boldsymbol{\beta}_{typ} * typ + \boldsymbol{\beta}_{fam} * fam + \boldsymbol{\beta}_{int} * int + \varepsilon_2$..(4)

Where Y^*_{JSHARP} is the binary variable with '1' belonging to the higher and indifferent likelihood of DC shared ridership to riding alone in DC and '0' otherwise for a particular respondent *i* and *i = 1, 2,.........500;* occ and $\boldsymbol{\beta}_{occ}$, are ±signs denoting occasional travel variable (occasional, regular) and its coefficient value, respectively; typ and $\boldsymbol{\beta}_{typ}$, are ±signs to denote shared ridership types (likelihood of sharing with a stranger, sharing with a known person with DC) and its coefficient value, respectively; fam and $\boldsymbol{\beta}_{fam}$, are ±signs to denote the presence of a family member in sharing (with and without family in sharing DC) and its coefficient value, respectively; and *int and* $\boldsymbol{\beta}_{int}$**,** are ±signs to denote the interaction types (interaction type defining shared ridership in a DC with a stranger in the presence of a family member) and its coefficient value. ε_2 denotes the error term following a standard normal distribution. The method of binary probit modelling method is described in Chapter 3.

Model estimation results for the JSHARP model

Model fitting statistics for the JSHARP model

Table 6-8 summarises the JSHARP model estimation results, including the base and the final model log-likelihood. A likelihood ratio test was performed to test the null hypothesis that all coefficient estimates except the error term are zero. The chi-square χ^2 (4) = 267.57 indicated that the null hypothesis could be rejected and the alternative hypothesis could be accepted. P-value proved significant model improvement in the final model to the base model. Besides, the value of $R^2_{Mcfadden}$ is 0.0523, implying that the model fits the variables used in model development.

Table 6-8: Model estimation results for the JSHARP model

JSHARP model variable estimations		
Explanatory variables	Coefficient	t-ratio
ε_2	0.528	11.025
Travel frequency (1 if occasional, 0 regular)	-0.108	-2.566
Ridership types (1 if the likelihood indicates the shared ridership preference with a strange, 0 if the likelihood indicates shared ridership preference with a known people)	-0.641	-10.767
Presence of family member (1 if with choose to share the ride with a family member, 0 without a family member)	0.009	0.143
Interaction type defining shared ridership with a stranger in the presence of a family member (1 if sharing with a stranger in the presence of a family member, 0 otherwise)	-0.067	-0.797
JSHARP model fitting statistics		
Final model log-likelihood ($\boldsymbol{\beta}$,μ)	-2425.59	
Base model log-likelihood ($\mathbf{c}$,μ)	-2559.38	
Chi-square χ^2	267.57	
Significance, ρ	0.0000	
$R^2_{Mcfadden}$	0.0523	
Degrees of freedom, df	4	
Number of observations, N	3723	

Discussion on JSHARP model findings

The significant error-term value (as shown in Table 6-8) for the JSHARP model indicates the higher and indifferent preference for the DC shared ridership to riding alone in DC. The following paragraphs describe the estimated coefficients with their magnitudes and signs:

1. In the JSHARP model findings, the trip frequency was significant with a negative coefficient estimate. This finding indicates that respondents showed a higher and indifferent likelihood of deciding on the DC shared ridership for regular trips than riding alone, and riding alone in DC for regular trips is less likely.

2. Model results proved the 'Ridership types are a significant explanatory variable. This explanatory variable has two values: sharing with a stranger and with known people. This model result implies respondents are not likely to choose a stranger in the DC shared ridership considering sharing with a known people as a reference. Instead, respondents are comfortable riding with their close contacts.

3. The explanatory variables' presence of a family member in DC sharing is insignificant in deciding DC shared ridership to ride alone. The positive sign proved that respondents showed their determination to share the ride with a family member than without a family member. Nevertheless, this variable estimate showed lower Significance and value. So, it can be inferred from this result that respondents showed the mindset to share the ride with known people rather than any third person outside their close contacts.

4. The explanatory variable concerning the interaction types defining shared ridership with a stranger in a family member’s presence is insignificant in explaining DC shared ridership likelihood to private DC. The preferences for DC shared ridership with a family member decrease if the trip is likely to happen with a stranger.

5. By comparing the sign and magnitude of the coefficient concerning the JSHARP model, the priority of explanatory variables can be justified concerning the higher and indifferent likelihood of DC shared ridership to riding alone in DC. The occasional travel behaviour and sharing types are guiding factors in deciding DC shared ridership. Variables concerning the 'presence of family in ridesharing and 'interaction type defining shared ridership with a stranger in the presence of a family member are less influential factors in deciding the likelihood of shared ridership with DC. Overall, respondents agreed to support the idea of shared ridership with DC if their close contacts accompany them in making regular trips.

6.2.3 Comparative analysis of JSHOP and JSHARP model results

Shared ownership preferences by the JSHOP model

The theoretical links between explanatory variables and model outcome are assessed in Table 6-9, with a priory hypothesis concerning the adoption of DC shared ownership. Respondents showed their likelihood for regular trips with shared used DC with a moderate acceptance level. This result indicated the shared usage propensity of DC in the context of a medium-sized European city like Edinburgh.

Table 6-9: Validation of priory hypothesis concerning explanatory variables of DC shared ownership by JSHOP model estimation

Explanatory variables	Expected relationship of hypothesis with the model outcome	Model outcome
Occasional travel (1 if occasional travel, 0 regular)	Shared-owned DC use for regular travel will be expected in future	Occasional use of shared DC is not very appreciated among the respondents
Shared ownership types (1 if driverless taxi, 0 if shared-owned)	Private DC use will be higher than shared use of DC	Despite private DC use will be dominant, for shared use of DC, driverless taxi use is preferred over shared-owned DC
Interaction of occasional taxi use for occasional trips (1 if occasional driverless taxi	Driverless taxi use will be prioritised for occasional trips	Occasional use of driverless taxis will be less likely than the priority of other forms of DC sharing

The primary idea is that private use of DC is a very likely scenario than shared ownership of DC. The JSHOP model outcome indicated a higher likelihood of accepting driverless taxis. That is logical enough to say that driverless taxis can be the preferred option in prioritising shared ownership with DC. However, due to very high Significance, variable findings can be conclusive in establishing driverless taxi use as an alternative to private DC use. So, the hypothesis stated in Table 6-9 proved to be justified in the case of driverless taxi use.

As stated in Table 6-9, the occasional driverless taxi use interaction was not preferred in DC shared ridership preferences. The insignificant model result proved that respondents are not likely to accept DC shared ownership to private DC when they make occasional trips. This result also proved a higher inclination toward driverless taxi use for regular trips.

Shared ridership preferences by the JSHARP model

Applying a priory hypothesis concerning DC shared ridership adoption, the theoretical relationships between explanatory variables and model outcomes are assessed in Table 6-10. The results revealed from the JSHARP model proved that DC shared ridership intention is practical if respondents prefer it for their regular trips, and this result rejects the hypothesis between occasional travel and DC shared ridership preferences based on the model calibration.

Table 6-10: Validation of priory hypothesis concerning explanatory variables of DC shared ownership by JSHARP model estimation

Explanatory variables	Expected relationship of hypothesis with the model outcome	Model outcome
Occasional travel (1 if occasional, 0 regular)	Riding with others in a DC will be higher for occasional trips	DC shared ridership likelihood will be significantly higher for regular trips
Ridership types (1 if the likelihood indicates the shared ridership preference with a strange, 0 if the likelihood indicates shared ridership preference with a known people)	DC ridesharing is preferred in the presence of known people	DC Shared ridership with a stranger is less preferred than riding alone with DC
Presence of family member (1 if choosing to share the ride with a family member, 0 without a family member)	Shared ridership of DC is preferred with a family member than without a family member.	The model predicts a less significant likelihood of DC shared ridership with family members.
Interaction type defining shared ridership with a stranger in the presence of a family member (1 if sharing with a stranger in the presence of a family member, 0 otherwise)	People are most likely to share the ride with known people when family members are sharing DC.	DC shared ridership likelihood with a family member is preferred in the presence of known people.

The ridership types' explanatory variable assessed the likelihood of DC sharing ridership with a stranger and a known person. The model results showed higher acceptability for DC shared ridership with known people and accepted the priory hypothesis. Therefore, regarding shared ridership with DC, a stranger is less acceptable as a sharing partner.

In line with the priory hypothesis, DC shared ridership propensity in family members' presence was assessed positively with a lower level of importance than sharing the ride without a family member. So, this explanatory variable cannot explain the higher acceptability of DC shared ridership than riding alone in DC.

Regarding the interaction variable defining DC shared ridership preference with a stranger in a family member’s presence, the prior hypothesis accepts a sharing with a known person. The JSHARP model estimation results accept this hypothesis with a less important result means this variable is strong enough to explain the DC shared ridership likelihood to private DC.

Comparison of factors for JSHOP and JSHARP model

JSHOP and JSHARP models yielded opposite estimates for error terms, trip frequency and sharing types, as depicted in Figure 6.4. The JSHOP model results revealed less likelihood for DC shared ownership than a higher likelihood for the DC shared ridership for regular urban trips. LIMDEP software output relating to JSHOP and JSHARP, model estimation results, are given in Appendix H.

The JSHOP model predicted that trip frequency (e.g., regular, occasional) is not crucial in deciding respondents' likelihood of accepting DC shared ownership. On the other hand, the JSAHRP model revealed that respondents are more likely to accept DC-shared ridership for their regular urban trips.

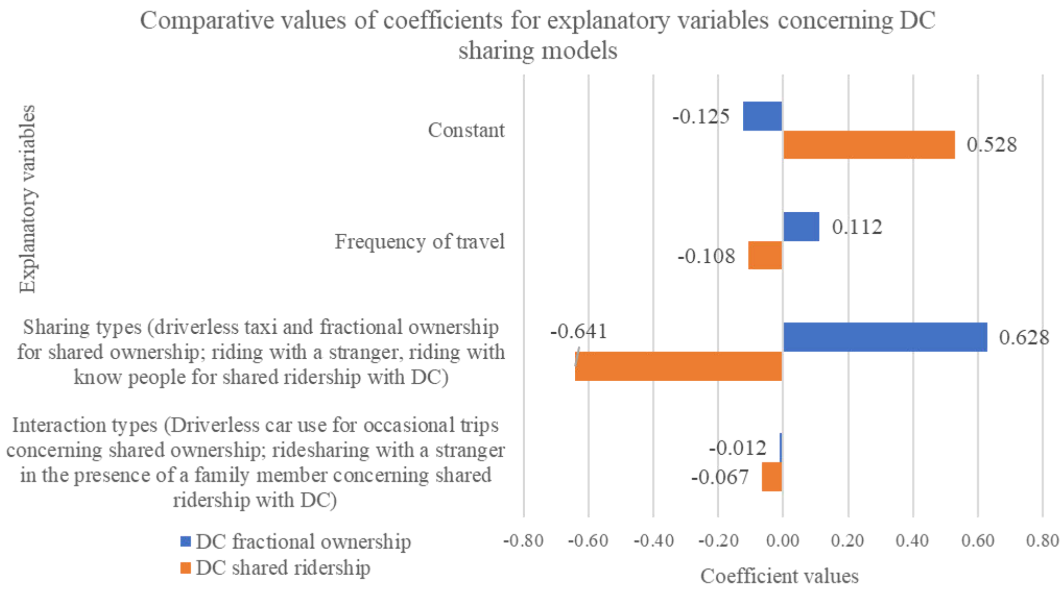


Figure 6.4: Comparative values of coefficients for explanatory variables concerning DC shared ownership (JSHOP) and shared ridership (JSHARP)

For the JSHOP and JSHARP models, sharing type is the crucial variable to explain shared DC use likelihood. Driverless taxi use is highly acceptable in deciding on DC shared ownership, and in contrast, riding with a known person is highly acceptable in deciding on DC shared ridership. These results reflect that sharing partners are pivotal in deciding between DC shared ownership and shared ridership. The propensity to share with a stranger is more in shared ownership, as it is highly likely driverless taxi will be shared with an unknown partner (a stranger). Respondents are more likely to share their rides with their close contacts for DC shared ridership.

Both for JSHOP and JSHARP models, interaction variables have less explanatory power to explain DC shared ownership (Driverless car use for occasional trips) and shared ridership (ridesharing with a stranger in the presence of a family member). The JSHOP model result revealed less likelihood of driverless taxi use for occasional trips. On the other hand, the JSHARP model result reflects the lower likelihood of shared ridership with a stranger in a family member's presence.

6.2.4 Conclusion about overall propensity towards shared DC options

Section 6.1 envisaged the likelihood of shared DC (e.g., DC shared ownership and shared ridership) use to private DC by applying a binary probit method. The common factors concerning DC shared ownership and ridership by models were explored. Also, data described in this chapter were collected from the Scottish city of Edinburgh, where car clubs are an essential feature of city-wide shared car ownership and ridership initiatives. Recent findings highlighted the uprising figure of carshare tendency with a long-standing contribution to Edinburgh's travel share (CarPlus, 2018).

The shared ownership model (JSHOP) proved that driverless taxi is likely a more popular DC-sharing option for regular urban trips than shared-owned DCs. This result suggests propensities for driverless taxi usage as an alternative to private DC. The descriptive analysis also showed a higher interest in driverless taxi use than in shared-owned DC regarding DC shared ownership. To this finding, research forecasted replacing ten conventionally driven cars with one driverless taxi (Bischoff and Maciejewski, 2016). A driverless taxi can be synonymous with shared DC use discussed in recent findings (Liu *et al.*, 2020; Dandl and Bogenberger, 2019), where their use was forecasted as the likely alternative to present ridesharing options.

The shared ridership model (JSHARP) results proved that riding with a known person is preferred to riding with a stranger. Besides, shared ridership supports regular trip-making behaviour. A study by Boston Consulting Group supports these findings relating to sharing DC with a stranger (Boston Consulting Group, 2016). This study found that only 37% of respondents chose a driverless taxi ride with a stranger. However, gender and age divide played a significant role in deciding the sharing proven by this study. Younger people (under 30 years of age) were more (45%) willing to share their ride with a stranger compared to (22%) of older people (over 50 years of age) who were less willing to share their ride with a stranger.

Concerning the sharing partner and trip frequency, the present study provides insight into DC shared ownership and ridership**.** While the willingness to share with a stranger is a factor in deciding DC shared ridership, the present research indicated a preference for shared ridership with close contacts. Trip frequency is less important in explaining DC shared ownership preference than DC shared ridership, and respondents are more inclined to use driverless taxis for regular trips. On the contrary, sharing with a known person is a good reason to choose DC-shared ridership for regular urban trips. Within the literature, trip-sharing regularity is also a factor in accessing carsharing and ride-sourcing behaviour (Dias *et al.*, 2017).

Despite discrepancies, these model results confirmed the priory hypothesis for each explanatory factor associated with DC shared ownership and ridership. Proper policy measures considering these factors can enhance the sharing tendency in both market segments (e.g., DC shared ownership, ridership) (Firnkorn and Müller, 2012; C. Wang *et al.*, 2020). In support of the policy measures, one study by Spieser *et al.* (2014) for the city of Singapore forecasted replacing the present passenger car fleet with one-third of shared DC. Service usage of DC can be introduced in many forms, with the standard type being the shared driverless taxi, driverless Uber, and driverless peer-to-peer sharing (Jaynes, 2016).

These binary probit analysis results could be associated with perception bias due to the new technology concept in the stated preference survey. There are typical difficulties in judging something (new technology or service) without testing or using it (Sheela and Mannering, 2019). Besides, socioeconomic data heterogeneity among the survey respondents is the practical reason. However, in this research survey, respondents are asked to express their willingness to use DC sharing options based on their present car and ridesharing experiences (e.g., taxi, hired car, car from car club) available in the market. These aggregated binary probit models used selected DC usage applications to measure the future sharing propensity within two market segments (DC shared ownership and ridership). Sociodemographic variables for a potential DC business model should be considered to establish the inclusiveness of these variables for DC shared use propensities.

6.3 Determinants concerning the likelihood of adopting some DC-sharing options

6.3.1 Introduction to the determinants concerning the likelihood of adopting some DC sharing options

The models described in section 6.1 convey the general propensity for sharing options without considering demographic, socioeconomic, personality and social norms characteristics. In this section, an effort was made to explain the respondents' present sharing behaviour, personality, social norm, and socioeconomic characteristics in determining various DC shared use propensities by utilising ordered probit models.

Considering the ordinal nature of the DC shared ownership and ridership choice data, the ordered probit method is considered an appropriate tool for analysis. Ordered probit models are handy tools for treating categorical ordered responses (e.g., the Likert scale). The OP model was initiated in 1975 by McKelvey and Zavoina (Mckelvey and Zavoina, 1975). Unordered response models like multinomial logit, ordinary probit, and nested logit models are inadequate to capture the ordered nature of the data (Greene and Hensher, 2009). Nonetheless, the multinomial logit model tends to generate errors relating independence of irrelevant alternatives. Besides, multinomial probit is associated with a lack of closed-form likelihood (Hensher *et al.*, 2008).

Several researchers conveniently applied ordered probit models for automobile ownership analysis and DC assessment (Chu, 2002; Menon *et al.*, 20 19; Lavieri *et al.*, 20 17; Sheela and Mannering, 2019). The ordered probit and logit generate similar results with variations in their data distribution pattern, such as the probit model following a standard normal distribution and the logit model following the standard logistic distribution (Greene and Hensher, 2009). Moreover, statistically ordered probit models generate a robust relationship between explanatory variables and the dependent variables when there are few explanatory variables.

An ordered probit model was an alternative to the ordered regression model (Mckelvey and Zavoina, 1975). For this research, ordered probit models were applied by defining observed variables related to DC shared ownership or ridership choices and used them as a basis to model peoples' choice variations recorded in an ordinal scale (e.g., very-unlikely, unlikely, neutral, likely, very likely) (Washington *et al.*, 2011).

6.3.2 Ordered probit modelling strategy for the present research

The modelling approach was based on a behavioural analysis that explains the factors influencing the respondent's decision about DC shared ownership and ridership in a medium-sized European city like Edinburgh. In addition to socioeconomic variables, the role of present sharing behaviour, personality, and social-norm behaviour was estimated for DC shared ownership and ridership options with successive modelling iterations. The estimation results uncover the interaction of these variables with six different DC shared ownership and 12 different DC shared ridership scenarios. Then, these model results are discussed to analyse the 6 best models concerning DC shared use (e.g., ownership and ridership) propensity and associated factors in broader detail.

Figure 6.5 shows the initial framework for the ordered probit model development process for 18 DC usage types with the abovementioned variables. A detailed list of explanatory variables is given in Appendix G. In Figure 6.2.1, PD, SDC, and DT represent the private DC, shared DC, and Driverless taxi, respectively.

Similarly, RA, RK, and RS represent riding alone with known people and strangers. For the equations, B1, B2, B3 and B4 signify the coefficients for present sharing behaviour, personality traits, social norms, and sociodemographic characteristics, respectively. The details of the Ordered Probit modelling methodology are given in Chapter 3.

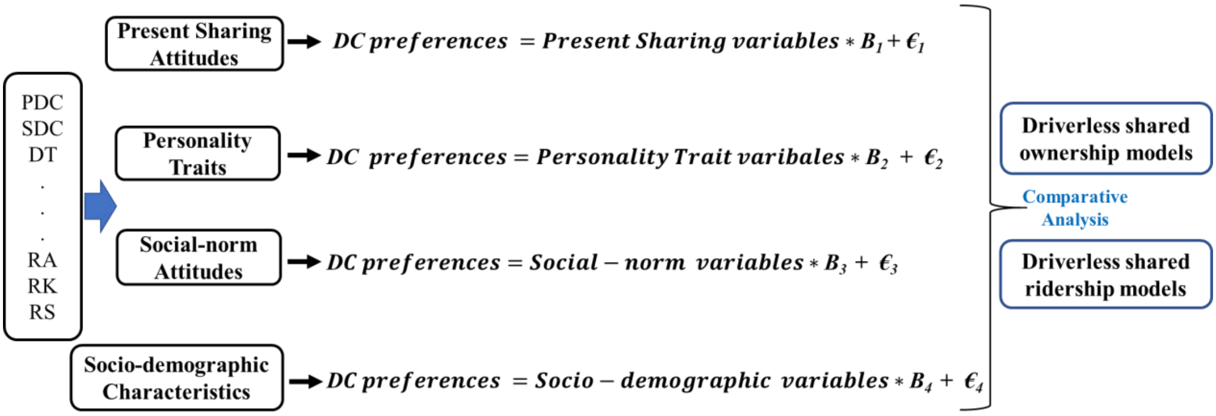


Figure 6.5: The initial framework for ordered probit model development for the 18 different DC shared options

DC sharing behaviour described by these 18 different sharing scenarios in this research are (1) DC shared ownership and (2) DC shared ridership. Two types of DC shared ownership, and four types of DC shared ridership options were chosen based on the number of responses from regular urban trips. Due to the hypothetical nature of the DC options, these six base options were tested only for regular travel intentions by a five-point Likert scale (e.g., very unlikely – very likely). Besides, in this research, driverless taxis and sharing with a stranger reflected the true nature of DC sharing possibilities. The types of DC shared ownership and ridership options are described in Chapter 3.

Figure 6.6 depicts the responses concerning DC shared ownership and ridership options. 43% of the respondents are "likely", and "very likely" to use a private DC for their regular trips. For driverless taxi use, the corresponding proportion is 41%. Regarding DC shared ridership, for regular trips not involving family members, riding alone is "likely", and "very likely" for 52% of the respondents compared to 15% of respondents who are willing to ride with a stranger. Regarding family members' presence in DC shared ridership, 64% of the respondents are "likely", and "very likely" to accept riding with a family member and a stranger, compared to 18% preference to ride with strangers, respectively.

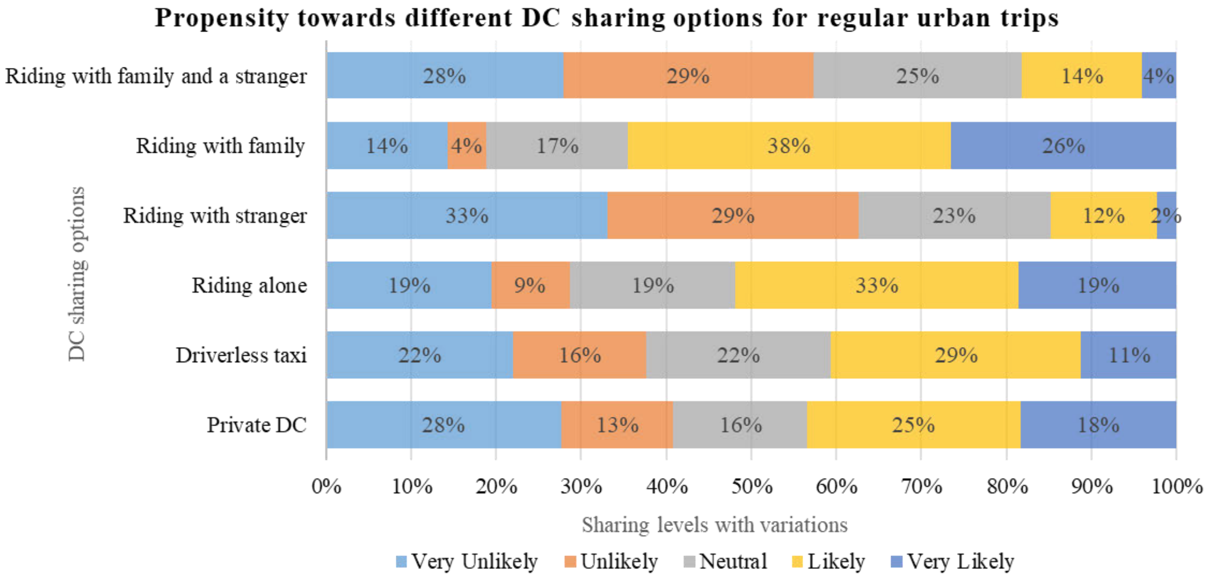


Figure 6.6: Likelihood to accept different DC sharing options for regular urban trips

6.3.3 Ordered probit model specification concerning the likelihood of DC shared ownership and shared ridership

Section 6.1 did not provide insight into determinants related to the adoption of DC shared ownership and ridership. Despite some observed correlation between ownership and rideshare markets, factors affecting these two types of sharing in the case of DC were not addressed satisfactorily in section 6.1. Section 6.2 addresses these shortcomings by determining explanatory variables that make the respondent more or less likely to choose DC shared ownership or shared ridership options. In this vein, ordered probit models were estimated by analysing explanatory variables for both these market segments.

The objective of the ordered probit analysis is to estimate the propensity of each DC sharing option as a function of several explanatory variables linked with present sharing behaviour, personality, social norm and socioeconomic characteristics. Figure 6.7 depicts the conceptual framework applied for this modelling exercise. Leveraging the data from the online survey, at first respondents clusters with different present carsharing and ridesharing habits were identified through a two-step cluster analysis, as Tan *et al.*(2014) described. The cluster analysis process was discussed in Chapter 5. Then, ordered probit models were estimated following the method described in Chapter 3.

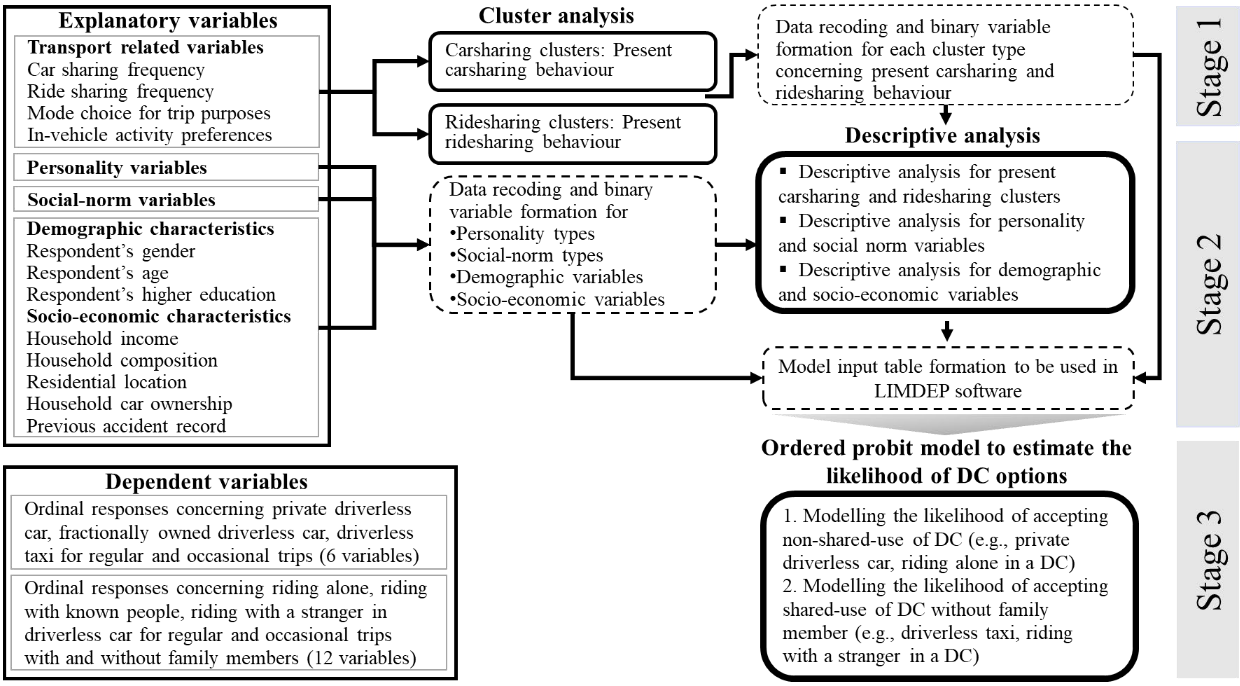


Figure 6.7: The analytical framework of ordered probit model development

6.3.4 Ordered probit model estimation results

Table 6-11 reports the ordered probit models (OP) estimation results obtained using the NLOGIT statistical package (Greene, 2016). The six scenarios of DC assessed by the OP models are relevant to the likelihood of choosing regular urban trips by private DC (Ow_Pr_Re), driverless taxi (Ow_Ta_Re), riding alone in a DC (Ri_NfRe_A), riding with a stranger in a DC (Ri_NfRe_S), riding in a DC with a family member (Ri_WfRe_A) and riding in a DC with a family member and a stranger (Ri_WfRe_S). Among all these six DC scenarios, the final models are significantly more predictive than the base models regarding log-likelihood, which indicates variations in respondents' perception concerning the likelihood of DC shared ownership and ridership. The variations in results happened due to a separate combination of explanatory variables used in models, and the variables themselves were not equally significant (statistical) for each DC shared ownership and ridership preference. A list of explanatory variables is given in Appendix G.

Our modelling approach does not directly compare the variables concerning different DC shared ownership and ridership types. Instead, the results show what variables increase or decrease the propensities of adopting various DC shared ownership and ridership estimated through OP models. When an explanatory variable has the same effect on multiple models regarding opposing sharing behaviour (e.g. it increases the likelihood of both riding alone and sharing rides), it was inferred that this effect is due to the driverless car technology rather than variations in DC use. LIMDEP software output relating to Ordered Probit model estimation results is given in Appendix I.

Table 6-11: Variable estimations for various ordered probit models concerning DC shared ownership and ridership

Indicator description	Likelihood to use private DC for regular trips (Ow_Pr_Re)		Likelihood of riding alone in a DC for regular trips (Ri_ReNF_A)		Likelihood to use driverless taxi for regular trips (Ow_Ta_Re)		Likelihood of ridesharing with a stranger in DC for regular trips (Ri_ReNF_S)		Likelihood of riding in a DC in the presence of a family member for regular trips (Ri_ReWF_A)		Likelihood of riding in a DC with a stranger in the presence of family members for regular trips (Ri_ReWF_S)	
	Coeff.	*t-ratio*	*Coeff.*	*t-ratio*	*Coeff.*	*t-ratio*	*Coeff.*	*t-ratio*	*Coeff.*	*t-ratio*	*Coeff.*	*t-ratio*
Error-term	0.157	0.967	0.519	3.041	0.471	4.412	0.289	3.051	0.882	7.192	0.635	4.874
Sociodemographic characteristics												
Millennial (1 if the respondent is between 24 - 43 years old, 0 otherwise)			0.256	1.933	0.339	2.515	0.334	2.943			0.285	2.504
Baby boomer (1 if the respondent is 56 -74 years old, 0 otherwise)	-0.607	-5.283	-0.256	-1.940					-0.326	-2.938		
Generation X (1 if the respondent is between 44 - 55 years old, 0 otherwise)					0.370	2.369						
Masters or higher degree holder (1 if respondent hold a masters degree or higher, 0 otherwise)	-0.222	-2.060									-0.261	-2.030
A family with at least one children (1 if the respondent is from a family with at least one child, 0 otherwise)			-0.262	-2.254	-0.281	-2.144						
A family without a child (1 if the respondent is from a family with no children, 0 otherwise)							-0.177	-1.673			-0.183	-1.747
Higher-income (>£50000/year) (1 if the respondent earn more than £50000 per year, 0 otherwise)					0.290	2.416						
City centre (1 if the respondent lives in the city centre, 0 otherwise)					0.307	2.58	0.206	1.904			0.279	2.553
Outer suburb (1 if the respondent lives in the outer suburb, 0 otherwise)									0.297	2.184		
Car ownership (1 if the respondent has at least one car, 0 otherwise)	0.634	4.208										
Current carsharing behaviour												
Frequent household car user (1 if the respondent is a frequent household car user who is not willing to share the ride others, 0 otherwise)	0.199	1.691	0.274	2.343					0.189	1.664		
Personality traits												
Agreeableness (1 if the respondent is cooperative and trusting, 0 otherwise)					0.274	2.250	0.244	2.145			0.243	2.147
Extraversion (1 if the respondent is highly energetic, active for the social life, 0 otherwise)									-0.298	-2.355		
Social norm indicators												
The social expectation for preserving the environment (1 if the respondent is guided by social expectation to preserve the environment, 0 otherwise)	0.295	2.314	0.334	2.686					0.461	3.687		
The social expectation for sharing (1 if the social expectation guides the respondent to share personal resources, 0 otherwise)					0.311	1.665	0.495	2.810			0.311	1.780
Mean	1.93		2.22		1.92		1.22		2.58		1.37	
Standard deviation	1.49		1.38		1.33		1.11		1.31		1.15	
Base log-likelihood *(c,μ)*	-605.78		-612.28		-558.79		-607.84		-571.72		-631.83	
Final log-likelihood *((β,μ)*	-634.90		-626.44		-574.90		-624.08		-586.67		-646.07	
Chi-square *(χ^2)*	58.24		28.31		32.22		32.47		29.92		28.49	
P-value	0.000		0.000		0.000		0.000		0.000		0.000	
$R^2_{Mcfadden}$	0.046		0.023		0.028		0.026		0.026		0.022	
Degrees of freedom (df)	5		6		7		5		5		6	
Number of observations	405		408		370		439		412		440	

6.3.5 Ordered probit model estimation results for DC shared ownership

Overall model results concerning private DC and driverless taxi

In terms of DC shared ownership, two separate ordered probit models for the private driverless car and driverless taxi use were tested with chi-squares stated in Table 6-11 :

1. For the private DC in regular use, the value of $\chi^2(5)$, $\rho<0.001$ = 58.24, shows significant model improvement for the final model than the base model. Table 6-11 revealed that the final model significantly differs in private DC ownership attitudes. Frequent household car users with a general tendency to preserve the environment are keen to use private DC, while respondents with more educated age brackets within 56 -74 years are less interested.
2. For the driverless taxi use on regular trips, the value of $\chi^2(7)$, $\rho<0.001$ = 32.22, showed significant model improvement for the final model over the base model, as in Table 6-11. Higher wage-earning (>£50000) and cooperative 24 – 55-year-old young adults, with a general tendency to share their resources, are keen on driverless taxi use. On the other hand, respondents from families with at least one child are unwilling to accept driverless taxi use.

Both these models showed a better $R^2_{McFadden}$ value away from zero to predict the model variables' better explanatory power. However, the private DC model proved better than the DT model regarding statistical fit. Thus, private DC and DT model results are heterogeneous regarding the explanatory power of the underlying variables.

Discussion on estimated findings concerning the likelihood of private DC use

Baby boomers among generations (aged 55– 74) are less open to private DC. This result can be explained by a reluctance to accept new technology due to the unknown features and technical usability. However, empirical findings suggested that respondents from this age group do not prefer shared DC over their private car (Krueger *et al.*, 2016). So, my findings contradict empirical findings regarding the age influence of private DC use.

Negative attitudes towards private DC for regular trips were shown by highly educated respondents (holding a master's degree or higher). In support of this finding, one study by Dias *et al.* (2017) suggested that highly educated people are more inclined to share DC than private DC. Current ownership of at least one car is also associated with a greater tendency towards private DC. The observed propensity to private DC for car owners can be attributed to their habitual patterns from their current car use behaviour (Wachenfeld *et al.*, 2016). In this context, Menon *et al.* (2019) proved that people are keen on the car ownership culture and its benefits in their everyday lives. Therefore, they are reluctant to accept the use of shared DC readily. Following previous research results (Kyriakidis *et al.*, 2015), it can be proved that past habits can explain the future acceptance of private DC. Respondents who frequently use the household car but don't use car rentals are more optimistic about private DC. Lee *et al.* (2019) found that this variation is associated with their car dependency and psychological disposition toward car use. In line with these findings, Zmud, Sener and Wagner (2016) found that people prefer to use private DC rather than carsharing by DC. The variable representing social expectation to preserve the environment is likely to affect DC preferences significantly.

Respondents who acknowledge the social expectation to preserve the environment are more receptive to private DC. This result may be driven by public expectations for low-emission technologies incorporated in DC. Prior research showed that pro-environmental attitudes are an essential determinant of acceptance of shared DC (Haboucha *et al.*, 2017). The marginal effects of explanatory variables are provided in Table 6-12.

Table 6-12: Marginal effects of explanatory variables concerning the likelihood of private DC and driverless taxis for regular use

Variable descriptions	Variable estimatio	Very unlikely	Unlikely	Neutral	Likely	Very likely
Marginal effects of explanatory variables concerning the likelihood of private DC						
Baby boomer	-0.6073	0.2047	0.0302	-0.0058	-0.1008	-0.1283
Master or higher degree holder	-0.2222	0.0719	0.0136	0.0011	-0.0354	-0.0512
Car ownership	0.6341	-0.2251	-0.023	0.0177	0.112	0.1185
Frequent household car user	0.1991	-0.0628	-0.013	-0.0024	0.0305	0.0477
The social expectation for preserving the environment	0.2946	-0.0992	-0.0157	0.0021	0.0497	0.0632
Marginal effects of explanatory variables concerning the likelihood of driverless taxi						
Millennial	0.3387	-0.0856	-0.0363	-0.0116	0.0695	0.0639
Generation X	0.3703	-0.0902	-0.0406	-0.0155	0.0731	0.0732
Higher-income	0.2899	-0.0764	-0.03	-0.0071	0.0619	0.0517
A family with at least one child	-0.2806	0.0771	0.0278	0.0041	-0.0618	-0.0471
Agreeableness	0.2741	-0.0697	-0.0293	-0.009	0.0568	0.0512
The social expectation for sharing resources	0.3114	-0.0741	-0.0348	-0.0146	0.0603	0.0632
City-Centre dwellers	0.307	-0.078	-0.0327	-0.0098	0.0637	0.0572

Discussion on estimated findings concerning the likelihood of driverless taxi use

Millennials are most influential in preferring driverless taxi use, and Menon *et al.* (2018) found that millennials are more likely to accept shared DC use. One-third of my survey sample are millennials, representing the dominant living generation in contemporary society (Fry, 2016).

They are the leading supporters of innovative technology solutions (Smith, 2013) and the adopters of alternative transport modes (Circella *et al.*, 2016).

Families with at least one child are unwilling to use a driverless taxi, indicating their preference to travel with family members. This finding is consistent with earlier research demonstrating that the likelihood of shared DC use by single-person households is higher than that of multi-person households (Lavieri and Bhat, 2019). Another recent study contradicted these findings, which suggested that a family without a child is unwilling to accept shared DC (Barbour *et al.*, 2019)**.**

Table 6-12 also shows that respondents from higher income groups may prefer driverless taxis as a second car for leisure travel or when another family member occupies the primary car. These findings echo previous findings suggesting that higher-income individuals are willing to share DC (Lavieri and Bhat, 2019). Financially affluent people are psychologically attached to their private space inside a taxi and, therefore, unwilling to share a driverless taxi with a stranger (S. Wang *et al.*, 2020).

Respondents with cooperative attitudes and belief in social harmony demonstrate a higher inclination towards driverless taxi use for regular trips. This result is supported by the finding of Kyriakidis *et al.* (2015) and deemed plausible since respondents with this type of personality are generally submissive, pro-environmental (Hirsh, 2010), and likely to adopt sustainable transport modes (Kim *et al.*, 2014). City-centre-dwelling respondents are generally willing to use driverless taxis for their regular urban trips, and this result is linked to the higher availability and greater familiarity of taxis in city centres. These results also indicated that social norms promoting shared resources might help enhance the DC sharing schemes.

6.3.6 Ordered probit model estimation results concerning the likelihood of DC shared ridership for trips without a family member

Overall model results concerning the likelihood of DC shared ridership for trips without a family member

Model results in Table 6-11 concerned the likelihood of riding alone and riding with a stranger in DC by applying the chi-square test.

1. The ordered probit model concerning riding alone with DC for regular travel is given a test statistic of $\chi^2(6)$, ρ<0.001 = 28.31, which showed a significant model fit. The final model was significantly different from the base model. In other words, explanatory variables explain part of the respondent's likelihood of riding alone with DC. Model results proved that most of the

respondents in the survey sample were car drivers inclined to drive their cars irrespective of age, income, personality, and living status. Frequent household cars-using millennials who feel about preserving the environment have shown their likelihood of riding alone with DC, while respondents in their upper ’55s with larger family sizes (with children) are not inclined to ride alone.

2. The chi-square test statistic of $\chi2(5)$, $\rho<0.001 = 32.47$, shows a significant model fit for the final model to show the intention to share the ride with a stranger. Unlike driverless taxi use behaviour, DC shared ridership with a stranger was favoured by city-centring millennials, who are friendly and willing to share resources and are highly inclined. In sharing the ride with a stranger in a DC, households without children are less inclined than those with children.

In the case of private DC and riding alone in a DC, the association of similar factors indicated people’s disposition in using DC, which is explainable by their present car ownership behaviour and social norms to preserve the environment.

Discussion on estimated findings concerning the Likelihood of riding alone in a DC without a family member

Baby boomers (55– 74) are less inclined to drive alone in DC and highly likely to ride with others. Respondents in this age bracket are likely to belong to small families, tend to live with their partners, and therefore benefit from riding together to support their additional transport needs. One of the reasons for this is to reduce the family travel budget. On the contrary, wealthy millennials are more inclined to ride alone in a DC, reflecting their tech-savvy attitudes.

Families with at least one child are less willing to ride alone in DC because they are more used to sharing their car with people around them. Regular car trips made by members of larger households are likely to accommodate the needs of more than one member.

Interestingly, Haboucha *et al.* (2017) found that individuals from multimember households are more inclined to share the ride in DC, and Barbour *et al.* (2019) found they like additional cars to meet their travel needs. This finding revealed that family structure is negatively associated with the private use of DC, while another study reflected that the multimember family accepts private use of DC (Nazari *et al.*, 2018). A respondent who doesn’t share their household car is willing to ride alone in a DC. These findings envisaged that the present car use tendency affects future choices (Hao and Yamamoto, 2018). A study found that people are not likely to change their car-owning attitudes despite DC’s arrival as a private DC or driverless taxi form (Bösch *et* *al.*, 2021). Past habits can reflect the future acceptance of private DC use (Kyriakidis *et al.*, 2015). Besides, a respondent obliged to preserve the environment intends to ride alone in DC, and this behaviour is linked with their intentions to choose the fully electric DC for environmental benefit. The present research findings contradict 2015 studies stating that shared DCs are potentially energy-saving and environment-friendly (Greenblatt and Saxena, 2015), and therefore, driverless carshare can help reduce environmental impacts (Thomopoulos and Givoni, 2015). Table 6-13 shows the marginal effects of explanatory variables concerning the likelihood of riding alone and riding with a stranger in DC for regular urban travel.

Table 6-13: Marginal effects of explanatory variables concerning the likelihood of riding alone in a DC and riding with a stranger in a DC for regular use

Variable descriptions	Variable estimatio	Very unlikel	Unlikely	Neutral	Likely	Very likely
Marginal effects of explanatory variables concerning the likelihood of riding alone in						
Baby boomer	-0.256	0.069	0.018	0.015	-0.04	-0.061
Millennial	0.256	-0.063	-0.019	-0.019	0.035	0.067
A family with at least one child	-0.262	0.070	0.019	0.016	-0.041	-0.064
Car ownership	0.211	-0.058	-0.015	-0.011	0.035	0.049
Frequent household car user	0.274	-0.068	-0.02	-0.02	0.038	0.071
The social expectation for preserving the environment	0.334	-0.093	-0.023	-0.016	0.056	0.076
Marginal effects of explanatory variables concerning the likelihood of riding with a stranger in a DC						
Millennial	0.334	-0.113	-0.017	0.047	0.064	0.018
A family without a child	-0.177	0.063	0.005	-0.027	-0.032	-0.008
City centre dwelling	0.206	-0.071	-0.008	0.031	0.039	0.010
Agreeableness	0.244	-0.084	-0.011	0.036	0.046	0.013
The social expectation for sharing resources	0.495	-0.154	-0.041	0.058	0.102	0.035

Discussion on estimated findings concerning the likelihood of riding with a stranger without a family member

Millennials are willing to accept strangers in their DC rides for regular trips. In support of these findings, Lavieri and Bhat (2019) proved that younger adults are less subtle about sharing their rides with strangers for commuting trips than on leisure trips. Table 6-13 shows that a family without a child is less interested in DC sharing with strangers. This result aligns with earlier research proving general unwillingness to share a confined space with a stranger (S. Wang *et al.*, 2020). These findings do not reflect any clear connotation for the family composition with shared use of DC. City-centre dwelling respondents are willing to share the ride with a stranger, reflecting their familiarity with ride-sourcing services extensively used in urban areas and city centres. This result contradicts recent research showing sharing with a stranger is unwelcoming for urban trips (Rahimi, Azimi, Asgari, *et al.*, 2020). Marginal effects of agreeable personality proved to affect sharing the ride with a stranger (Table 6-13) with propensity at higher acceptance levels. The presence of a stranger is a factor of safety and privacy in riding with DC. Respondents with aggregable personalities are less concerned about lack of security due to the presence of strangers, as Kyriakidis *et al.* (2015) found. Respondents with a general tendency for sharing are found positive about sharing their rides with strangers for their regular urban trips. This result indicates that favourable social norms may help to increase DC sharing.

6.3.7 Ordered probit model estimation results concerning the likelihood of DC shared ridership for trips with a family member

Overall model results concerning the likelihood of DC shared ridership for trips with a family member

Shared ridership options with family members are 1) ride only with a family member, 2) ride with a family member and known people, and 3) ride with a family member and a stranger. Model results to show the likelihood of riding with family members are presented in Table 6-11.

1. The model for understanding the likelihood of accepting shared ridership with family members for regular travel was assessed with $\chi^2(5)$, $\rho<0.001 = 29.92$, proving a significant improvement from the base model. Frequent household car-using suburban dwellers who are socially influenced to preserve the environment are inclined to share the ride with their family members, and this group usually belongs to larger families living outside the city area. On the contrary, nature lovers who don't drive, are older and don't have young children were less inclined to accept family rideshare with DC.
2. To model the likelihood of shared ridership with a stranger in a family member's presence, the test statistic, $\chi2(6)$, $\rho<0.001 = 28.49$, proved significant improvement in the final model over the base model. To better explain this model, agreeable personality, the social expectation for sharing, city centre dwelling, and belonging to millennials are significant factors.

Discussion on estimated findings concerning the likelihood of riding only with a family member

Regarding current travel-sharing patterns and social norm behaviour, the likelihood of riding in a DC with a family member followed the same pattern as that of a private DC or riding alone in a DC. Baby boomers are unwilling to accept DC shared ridership with a family member, and outer suburban dwellers are more inclined to share their DC rides with a family member. Among other possible reasons, this might be linked with the longer travel distance of outer suburban locations to amenities and work that makes them share the ride with DC to reduce the household travel cost burden and avoid long waiting times for public transport. Outer suburbia is the living place for older adults and people with disabilities, for whom DC can be helpful for weekend visits and occasional visits to health facilities.

Respondents with frequent household car use are more willing to share their DC ride with family members. This result reflects that people mostly think about ridesharing in DC with close contacts. Respondents with a social obligation to preserve the environment are more inclined to share their rides with family members. This social obligation helps people find more environment-friendly travel options and save multiple journeys using one single DC from a single household. According to my findings, respondents who search for stimulation and social life are less likely to share rides with their family members. This result indicates that family respondents are more likely to use DC for their exclusive business travel in the form of driverless taxis. Personality-wise, this result showed no clear pattern for sharing DC.

Table 6-14: Marginal effects of explanatory variables concerning the likelihood of riding with a family member and riding with a family member and a stranger

Variable descriptions	Variable estimatio	Very unlikel	Unlikely	Neutral	Likely	Very likely
Marginal effects of explanatory variables concerning the likelihood of riding with a family member in a DC						
Respondents over 55's	-0.326	0.069	0.014	0.037	-0.016	-0.104
Outer suburban dwellers	0.297	-0.054	-0.013	-0.037	0.002	0.102
Extraversion	-0.298	0.066	0.013	0.033	-0.019	-0.092
Frequent household car user	0.189	-0.037	-0.008	-0.023	0.005	0.063
The social expectation for preserving the environment	0.461	-0.107	-0.02	-0.048	0.036	0.139
Marginal effects of explanatory variables concerning the likelihood of riding with a family member in the presence of a stranger in a DC						
Millennial	0.285	-0.09	-0.023	0.035	0.055	0.023
Educated to bachelor or higher	-0.261	0.081	0.022	-0.031	-0.051	-0.022
A family without a child	-0.183	0.06	0.011	-0.025	-0.034	-0.013
City centre dwelling	0.279	-0.089	-0.022	0.035	0.053	0.022
Agreeableness	0.243	-0.077	-0.019	0.03	0.046	0.02
The social expectation for sharing resources	0.311	-0.093	-0.03	0.033	0.061	0.029

Discussion on estimated findings concerning the likelihood of riding with a family member and a stranger

The likelihood that DC shared ridership with a family member and a stranger means sharing a family-used DC with someone outside of close contact. In such cases, generation, residential location, personality, and social norm feelings are guiding factors. For example, city centre-dwelling millennials with cooperative and sharing attitudes are most likely adopters of DC sharing with a family member and a stranger. On the other hand, respondents with a bachelor’s degree and from a family without a child are most reluctant to use such DC-shared ridership with a stranger.

However, millennials are willing to share their family DC with a stranger. As shown in Table 6-14, city centre-dwelling respondents are flexible about sharing their family DC with strangers. Agreeable, trusting personalities and social-norm feelings for sharing resources help respondents accept a stranger in DC sharing, despite their family members present.

6.3.8 Conclusion on the determinants of the likelihood of some DC shared ownership and ridership options

This section presents an exploratory analysis of attitudes towards accepting DC shared ownership and ridership options across respondents in line with the research objective. Using data collected through an online survey in Edinburgh, UK, this section applied a sequential ordered probit modelling approach to identify factors affecting the likelihood of DC shared ownership and ridership options for regular urban trips based on hypothetical market choices. Even though this research aims to identify DC shared ownership and ridership, the statistical analysis results divided model explanatory factors into two broad headings: (1) non-shared DC and (2) shared DC usage factors.

The statistical analysis showed that millennials are the likely adopters of shared-use DC while ageing seniors (baby boomers) are indifferent in their choices for non-shared-use DC. In addition, present car ownership and feelings for social expectation to preserve the environment increase the willingness for non-shared-use DC. The model results reflect the respondents’ heterogeneity of attitudes towards DC sharing, especially regarding age, car ownership, personality and social norm attitudes. Respondents' cooperative attitudes could enhance shared DC use with a general tendency towards sharing.

Interestingly, this section reveals that some car users may not switch to DC in exchange for their conventional car, irrespective of technological innovation. Age, present car ownership, and residential location are essential factors in deciding DC shared ownership and ridership. Young urban adults are pioneers in using DC shared ridership while ageing seniors are likely to accept DC for private and family use. Therefore, the insights relating to the impact of present car ownership and sharing behaviour on future DC sharing options should be further studied to understand how the switch from private to a shared mode of transport can be facilitated through the emergence of DC.

Age, personality, and social norm factors are similar in explaining the likelihood of driverless taxis and sharing DC with a stranger. However, substantive variations were found between these two options. Results reflected that the higher-income society valued driverless taxis as a single-use version of the DC. But 'sharing with a stranger is the intrinsic feature of a shared driverless taxi with promising potential to reduce traffic from the road network by offering shared travel. But, convincing people to share the ride with a stranger is a crucial barrier to overcome (Parkhurst and Seedhouse, 2019). Such variations set new challenges for transport planners and policymakers to formulate new policy measures to facilitate the modal shift from single-use to shared-use driverless taxis. For example, possible privacy issues in a shared driverless taxi may constitute an array of issues hampering this modal shift. Future policy interventions may encourage DC service providers to redesign the DC interior with privacy-preservative space to attract private, concerned individuals to use shared driverless taxis.

Nonetheless, due to the hypothetical nature of DC scenarios and lack of proper DC use information, an individual's likelihood of accepting DC is prone to biased model estimation. Moreover, built environment factors such as population density, road types, surrounding land-use types, and parking facilities were not considered. Also, attitudes like applicable speed, time of travel, long-distance travel needs and time-varying approach of shared travel should be investigated further.

The research analysis applied section opens up the scope for future research. Personality traits and social norms are two elements from behavioural psychology introduced in this research and proved very effective in explaining sharing attitudes with DC. Such factors should be evaluated in greater detail with stated choice experiments to understand the behavioural constraints in transforming the private use of DC to service use. Comparing the likelihood of carsharing and ridesharing by DC at the household level is an emerging field for further research. Simultaneous model assessment with common unobserved factors for these two types of sharing could be a helpful approach to achieving such research goals. Focusing on the recent world pandemic due to COVID-19, this behavioural study should include the factors concerning public health issues in sharing DC.

6.4 Determinants of the preferences between some shared and non-shared DC options

6.4.1 Introduction to modelling the preferences between shared uses and non-shared uses of driverless cars

Univariate ordered probit models described in Section 6.2 relating 18 different ordered outcome variables were estimated to understand the propensities of accepting different DC options with explanatory variables concerning sharing behaviour, personality, social norm, and socio-demographic characteristics. The ordered probit modelling exercise selected all principal determinants for DC choice variations. However, these models are inadequate in shedding light on comparing the propensity to accept shared DC use (e.g., driverless taxi, rideshare with a stranger) over non-shared DC options (e.g., private DC, riding alone in DC) and their determinants (variables). To address this issue, in this section, the Binary logistic regression (BLR) model was described to help determine the relationship between one or more determinants (variables) and one binary dependent variable, such as the likelihood (greater and equal) of shared DC options over the non-shared DC options. In BLR, an effort was made to address the weak propensity of DC shared ridership (e.g., Driverless taxi, riding with a stranger, ridesharing with a stranger and a family member) as a binary dependent variable with some predictor variables in the model. So, the BLR model assessment focuses on the following three relations:

1. Weak propensities of (Higher or equal likelihood) Driverless taxi use (Ow_Ta_Re) to Private DC (Ow_Pr_Re) use for regular travel, which is termed as DVT
2. Weak propensities of (Higher or equal likelihood) riding in DC with a stranger (Ri_ReNF_S) to riding alone (Ri_ReNF_A) in DC for regular urban trips, which is termed as RST
3. Weak propensities of (Higher or equal likelihood) ridesharing with a stranger along with a family member (Ri_ReWF_S) to riding only (Ri_ReWF_A) with a family member in DC for regular urban trips, which is termed as RSF

These models are assessed with explanatory (predictor) variables concerned with sharing behaviour, personality, social norm, and socio-demographic characteristics. These explanatory variables were behavioural indicators (mentioned in Appendix G) and converted to binary forms to account for data non-linearity. The coefficients of these variables in BLR models represented the log odds of reporting a positive intention to accept one mode (e.g., Driverless Taxi) over the other (e.g., Private DC). The results are reported in terms of Odds Ratio (OR), representing the odds for preferring (i.e., '1' being the acceptance, '0' otherwise) one DC option to the other. The framework for the BLR model is given in Figure 6.8. The dependent variables for binary logit modes are listed in Table 6-8.

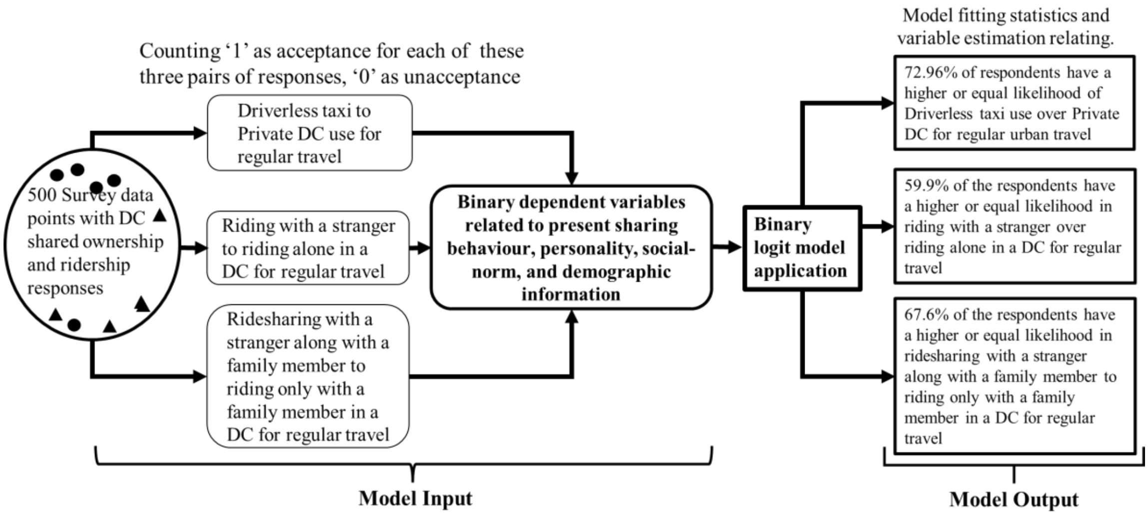


Figure 6.8: BLR model variables formation and model specification with binary dependent variables

6.4.2 Binary-logit Regression (BLR) model specification

In the original data source, responses for both the private DC (Ow_Pr_Re) and driverless taxis (Ow_Ta_Re) are collected in the ordered form with a five-point Likert scale (e.g., very unlikely - very likely). The likelihood of accepting Ow_Ta_Re use over Ow_Pr_Re use was counted by the logic mentioned below, resulting in a binary dependent variable, DVT,

$$DVT_{Ji} = \begin{cases} 1 \; if \; Ow\_Ta\_Re_{J,i} \geq Ow\_\mathrm{Pr}\ \_Re_{J,i} \\ 0 \; if \; Ow\_Ta\_Re_{J,i} < Ow\_\mathrm{Pr}\ \_Re_{J,i} \end{cases} \quad \text{.......(5)}$$

For any pair of responses, the indifferent and greater responses for Ow_Ta_Re to Ow_Pr_Re were counted as '1' and '0' otherwise. For instance, if the Ow_Ta_Re response was 3 and the Ow_Pr_Re response was 2, the likelihood of accepting Ow_Ta_Re over Ow_Pr_Re was coded as '1'. All other lower responses for Ow_Ta_Re than Ow_Pr_Re were converted to '0'.

A BLR structure was used to estimate the resulting binary dependent variable DVT describing the propensities of accepting Driverless taxis over private DC. Similarly, RST and RSF dependent variables are also derived and assessed. The detailed modelling methodology is described in Chapter 3. The following Table 6-15 describes the observed median and mean responses for the binary dependent variables along with standard deviation statistics resulting from the NOGIT coding exercise:

Table 6-15: Description of binary dependent variables with statistics

Difference in attitudes	Mean	Median	Standard Deviation
DVT (1 if the respondent shows a weak preference for a driverless taxi than private DC, 0 otherwise)	0.69	1.00	0.46
RST (1 if the respondent prefers and is indifferent to sharing the ride with a stranger to riding alone, 0 otherwise)	0.45	0.00	0.50
RSF (1 if respondent prefers and is indifferent to riding with a stranger in the presence of a family member than to ride only with a family member, 0 otherwise)	0.42	0.00	0.49

Table 6-15 indicates that 69% of respondents had weak preferences for driverless taxi use to private DC. Similarly, 45% of the respondents from the survey sample were more interested and indifferent to riding with a stranger than riding alone in DC. Regarding DC shared ridership with a family member, 42% of respondents were indifferent to riding with a stranger than riding only with a family member. The median values for each of these attitudes showed the skewness reflecting the middle highest preference of respondents.

BLRs were processed in SPSS software, where the model results were estimated in sequential steps with a forward variable loading method. Forward regression involves adding predictor variables in several steps to the BLR model estimation process to determine variable numbers and estimations at the final step (Pituch and Stevens, 2019). The initial model contains the largest significant dependent predictor variable, and the next model step identifies the predictor variable that results in the largest significant R-square change. The way forward is that if no further predictors would contribute to a significant R-square change, the model will terminate with only the first few predictors selected. The predictor selection procedure continues until that point, in which any remaining predictors do not add significant predictive power. Notably, with the addition of predictors at later steps, selected significant predictors earlier may become non-significant with their presence in the model.

With the BLR model sought for this study, an effort was made to explore the variables that help determine the respondents' strong and weak acceptances in shared DC (e.g., driverless taxi, riding with a stranger in a DC) options over private or individually used DC (e.g., private DC, ride alone in a DC) options. Through BLR, the question was addressed, such as, “What is the probability of choosing a driverless taxi for private DC use, given the categorical explanatory variables in the model?”. In the case of DC shared ridership, the question was, “What is the probability of choosing a stranger for DC shared ridership to riding alone in DC, given the categorical explanatory variables in the model?”. The following points are evaluated to discuss the results of the BLR:

1. The number of variables and cases that help predict the model results
2. The observed percentage of the cases satisfying the condition mentioned in Table 6-15.
3. The model fitness check with the log-likelihood chi-square test, which compares the final model with a null, or intercept-only, model
4. Hosmer & Lemeshow test to show the significance of *p-value* indicating a good model fit statistics
5. The final table provides the variables' names and their significance to which they interpret the model correctly with the variations for the logit values

6.4.3 Binary-logit model estimation results

Model estimation result assessment concerning the weak preference for driverless taxi use over private DC

SPSS software was applied to run this model, resulting in 307 responses to satisfy the set condition in Table 6.15. Without any variables, the null model estimation result shows that the constant is positive, indicating that the number of choice responses for choosing driverless taxis to private DC is significant. Besides, the Omnibus tests of model coefficients predict whether a model including the complete set of predictors significantly improves model fit over the null (intercept-only) model. Effectively, an omnibus test of the null hypothesis proves that the regression slopes with all predictors in the model are equal to zero (Pituch and Stevens, 2019). The results indicated that data fit significantly better for the final modelling step than a null model, $\chi^2(5)=42.101$, $p<.001$, as in Table 6.16.

The Model Summary contains the log-likelihood measures. The log-likelihood helps compare competing models when distributed as a chi-square to indicate the model deviance. In this model, the log-likelihood values improved with the number of steps it took to terminate. Along with the tests for model fitness above, the Hosmer & Lemeshow test (Hosmer *et al.*, 2013) can be used to evaluate global fit by non-significant test results. Considering $p < 1.00$, all the modelling steps indicate a good model fit.

Based on the modelling results, the classification within modelling steps provides the frequencies and percentages reflecting the degree to which the BLR model correctly and incorrectly predicts category membership on the dependent variable. The BLR modelling process predicts that 72.96% of the data sample can relate to the outcome variable (Higher or Equal likelihood of Driverless taxi use than Private DC). The rest of the Model estimation results are described in the next section and depicted in Table 6.16.

Model estimation results concerning the weak preference of sharing a DC with a stranger to riding alone in a DC

For this model overall, 307 responses are considered. Following the same process mentioned above, the model results are derived. Detailed results are found in Table 6-16.

Model estimation results concerning the weak preference for DC shared ridership with a family member in the presence of a stranger than to share the DC with family alone

Overall, 312 responses are considered for this model. The rest of the model estimation results are described in Table 6-16.

Table 6-16: Binary Logit Model estimation results with model statistics

Explanatory variables defining outcomes of binary logit models	Higher or indifferent likelihood for a driverless taxi (Ow_Ta_Re) use than private DC (Ow_Pr_Re)			The higher or indifferent likelihood of riding with a stranger (Ri_ReNF_S) than riding alone with DC (Ri_ReNF_A)			The higher or indifferent likelihood of riding with a family member and a stranger (Ri_ReWF_S) than riding only with a family member with DC (Ri_ReWF_A)		
	Coeff.	ρ-value	Exp(*Coeff.*)	*Coeff.*	ρ-value	Exp(*Coeff.*)	*Coeff.*	ρ-value	Exp(*Coeff.*)
Only with Constant	0.83	0.00	2.30	-0.14	0.23	0.87	-0.47	0.00	0.63
With variables and constant	-0.50	0.05	0.61	-0.62	0.00	0.54	0.03	0.92	1.03
Socio-economic indicators									
Masters or higher degree holder (1 if respondent hold a master's degree or higher, 0 otherwise)	0.76	0.00	2.15	-	-	-	-	-	-
Baby boomer (1 if the respondent is 56 -74 years old, 0 otherwise)	1.35	0.00	3.84	0.81	0.00	2.25	-	-	-
A family with at least one child (1 if the respondent is from a family with at least one child, 0 otherwise)	-	-	-	0.82	0.00	2.27	-	-	-
Two car-owner (1 if the respondent has two cars, 0 otherwise)	-	-	-	-0.88	0.00	0.41	-	-	-
Zero car ownership (1 if the respondent has no car, 0 otherwise)	1.24	0.01	3.46	-	-	-	-	-	-
Outer suburb (1 if the respondent lives in the outer suburb, 0 otherwise)	-	-	-	-	-	-	-0.85	0.01	0.43
Higher Income (1 if the respondent earns between £30000 - £40000)	-	-	-	-	-	-	0.62	0.05	1.86
Existing carsharing behaviour indicators									
Frequent household car user (1 if the respondent is a frequent household car user who shares the ride with others sometimes, 0 otherwise)	0.64	0.03	1.90	-	-	-	-	-	-
Personality-traits indicators									
Neuroticism (1 if the respondent can handle stress well but get nervous easily, 0 otherwise)	0.727	0.01	2.07	-	-	-	-	-	-
Social-norm indicators									
The social expectation for a better quality of life (1 if the respondent is willing to accept the social expectation for a better quality of life, 0 otherwise)	-	-	-	-	-	-	0.57	0.04	1.77
The social expectation for sharing (1 if the social expectation guides the respondent to share their	-	-	-	0.91	0.02	2.49	-	-	-
The social expectation for preserving the environment (1 if the respondent is willing to accept the social expectation to preserve the environment, 0 otherwise)	-	-	-	-	-	-	-1.05	0.00	0.35
Model Estimation Results									
Selected Cases Included in Analysis	307.00 (61.5%)			307.00 (61.5%)			312.00 (62.5%)		
The observed percentage of the classification satisfying the condition	69.71%			53.40%			61.50%		
Final Model Log likelihood	334.48			401.00			392.23		
Hosmer & Lemeshow test result with significance (Chi-square)(Significance)	6.59(0.47)			0.73(0.98)			5.54(0.48)		
Percentages of correctly predict category membership on the outcome variable	72.96			59.90			67.00		
Nagelkerke R Square (Nagelkerke, 1991)	0.181			0.097			0.099		

6.4.4 Discussion on model estimation results

Estimated result assessment concerning the greater and indifferent likelihood of driverless taxi use than private DC

BLR model estimation results are given in Table 6-16. 69.71% of the respondents are more or equally likely (this was referred to as a "weak preference" relation) to use driverless taxis than to own private DC or are indifferent in choosing for their regular urban trips. Being a frequent household car user, highly educated, 56 -75 years old, not owning a car, and having positive power to handle stress can enhance the likelihood (found as statistically significant predictors) of preferring driverless taxi use to private DC.

Table 6.16 calculates the odd of a particular choice factor as Exp(β). Each coefficient increases the odds by a multiplicative amount, which is e^b, and every unit increase in the variable value increases the odds by e^b. Frequent household car users have nearly 90% more chances than their counterparts to choose driverless taxis over private DC. High-stress handlers are 1.07 times more adaptable in using driverless taxis over private DC, and highly educated people have a 1.15 times more likelihood of accepting similar preferences.

Most importantly, people who don't have cars were 2.46 times more likely to accept driverless taxis over private DC. This behaviour is related to people who cannot afford to drive a car or don't have access to such cars, so they prefer someone to dive for them.

The results revealed that a higher age band makes people prefer driverless taxis over private DC. Likewise, baby Boomer prefers driverless taxis over private DC 2.84 times more than other age bands.

Estimated result assessment concerning the greater and indifferent likelihood of sharing a DC with a stranger than riding alone in a DC

53.4 % of the respondents showed a weak preference for sharing a ride with a stranger to riding alone in a DC for regular urban trips. Such weak preference is common among respondents subject to social norms favouring sharing resources belonging to a family with children and within the age bracket of 56 – 74. Two (or higher) car ownership is a negative factor in this result that indicates people with this car ownership are less attracted to sharing a ride with a stranger.

A negative model constant and its odd ratio indicate that, except for the factors describing this sharing class, other factors make a difference, which is not captured in this modelling exercise.

The odds ratio calculation revealed that the odds for a household with at least one child is more likely to share DC with a stranger by a factor of 1.27. The age results showed that people in the upper age band (Baby Boomers) are more likely to share with a stranger by a factor of 1.25. This result revealed that baby boomers are more able to use shared rides with strangers in DC to meet their occasional travel needs. A larger family size indicates a higher number of occasional trips that cannot be met by any regular family car. Regarding social norms, people who are socially influenced to share their resources are 1.5 times more inclined to share their rides with strangers than the other social classes. This result revealed that people are likely to follow the same path of sharing if they grew up in an environment of sharing and caring.

For car ownership, the odds of sharing a ride with a stranger are decreased by 41.4% for two car owners and thereby increased by 58.6% for less than two car owners. This result is logical as the more cars a household has, the lesser the chance of sharing they prefer with someone.

Estimated result assessment concerning the greater and indifferent likelihood of sharing a DC with a stranger along with a family member than sharing with family alone

As mentioned in Table 6-16, 61.5% of the respondents are more or equally likely to share a DC ride with a stranger while a family member is in the ridesharing or are indifferent to choosing this type of DC sharing for regular urban trips. Such preference is common among rideshares who are higher income holders (Yearly income between £30000 - £40000) and are subject to social norms favouring a higher quality of life. Besides, respondents living in outer suburbs and subject to social norms to preserve the environment are less inclined to prefer shared DC with family members on regular urban trips. Additionally, an insignificant lower positive value of the constant reveals that underlying factors are insufficient to explain the model's relationship.

The odd ratio of sharing a ride with a stranger with a family member is increased by 85.5% for the higher income range between £30000 - £40000. More household income proved more occasional car rental support that helps people's mentality to share their ride with someone. The sharing tendency also flourished with the technological advancement that DC can bring.

The odd ratio is increased by 77.2% for the social norms relating to a better quality of life. Enhancing the quality of life is strongly associated with how things are in our surroundings and how likely we are to share our belongings with others. Therefore, the sharing tendency goes positive with DC sharing with a stranger, even when family members are present.

Living in an outer suburb decreased the sharing tendency by 42.6%, revealing that people from inner suburbs and city centres are more open to sharing a DC with a stranger, even when family members are with them. Similarly, the odd social influence to preserve the environment will likely decrease the sharing tendency with strangers by 35%. This result related to environmental influence on sharing is unexplainable, as empirical evidence shows that people with environmental concerns are more likely to accept DC sharing. Detailed statistics for the binary-logit models are given in Appendix J.

6.4.5 Conclusion on modelling the preferences between shared uses and non-shared uses of driverless cars

This section represents a comparative analysis of respondents' attitudes towards accepting DC shared use over non-shared options. The data set used in this section is the same as that collected through an online survey in Edinburgh, UK. In support of this comparison, this section applied a Binary Logistic Regression (BLR) modelling approach to identify factors affecting the likelihood of DC shared use over non-shared use for regular urban trips in a hypothetical market scenario. The following three dependent variables are extracted to perform the BLR analysis, related to (1) the higher or equal likelihood of Driverless taxis to Private DC; (2) the higher or equal likelihood of riding in DC with a stranger to riding alone in DC; (3) the higher or equal likelihood of ridesharing with a stranger along with a family member to riding only with a family member in DC for regular urban trips. These models are estimated with explanatory (predictor) variables concerned with sharing behaviour, personality, social norm, and socio-demographic characteristics.

The BLR model for the Driverless Taxi use to Private DC correctly predicted 72.96% of the respondents in this category who tend to be frequent household car users, highly educated, 56-75 years old, do not own a car and showed a positive power to handle stress well.

The BLR model for DC riding with a stranger to riding alone in DC predicts 59.9% of the respondents in this category possess social norms favouring sharing resources, belong to a family with children and are within the age bracket of 56 – 74 years. Two car owners are less attracted to sharing with a stranger in a DC.

The BLR model to determine the propensity of DC shared ridership with a stranger and family to shared ridership only with family predicts 67% of the respondents in this category who are higher income holders (e.g., yearly income between £30000 - £40000) and in favour of social norms for the higher quality of life.

The model results reflected that respondents' attitudes towards DC shared use to DC single-use were heterogeneous, mainly due to age, car ownership, and social norm status. In addition, income and social influence to run a better quality of life increase the willingness for shared use of DC.

Baby boomers (age bracket of 56 – 74 years) are the likely adopters of a driverless taxi or sharing with a stranger to the single use of DC. Frequent household car users and no-car owners are inclined to use driverless taxis, while two or more car owners are less inclined to share DC with strangers. These results reflect that higher car ownership is unfavourable in deciding the DC sharing than private DC.

Besides age and ownership, social norm factors are essential to explain the likelihood of sharing DC with a stranger rather than riding alone in DC and sharing DC with a stranger with family to only family members. However, variations between these two comparisons were observed. Results reflected that respondents with social expectations for sharing personal resources are more inclined to share their ride with a stranger, as opposed to attitudes for sharing with family in the presence of a stranger than only with family presence in DC is embraced by those who are looking for the better quality of life.

Results reflected that the higher-income society valued sharing with strangers in the presence of family members. This result contradicts findings from section 6.2, where they prefer the single-use version of the DC. Besides, the highly educated regular travel makers are the adopters of driverless taxis to private DC. Therefore, findings in this section reflected that due to age, income, and education, respondents are heterogenous in their behaviour for synchronous sharing or sharing with a stranger. Unless DC can be shared, DC may not be so promising to reduce traffic from the road network by offering shared travel. Analogous to the findings in section 6.2, sharing the ride with a stranger, people need to change their behaviour of travel sharing (Parkhurst and Seedhouse, 2019), which is an issue that can take a prolonged time to get populated among the mass population.

These comparison factors to guide the shared to non-shared DC choices are subject to behavioural changes that can be observable as DC technology flourishes over time. However, these models are specified based on the collected DC choice responses, where perception bias for DC use is likely to occur. So, these model findings are justifiable considering the bias in the questionnaire design and answering the questions.

6.5 Joint analysis to identify determinants towards non-shared and shared DC options

6.5.1 Introduction for joint analysis to identify determinants towards non-shared and shared DC options

The ordered probit models described in Section 6.2 reflected the variation of determinants in deciding the likelihood concerning each DC shared ownership and shared ridership options. Despite two distinctive user groups associated with DC shared ownership and DC shared ridership, similarities are observed in the likelihood of non-shared (private DC, riding alone with DC) and shared (driverless taxi, riding with a stranger) DC use. In this Chapter, an effort was made to estimate the individual motivations in choosing non-shared and shared options of DC. Also, variations are assessed within the likelihood of non-shared and shared DC use with multinomial logit models defined by two separate sets of explanatory variables. Based on their current sharing attitudes, personality, social norms and socio-demographic characteristics, individuals are heterogeneous in their likelihood of DC usage preferences. Therefore, to identify these variations, model 1 and model 2 were formed. Private DC (Ow_Re_Pr) and riding alone in DC (Ri_ReNF_A) are two outcome variables that constitute the non-shared likelihoods of DCs with model 1. Analogously, the likelihood of driverless taxi use (Ow_Re_Ta) and riding with a stranger in a DC (Ri_ReNF_S) variables are associated with shared DC options, which form model 2. Therefore, discussions are limited only to the regular use of DC, and DC shared use propensities with family members were considered. The binary probit models in Section 6.1 and the binary logit model in Section 6.3 described variations in different DC usage types (propensities) with their determinants. In contrast, this Chapter studies the variation in determinants between two distinctive DC usage types.

Four variations were assessed for non-shared DC usage through the multinomial logit model. Privately-owned DC (Ow_Pr_Re) and riding alone in a household DC (Ri_ReNF_A) bear the same behavioural configuration that can be identified as non-shared use of DC. Several iterative model estimation processes checked these models' explanatory variables (determinants) to attain the best model fitness. The model fitness was checked by comparing the final and the base model log-likelihood estimation. Likewise, model 2 estimates the four usage variations of shared use of

DC that combine the likelihood of driverless taxi (Ow_Re_Ta) use and riding with a stranger in a DC (Ri_ReNF_S). A separate set of explanatory variables is obtained for the shared use of DC to establish the best model fitness, as defined by the difference in the final and the base model log-likelihood estimation. The following section describes the non-shared and shared DC usage classes to form a multinomial logit model.

6.5.2 Variable formation and specification of joint analysis of determinants towards non-shared and shared DC options through multinomial logit model

A variable called PrRa (private DC and riding alone in DC) was formed, defining the combination of ordinal responses concerning private DC (Ow_Pr_Re) and riding alone in a DC (Ri_ReNF_A). The variable PrRa finally constitute four usage types and proportions concerning private DC and riding alone in a DC.

In the first step, the survey responses concerning Ow_Pr_Re and Ri_ReNF_A are collected on a five-point ordered scale (e.g., from 0 to 4, where '0' is very unlikely and 4' is very likely). This process turned the survey data into two binary variables called *'Pr_i'* and *'Ra_i',* where '*Pr_i*' defines the acceptance of private DC, and '*Ra_i*' defines riding alone in a DC. Since these two variables are binary, '1' represents the acceptance of the DC option, and '0' is otherwise. Mathematically,

$$Pr_i = \begin{cases} 1 \; if \; Ow\_\mathrm{Pr}\;\_Re_i \geq 2 \\ 0 \; if \; Ow\_\mathrm{Pr}\;\_Re_i < 2 \end{cases} \quad \text{.......(6)}$$

$$and \;\; Ra_i = \begin{cases} 1 \; if \; Ri_{ReNF_{A_i}} \; \geq \; 2 \\ 0 \; if Ri_{ReNF_{A_i}} < 2 \end{cases} \quad \text{.......(7)}$$

In the second step, these *'Pr_i'* and *'Ra_i'* binary variables are combined to form the Z_{mi} variable defining four types of non-shared DC usages shown by equation (8) below,

$$Z_{mi} = \begin{cases} 0 \text{ if } Pr \; = \; 0 \; and \; Ra \; = \; 0 \\ 1 \text{ if } Pr \; = \; 0 \; and \; Ra \; = \; 1 \\ 2 \text{ if } Pr \; = \; 1 \; and \; Ra \; = \; 0 \\ 3 \text{ if } Pr \; = \; 1 \; and \; Ra \; = \; 1 \end{cases} \quad \text{.......(8)}$$

These four variations in Z_{mi} variable defines four types of DC usages (m = 0, 1, 2, 3) for respondent *i* to be utilised in the next multinomial logit model development step. Following a similar method, Y_{mi} a variable was formed to show the four DC usage variations concerning driverless taxi (Ow_Ta_Re) use and riding with a stranger in the absence of family members in a DC (Ri_ReNF_S), as shown in the equation (9) below:

$$Y_{mi} = \begin{cases} 0 \; if \; Ta = 0 \; and \; Rs \; = 0 \\ 1 \; if \; Ta = 0 \; and \; Rs \; = 1 \\ 2 \; if \; Ta = 1 \; and \; Rs \; = 0 \\ 3 \; if \; Ta = 1 \; and \; Rs \; = 1 \end{cases} \quad \text{.........(9)}$$

Here, Y_{mi} , designates the four usage preference types for individual *i* (from a list of four types of shared DC use) concerning driverless taxi use and riding with a stranger in a DC. The overall process of model variable formation and multinomial-logit model estimation are given in Figure 6.9.

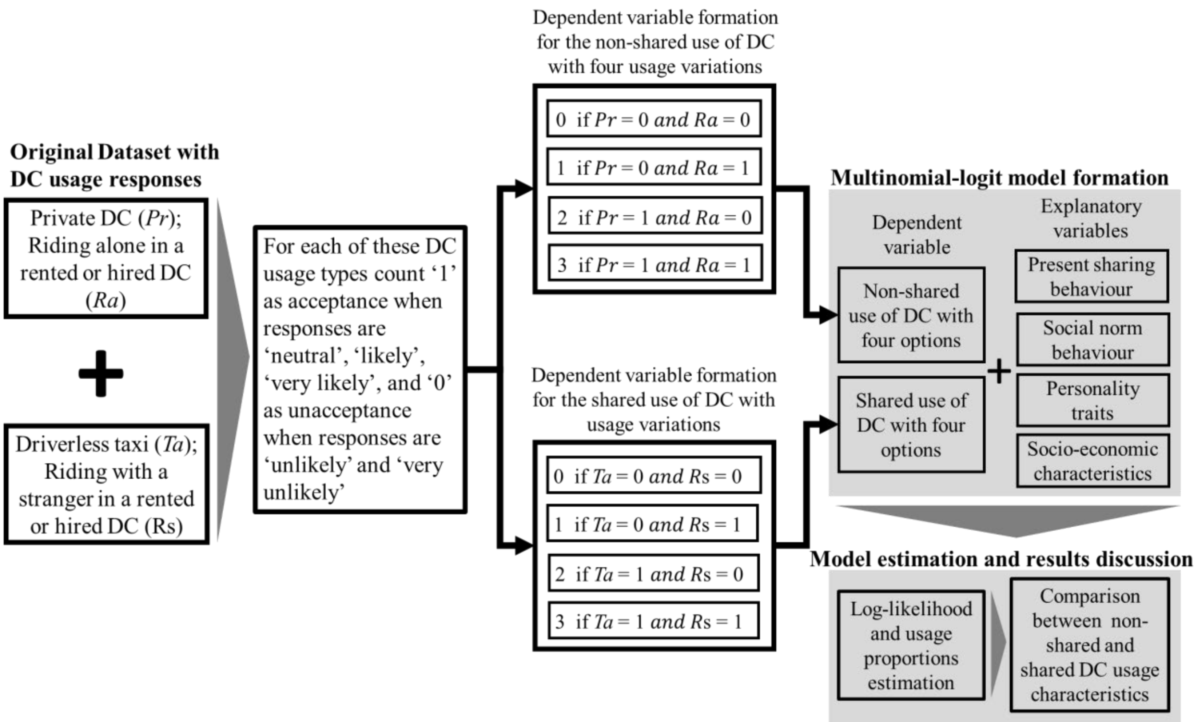


Figure 6.9: Variable formation and multinomial-logit model estimation to access the non-shared and shared DC use

Due to the ordinal discrete nature and variations in the outcome variables, standard multinomial logit (MNL) models (with separate utility functions for each DC usage type described by equations (8) and (9)) were estimated. The aim is to explain the variations in individual preferences associated with each DC usage type. Consistent with the random utility maximisation approach, the multinomial logit model is applied here with determinants such as sharing behaviour, personality, social norm, and socio-demographic characteristics. Four utility functions will be used aligned with four DC usage types considering non-shared and shared variations. Therefore, each survey response should be repeated four times, resulting in 2000 observations from 500 responses. Section 3.8.4 of Chapter 3 described the Logit model development process in detail. In this section, the marginal effects of the variables were highlighted.

As described by equation (10), the marginal effect shows the change in the outcome variable associated with a unit change in an explanatory variable, keeping other explanatory variables constant. In MNL assessment by the LIMDEP package, the marginal effects were calculated with average partial effects to ascertain the change of an explanatory variable over the response propensities for DC usage. Therefore, the derivatives of the choice probabilities for respondent *i* choosing DC usage type n were observed for a change in explanatory variable X_{in}. Considering the representative utility of that DC usage type (keeping the representative utility for other DC usage types constant) P_{in}, the derivative is:

$$\frac{\partial P_{in}}{\partial X_{in}}=\frac{\partial \frac{e^{(\beta_i X_{in})}}{\sum_n^N e^{(\beta_i X_{iN})}}}{\partial X_{in}}=\partial\frac{\beta_i X_{in}}{\partial X_{in}} P_{in}(1 - P_{in}) \ldots\ldots (10)$$

If the representative utility is linear in $\mathbf{X_{in}}$, each respondent had an individual partial effect; these effects are averaged over all respondents as presented in Table 6-20 and Table 6-21 of Chapter 6 with coefficient $\boldsymbol{\beta_i}$. The derivative indicating partial effect will be $\boldsymbol{\beta_i} P_{in}$ $(1 - P_{in})$. This partial effect is the largest when $P_{in} = (1 - P_{in})$. It becomes smaller as P_{in} approaches zero or one (Train, 2009).

6.5.3 Multinomial-logit model estimation results in identifying determinants towards non-shared and shared DC options

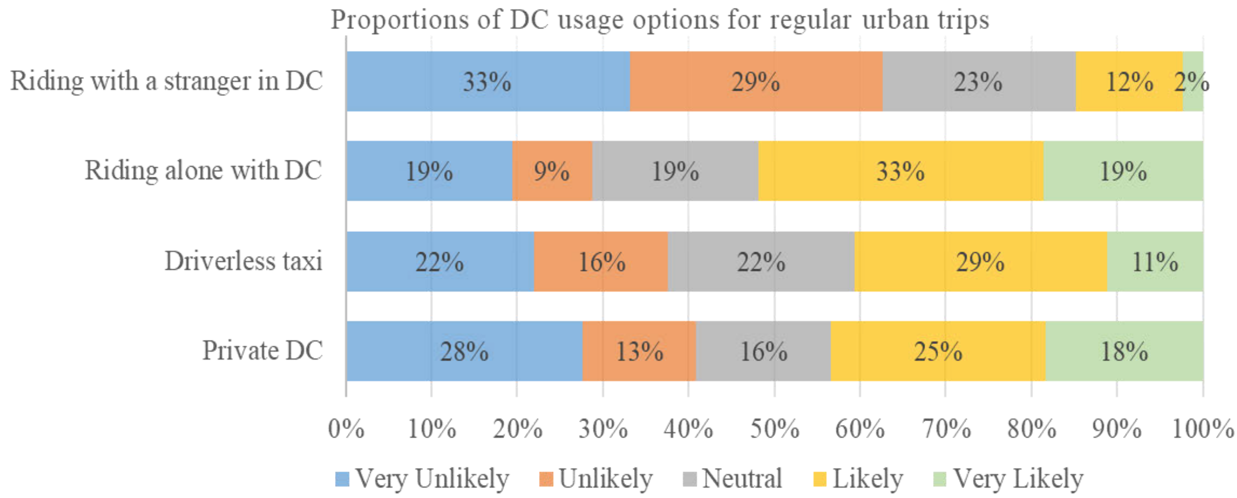


Figure 6.10: Usage proportions for DC options for regular urban trips used for the MNL model

Figure 6.10 shows the summary statistics for the responses relating to different DC usages, as reported in Section 6.2. Neutral responses in all these cases are counted as acceptances for model-building purposes. Table 6-17 shows the number of non-shared and shared DC responses used for MNL model development. This table shows DC use proportions as observed and modelled output.

Table 6-17: Number of responses (observed and modelled) for DC usage types concerning non-shared and shared DC usage

Model 1: Responses for MNL model formation for the private DC and riding alone in DC		
Non-shared DC usage types	Percentages of DC use based on 500 observed responses	Percentages of DC use based on 327 model responses
No preference (NP)	22%	22%
Riding alone in DC preference (RA)	17%	17%
Private DC preference (DP)	5%	6%
Both private DC and riding alone in DC preference	55%	55%
Model 2: Responses for MNL model concerning driverless taxi and riding with a stranger in DC		
Shared DC usage types	Percentages of DC use based on 500 observed responses	Percentages of DC use based on 328 model responses
No preference (NPS)	27%	27%
Ride with a stranger in DC preference (RS)	7%	7%
Driverless taxi preference (DT)	32%	32%
Both riding in DC with a stranger and driverless taxi preference (BPS)	34%	34%

In addition to socioeconomic factors, respondents' personality, social norm behaviour and present sharing behaviour are explanatory variations in MNL model estimation to examine the impact of these variables on the propensity towards (a) non-shared (private DC, riding alone in DC) DC use, and (b) shared (driverless taxi, riding with a stranger in DC) DC use. The respondent-specific variables are entered as dummy variables to ensure data non-linearity associated with DC usage decisions (Ben-Akiva and Lerman, 2010). This assumption, 'piecewise linear approximation' (Ben-Akiva and Lerman, 2010), helps to observe different values and directions of these variables concerning each DC usage type.

Estimation results for model 1

Table 6-18 presents the MNL modelling results concerning the Model 1 exercise described above, while Table 6-20 presents the average partial effects of explanatory variables concerning non-shared DC use. Model 1 results in Table 6-18 show better performance in the final model from the base model defined by the log-likelihood ratio test. A significant chi-square test value of 63.92 [χ^2 *(15)=63.92, p<0.001*] was obtained. This result indicates that the null hypothesis can be rejected and that stated coefficient estimates except the constant are equal to zero, and therefore, alternative hypotheses can be accepted related to model variables.

The DC usages that are highlighted by model 1 are (1) no preferences for both private DC and riding alone in DC; (2) preference for riding alone with DC; (3) preference for private DC; and (4) preferences for both private DC and riding alone in DC. Explanatory variables for Model 1 are explained by education, age of the respondent, household income, car ownership, location, respondent's existing travel behaviour, personality and social norm attitudes. These explanatory variables' values and directions differ for the four non-shared DC usage types. The relative number of responses for usage types in model 1 is given in Table 6-17, which shows 327 responses are utilised for this model compared to the original 500 responses.

The descriptive statistics in Table 6-17 described that 73 responses are explicitly related to no preferences, while 179 respondents expressed their intentions explicitly for private DC and riding alone in DC. A few respondents (57) explicitly expressed their intentions to ride alone in DC, and a handful (18) intended to use private DC. It is evident from Model 1 that zero-car-owning baby boomers prefer the non-shared DC option, except below Bachelor's degree holders are devoid of using any form of non-shared DC. Millennials prefer private DC and riding alone in DC, although regarding education, Bachelor's degree holders prefer to use private DC and ride alone in DC. According to the results, lower-income respondents are interested in private DC, while those from the higher-income class are interested in private DC and riding alone in DC. Zero-car-owning respondents showed explicit interest in riding alone in DC, while two or more car owners are interested in private DC and riding alone in them. Respondents with distinctive experience and interests are not inclined to ride alone in DC, and private DC is the least preferred option for those who don't drive or ride in a car very frequently. Location-wise, inner-suburban dwellers are less inclined to use private DC, while outer-suburban dwellers are interested in using private DC and riding alone in DC. Besides, respondents who bear social norm attitudes to preserve the environment are primarily inclined to support both forms of non-shared DC use.

Estimation results for model 2

Table 6-19 presents the MNL modelling results concerning the Model 2 exercise described above, while Table 6-21 presents the average partial effects of explanatory variables concerning shared DC use. Model 2 deals with explanatory variables that explicitly indicate DC choice variations concerning driverless taxi use and sharing a DC with a stranger. This model performed better in the final model than the base model defined by log-likelihood ratio results. In this line, the significant chi-square test value of 35.97 [χ^2 (12)=35.97, p<0.001] was obtained, with 12 degrees of freedom. This result indicates that the null hypothesis can be accepted concerning coefficient estimates except the constant equals zero, and alternative hypotheses related to model variables can be accepted. Besides, the ρ^2 value *of* 0.043 implies that the explanatory variables adequately define model fitness.

The DC usages that are highlighted by model 2 are (1) no preferences for both driverless taxis and riding with a stranger in DC; (2) preference for riding with a stranger in DC; (3) preference for driverless taxies; and (4) preferences for both driverless taxi and riding with a stranger in DC. Explanatory variables for model 2 are education, age of the respondent, household income, car ownership, location, existing travel behaviour, personality and social norm attitudes. The relative number of responses for usage types in Model 2 is given in Table 6.17, which shows 328 responses are utilised for this model compared to the original 500 responses. Values and variable coefficient directions vary for the four shared DC usage types.

The descriptive statistics of model estimation in Table 6.17 described that 88 responses are explicitly related to no preferences, while 110 respondents expressed their intentions for driverless taxis and riding with a stranger in DC. Very few respondents (24) expressed their intentions explicitly to share their ride with a stranger in DC, while a substantial number of respondents (106) expressed their intention to use driverless taxis. It was evident from Model 2 that city-centre-dwelling millennials are primarily inclined to use shared DC, while minor preferences were observed for shared DC use by low-income earning respondents. Car-owning, postgraduate degree-holding, and higher-earning professionals disapproved of sharing their ride with a stranger in DC.

Driverless taxi use was highly linked to respondents who drive household cars and have no children. People who use conventional taxis are likely to use DT as their second car for leisure trips. Aged respondents (over 55 years of age) who are incapable of driving, with cooperative and sharing attitudes, are inclined to use driverless taxis and ride with strangers in DC. This result reflects that those unable to drive are highly inclined to DC sharing, and their cognitive attitudes towards sharing also helped them do so.

Summary of model estimation results

Model 1 and Model 2 differ in coefficient values and the directions of explanatory variables, as mentioned in Table 6-18 and Table 6-19. These two models were estimated with explanatory variables related to the respondent's education level, age, household income, car ownership, residence, present sharing behaviour, personality types, and social norm behaviour. All coefficients are statistically significant with negative and positive values, explaining respondents' heterogeneity in attitudes towards non-shared and shared use of DC.

Table 6-18: MNL model estimation results for the likelihood of non-shared (Model 1) DC usage and determinants

Explanatory variables concerning MNL model estimation for four usage types of private driverless cars and riding alone in a DC	Model 1 estimation for private driverless car and riding alone in DC, where NP-no preference, RA-riding alone in DC, DP-private DC, BP-both				
	Mean	*St. dev*	*Coeff.*	*St. error*	*T-ratio*
Socio-demographic indicators					
Constant			0.22	0.25	0.85
Lower education level (1 if respondent have secondary level education, 0 otherwise) for NP	0.21	0.41	-0.73	0.42	-1.73
Bachelor's degree holder (1 if the respondent holds a bachelor's degree, 0 otherwise) for BP	0.33	0.47	0.96	0.55	1.74
Millennials (1 if the respondents age between23 - 43, 0 otherwise) for BP	0.29	0.46	0.48	0.27	1.75
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for RA	0.37	0.48	1.16	0.33	3.55
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for NP	0.37	0.48	0.83	0.34	2.46
Lower-income earner (1 if the respondent is earning less than £20000, 0 otherwise) for DP	0.12	0.32	0.96	0.55	1.74
Higher-income earner (1 if the respondent is earning £50000 - £70000, 0 otherwise) for BP	0.18	0.38	0.68	0.34	2.01
Zero car holder (1 if the respondent owns no car, 0 otherwise) for RA	0.18	0.39	1.10	0.37	2.98
Zero car holder (1 if the respondent owns no car, 0 otherwise) for NP	0.18	0.39	0.88	0.37	2.37
Two car holders (if the respondent owns two cars, 0 otherwise) for BP	0.26	0.44	0.59	0.29	2.03
Inner-suburb dwellers (1 if the person lives in the inner-suburb, 0 otherwise) for DP	0.44	0.50	-1.07	0.46	-2.34

Outer-suburb dwellers (1 if the respondent lives in the outer suburb, 0 otherwise) for BP	0.43	0.50	1.10	0.33	3.30
Existing travel behaviour indicators					
Non-frequent household car user (1 if the respondent is an infrequent household car user, 0 otherwise) for DP	0.24	0.43	-1.83	0.75	-2.45
Personality-traits indicators					
Open personality (1 if the respondent has a variety of experiences, diversity of interests, 0 otherwise) for RA	0.43	0.50	-0.66	0.30	-2.23
Social-norm indicators					
The social expectation for preserving the environment (1 if the respondent has feelings for social expectation to preserve the environment, 0 otherwise) for BP	0.76	0.43	0.89	0.22	3.96
Model fitting statistics					
Number of observations, N	327				
Final model log-likelihood, LL(**β**)	-337.13				
Base model log-likelihood, LL(**c**)	-369.09				
Chi- square, χ^2 *(df), significance (ρ)	63.92 (15), *ρ<0.001*				
Rho-square, ρ^2	0.0866				
Adjusted ρ^2	0.0714				

**df = degrees of freedom; LL (β) = log-likelihood of the final model; LL (c) = log-likelihood of the base model*

Table 6-19: MNL model estimation results for the likelihood of shared (Model 2) DC usage and determinants

Explanatory variables concerning MNL model estimation for four usage types of driverless taxi (DT) and riding with a stranger (RS)	Model 2 estimation for driverless taxi and riding with a stranger in DC, where NPS-no preference, RS-riding with a stranger in DC, DT-driverless taxi, BPS-both preference				
	Mean	*St.dev*	*Coeff.*	*St. error*	*T-ratio*
Socio-demographic indicators					
Constant			0.521	0.214	2.437
Masters or higher degree holder (1 if respondent holds a master's degree or higher, 0 otherwise) for RS	0.46	0.5	-0.896	0.403	-2.222
Millennials (1 if the respondent's age is between 23 - 43, 0 otherwise) for NPS	0.29	0.46	-0.535	0.288	-1.862
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for BPS	0.37	0.48	0.425	0.25	1.698

Lower-income earner (1 if the respondent is earning below £20000 per year, 0 otherwise) for NPS	0.12	0.32	0.725	0.37	1.962
Higher-income earner (1 if the respondent is earning £50000 - £70000, 0 otherwise) for RS	0.45	0.5	-0.826	0.432	-1.91
Zero car holder (1 if the respondent owns no car, 0 otherwise) for BPS	0.18	0.39	0.614	0.285	2.157
Car owner (1 if the respondent owns at least one car, 0 otherwise) for RS	0.29	0.46	-1.276	0.614	-2.078
City centre dwellers (1 if the respondent lives in the city centre, 0 otherwise) for NPS	0.34	0.47	-0.471	0.284	-1.659
No-children household (1 if the respondent is from a household without children, 0 otherwise) for DT	0.42	0.49	0.489	0.212	2.308
Existing travel behaviour indicators					
Frequent household car user (1 if the respondent is a frequent household car user, 0 otherwise) for DT	0.3	0.46	0.542	0.2309	2.3488
Personality-traits indicators					
Agreeable personality (1 if the respondent is cooperative and trusting, 0 otherwise) for BPS	0.28	0.45	0.611	0.24	2.544
Social-norm indicators					
The social expectation for sharing resources (1 if the respondent bears feelings to share resources with others, 0 otherwise) for BPS	0.09	0.29	0.606	0.367	1.65
Model fitting statistics					
Number of observations, N	328				
Final model log-likelihood, LL(**β**)	-400.47				
Base model log-likelihood, LL(**c**)	-369.09				
Chi- square, χ^2 *(df), significance (ρ)	35.97 (12), ρ<0.001				
Rho-square, ρ^2	0.043				
Adjusted ρ^2	0.0302				

**df = degrees of freedom; LL (β) = log-likelihood of the final model; LL (c) = log-likelihood of the base model*

6.5.4 Discussion on the multinomial-logit models and related explanatory variables

Model 1 deals with variables concerning the private DC use and riding alone in DC, and Model 2 deals with variables defining shared DC (e.g., driverless taxi, sharing with a stranger in DC) use propensities.

Education

Respondents below bachelor's level education are less supportive of non-shared DC use (a -0.1166 less probability, as indicated by Table 6.20), consistent with earlier findings that stated respondents without high-school degrees are less supportive of DC use (Pakusch *et al.*, 2018). Contrary to that, bachelor's degree holders are interested in both types of non-shared DC. These results resonate with a similar DC study in Japan that showed a higher preference for DC among the higher educated class (Jiang *et al.*, 2019). DC preference is related to the academic background of the respondent, which was revealed by one USA study that investigated the link of information provision with DC preference (Sheela and Mannering, 2019). This study found that highly educated respondents with better information provision are highly likely to prefer DC, and below-educated respondents are less likely to accept DC. Saeed *et al.* (2020) found that highly educated respondents are more interested in DC. The association between education and DC technology acceptance is crucial to enhancing the popularity of DC among respondents. A high level of education is related to higher tech-savviness and ICT, allowing greater access to news and media highlighting DC technology (Astroza *et al.*, 2017).

Contrary to the abovementioned results, postgraduate degree-holding respondents are less inclined (a -0.0620 less probability, as mentioned in Table 6-21) to share their trips with a stranger in DC. This result reflected that despite having an interest in DC (Haboucha *et al.*, 2017) and shared DC use (Barbour *et al.*, 2019), sharers are intrinsically motivated by their convenience of using private DC and its privacy provision. Few recent studies indicated that individuals are reluctant to share a confined automobile space with unfamiliar faces due to privacy, security, and trust issues (Lavieri and Bhat, 2019; Wang, S. *et al.,* 2020). Our findings contradict an earlier study conducted in Florida that found that highly educated individuals are most willing to give up their private car to utilise shared DC (Menon *et al.*, 2018). Respondents with a postgraduate degree are in more responsible jobs that may require them to utilise their in-car time and, therefore, do not like being hindered by the presence of a stranger on board.

Generation (age)

Age variation is an essential factor in deciding DC usage. Age variations are converted to several dummy generation variables where centennials (age range 18 – 23) are taken as the reference. The model estimation results showed that millennials prefer private DC and riding alone in a DC (a 0.0982 higher probability mentioned in Table 6-20). This result also contradicts recent findings that proved that younger people in Japan are less inclined to DC ownership (Jiang *et al.*, 2019), even though they do not explicitly mention millennials' preferences for DC owning.

Considering age influence for non-shared DC use, respondents over 55 years old or higher are more inclined (0.1603 higher probability as mentioned in Table 6-20) to ride alone in DC, while a substantial part (0.1319 higher probability than the rest of the respondents as mentioned in Table 6.4.4) expressed no preference for either form of non-shared DC use. These results indicated the parsimonious DC usage intentions among ageing seniors, supporting Wadud and Chintakayala (2021) research. Respondents over 55 are less flexible, unwelcome to innovative technology solutions, and concerned about using DC (Bansal *et al.*, 2016). Besides, people in this age group cannot interact with the disruption associated with DC use and are less likely to accept a new way of life. Conversely, a few members in this age group prefer riding alone in DC to be less dependent on others to meet their mobility needs and relish their privacy while riding in DC. Saeed *et al.*, (2020) also addressed these opposing behavioural preferences among ageing seniors for non-shared DC usage.

In the case of shared DC preference, negative modelling results indicated that millennials are likely to accept shared DC while in the city centre and are willing to share the ride with a stranger (a 0.0455 more probability to travel with a stranger on DC, as indicated by Table 6-21). This result is similar to a study by Lavieri and Bhat (2019), which found a positive association of pooled DC ride-hailing for millennials in the presence of a human driver. Other studies reflect a significant swing among respondents when sharing the DC ride with strangers (Wang.S *et al.*, 2020). Wang, S. *et al.* (2020) found that only 21% of the sample accepted strangers in DC riding, while 40% supported the same as Fagnant, Kockelman and Bansal (2015). Overall, the present study's findings echoed earlier findings that younger adults support DC sharing more (Krueger *et al.*, 2016; Clayton *et al.*, 2020) than ageing seniors.

Regarding shared DC use, ageing seniors (over 55's) support driverless taxis and are likely to share the ride with a stranger. Even though this age group is anxious and less interested in using DC (Bansal *et al.*, 2016), they might opt out of their negative mindset about sharing and are likely to accept driverless taxis with and without a stranger. Wadud and Chintakayala (2021) found that respondents from this age group who use public transport prefer pooled DC ride services. The opposite effect for this age group was found in a study by Saeed *et al.* (2020), which indicated that ageing seniors are inclined to use conventional private cars instead of shared DC.

Income influence

Regarding household-level variables, the higher household income increases the propensity of private DC and riding alone in DC (a 0.1405 probability, as mentioned in table 6.4.4). These results indicate that higher-income people indulge in their lavish lifestyle and higher spending behaviour on cars, consistent with findings from Lavieri and Bhat (2019). This study suggests that increased income may lead to a higher spending probability on non-shared DC use. Contrary to these findings, Wang, S. *et al.* (2020) found that a future household income increase is inadequate to explain the higher propensity for DC purchases, while a decrease in income is significant for the lower propensity.

Even though higher income is related to greater spending power, the present study reflected that lower-income respondents are more inclined to private DC. Since they know the latest DC technology, their positive mindset showed their propensity for private DC controlling the other aspects of car-owning (e.g., maintenance, insurance). Considering the lower energy consumption (Taiebat *et al.*, 2018), possible lower cost burden Wadud, MacKenzie and Leiby (2016), environmental friendliness (Fagnant and Kockelman, 2014), and lower parking demand (Zhang and Guhathakurta, 2017b), DC can be a feasible mobility option for lower-income households. However, since this result is based on a fraction of the respondents (18), it is hard to judge the DC use types among lower-income holders.

Along with the findings above, MNL model results for higher income indicated a lower propensity (0.0571 less probability stated in Table 6-21) to share the DC ride with strangers, consistent with the findings from Lavieri and Bhat (2019). This study found that higher income decreases the propensity for pooled use of DC. A respondent from a higher income household is highly sensitive to personal space inside DC, positively impacting their decision to avoid a stranger in a shared DC. In line with this finding, Wang, S. *et al.* (2020) proved that higher-income holders are less willing to share a DC.

Car ownership

According to the findings from this research, respondents who currently do not own a car are highly likely to ride alone in DC and show no preference for private DC, which is possible because they ignore non-shared DC usage. This group is also statistically indifferent between exclusive DC use and non-use. Respondents who presently own more than one car are highly inclined to the private DC and ride alone in DC. My result can partially be supported by Lavieri and Bhat (2019), whose findings suggested that non-car commuters are influenced to accept both exclusive and shared ride services. This study also found that respondents from at least one-car households are more inclined to ride-hailing (sharing) for their one-way non-essential trips.

In my result, a greater willingness was found to accept shared DC rides among multiple car-holders, which is inconsistent with recent research findings showing a lower car abandoning tendency by multiple car owners with the advent of DC (Menon *et al.*, 2018). Conversely, Wadud and Chintakayala (2021) found that respondents might not be interested in owning DC in the presence of a DC ridesharing system, which supports my findings concerning DC owning.

Regarding DC ridesharing, present car owners are reluctant (a -0.0883 probability, as mentioned in Table 6-21) to share their rides with a stranger in DC. Along with higher income, present car-owning reflects the symbolism and status quo in mobility behaviour that imposes travellers not sharing a confined space inside the car and not being disturbed by anyone while socialising over mobile devices. This finding echoed the concept derived by Lavieri and Bhat (2019) that suggested household car ownership reduces the inclination towards shared DC use for commuting trips.

Respondents from the zero-car owning households are open to using driverless taxis and sharing with a stranger in DC. This tendency within this group may be related to their lack of car ownership in a household or respondent's inability to drive (due to age, not licensed, injured) that helped them choose shared DC. On the other hand, sharing opportunities with DC allows people to enjoy a greater mobility benefit, making them less dependent on other drivers to help them fill their mobility needs.

Household location

Respondents living in places within an inner-city suburb are unwilling to use private DC, while respondents in suburban areas usually prefer to use private DC and ride alone in DC. These findings are consistent with Saeed *et al.* (2020), who proved that city-centre and inner-suburban dwellers are inclined to use shared DC rather than owning a DC. Respondents who prefer shared DC in urban centres value their travel time and are likely to avoid congestion in city centres. The high demand for private DC among suburban dwellers is relevant to the number of families living in these areas that are not interested in using shared DC.

Regarding shared DC use, the result reflected that city-centre dwellers are not likely to choose shared DC for their mobility needs, consistent with the findings of Lavieri and Bhat (2019). This study found no preferences for DC pooling for work travel within urban areas. City-centre dwellers showed a set behaviour regarding shared rides and taxi use with a stranger on short journeys, which affects their decision to choose shared DC.

This finding showed suburban consumers' interest in non-shared DC, which could help prospective DC ride-hailing companies and TNCs identify future markets in these areas. Subsidised rental costs for driverless taxis can attract people to use them in the city centres. But along with price, the riders' income class should also be carefully judged to enhance the popularity of these modes. Presently, security and privacy are the issues when sharing with a stranger in urban areas (Lavieri and Bhat, 2019), which are likely to be solved by privacy-preservative vehicle interiors for upper-income holders.

Family composition

Family composition indicators are insignificant except for the no-children household for shared DC preference in a non-shared form of DC. Respondents from households without children are inclined to use driverless taxis as shared ride options. This group of respondents is generally young and less inclined to a private car than other age groups, making them choose driverless taxis as a shared form of transport (Rahimi, Azimi and Jin, 2020). My findings can also be backed by a recent study by Spurlock *et al.* (2019), which found that households with 8-year-old children are less interested in shared ride-hailing and adopting traditional carsharing services than households without children. Ridesharing is concerned with privacy provision, flexibility, comfort, and convenience provision of DC, which vary among different population cohorts. For instance, more family members mean greater use and acceptance of private DC use (Saeed *et al.*, 2020), considering DCs allow flexible and efficient operations. Contrary to these findings, Barbour *et al.* (2019) found a lower tendency of shared DC use among small households.

Current sharing behaviour

The indicators of current sharing behaviour are estimated through cluster analysis in this research. Clusters were estimated through the frequency and types of travel-sharing modes, resulting in three present-sharing behaviours. Among these behavioural types, non-frequent household car users are not willing to use private DC, which is well expected and supports what Saeed *et al.* (2020) found concerning commuters, as they are most willing to use private DC. These non-frequent household car users belong to older adults, disabled, homemakers, or those who do not drive and depend on other family members to satisfy their mobility needs. In contrast, earlier research suggested that people who own a private car and drive their car are more likely to own a private DC or ride alone in DC (Becker and Axhausen, 2017). Besides, the observed propensity of not owning DC can be attributed to respondents' habitual patterns stemming from their current car use behaviour (Wachenfeld *et al.*, 2016). Those who do not drive lack familiarity with DC use and carsharing services (Saeed *et al.*, 2020), attributed to private DC use and riding alone in DC.

On the contrary, respondents who frequently use household cars but are not interested in ridesharing are more optimistic (with 0.1130 more probability mentioned in Table 6-21) about driverless taxis as a shared form of DC use. In this research, almost 34% of the respondents belong to this behaviour class, who might be interested in using taxis for their infrequent travel needs and are likely to use them when another family member engages their primary car. The disposition of frequent household car users with driverless taxi use is linked with their willingness to spend more on the privately-used on-demand form of the DC ridership system (Clayton *et al.*, 2020). Partly, this intention is to satisfy respondents' car dependency and psychological association concerning personal car use, as mentioned in earlier studies (Lee *et al.*, 2019).

Present sharing behaviours and car ownership affect the likelihood of DC acceptance in the future. A study by Sener and Zmud (2019) suggested that present ridesharers are more interested in shared DC, and the effect is the opposite for present car owners. These findings help policymakers identify potential consumers for DC's non-shared and shared use possibilities. Frequent travellers and their demands should be carefully determined to keep the DC fleets minimum. To promote shared DC in a particular area or city, car dealers and mobility providers can use customers' mobility profiles (e.g., time to use, distance travel, frequency of use). DC car fleet size and availability in terms of car number and geographic coverage of services should be well maintained to offer them the best DC ride match at a lower price (or combo offer).

Personality traits

From a socio-psychological perspective, respondents' personality traits play a role in adopting DC sharing. Respondents seeking innovation and having various experiences are less likely to prefer driving alone in DC (a -0.0906 less probability, as mentioned in Table 6-20). Respondents with this personality constituted 43% of the sample. By their very nature, they were interested in mixing varieties of people, likely to have more family connections, indicating their lower preference for riding alone and more preference for riding in groups. These findings reflect only one aspect of personality to support shared DC use, inspiring further personality assessment concerning shared DC adoption. Similarly, another study found that respondents who appreciate the environment and bear high energy for social life (extroverted personalities) are more interested in DC sharing with a stranger (Clayton *et al.*, 2020).

Respondents with cooperative attitudes and belief in social harmony demonstrate a higher (a 0.1290 higher probability as mentioned in Table 6-21) inclination towards driverless taxis and are likely to share their regular urban trips with a stranger. This result is supported by the findings of Kyriakidis, Happee and De Winter (2015) and deemed plausible since respondents with this type of personality are generally submissive, pro-environmental (Hirsh, 2010), and likely to adopt sustainable transport modes (Kim *et al.*, 2014). In contrast, another study on ridesharing behaviour found that respondents with agreeable, open personalities are more interested in DC carsharing (Spurlock *et al.*, 2019).

Social norm behaviour

The indicators related to social norm behaviour are assessed through some statements concerning the subjective social norm of the respondents. For this research, subjective social norms are related to social expectations for preserving the environment and social expectations for sharing resources.

The variable representing social expectation to preserve the environment is likely to affect DC preferences significantly. Respondents who acknowledge the social expectation to protect the environment are more receptive to private DCs and more likely to drive alone in a DC for their regular urban trips. This result may be driven by public expectations for low-emission technologies incorporated in DC. However, these findings need to be investigated further since the impact of social norms in accepting DC has not been fully identified to date. Considering the reduction of environmental impact, the people of San Francisco expressed their interest in the DC use and carsharing services (Spurlock *et al.*, 2019). Another prior research contradicted my findings and identified that people who support preserving the environment are more likely to accept shared DC use (Haboucha *et al.*, 2017). In my literature search, environmental preservation by utilising DC is linked with the possibility of pollution-free electric technology in DC sharing systems (Fagnant and Kockelman, 2015; Martinez and Viegas, 2017).

Respondents who are socially motivated to share resources are optimistic about driverless taxi use and sharing their rides with strangers for regular urban trips. These results indicate that users with sharing tendencies may help enhance the DC sharing schemes. The subjective social norm for sharing resources reflects the behavioural intention inspired by their close contacts, and people's socialisation and learning experiences are the guiding force behind these social norm values (Schwartz, 1977). Even though social norm influences were not discussed elsewhere, recent literature identified that social interaction-seeking respondents are optimistic about carsharing but less interested in fully automated DC use (Spurlock *et al.*, 2019).

Detailed LIMDEP software output relating to the MNL results is given in Appendix K.

Table 6-20: Multinomial logit model results concerning the likelihood of the private DC use and riding alone in DC: model 1

Explanatory variables for MNL model with four usage types concerning private DC and riding alone in DC	**Model estimation**					**Average partial effects of variables**			
	Mean	*St. dev*	*Coeff.*	*St. error*	*T-ratio*	No preference (NP)	Riding alone (RA)	Private DC (DP)	Both preference (BP)
Socio-demographic indicators									
Constant			0.215	0.254	0.849				
Lower education level (1 if respondent have secondary level education, 0 otherwise) for NP	0.21	0.41	-0.730	0.423	-1.726	**-0.1166**	0.0360	0.0102	0.0703
Bachelor's degree holder (1 if the respondent holds a bachelor's degree, 0 otherwise) for BP	0.33	0.47	0.961	0.554	1.735	-0.0449	-0.0360	-0.0155	**0.0963**
Millennials (1 if the respondent’s age is between 23 - 43, 0 otherwise) for BP	0.29	0.46	0.476	0.272	1.751	-0.0458	-0.0367	-0.0158	**0.0982**
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for RA	0.37	0.48	1.162	0.328	3.546	-0.0573	**0.1603**	-0.0133	-0.0896
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for NP	0.37	0.48	0.827	0.336	2.463	**0.1319**	-0.0408	-0.0116	-0.0796
Lower-income earner (1 if the respondent is earning less than £20000, 0 otherwise) for DP	0.12	0.32	0.961	0.554	1.735	-0.0134	-0.0110	**0.0563**	-0.0319
Higher-income earner (1 if the respondent is earning £50000 - £70000, 0 otherwise) for BP	0.18	0.38	0.680	0.338	2.011	-0.0655	-0.0525	-0.0226	**0.1405**
Zero car holder (1 if the respondent owns no car, 0 otherwise) for RA	0.18	0.39	1.101	0.369	2.983	-0.0543	**0.1519**	-0.0126	-0.0850
Zero car holder (1 if the respondent owns no car, 0 otherwise) for NP	0.18	0.39	0.880	0.371	2.372	**0.1404**	-0.0434	-0.0123	-0.0847
Two car holders (if the respondent owns two cars, 0 otherwise) for BP	0.26	0.44	0.593	0.292	2.031	-0.0571	-0.0458	-0.0197	**0.1225**
Inner-suburb dwellers (1 if the person lives in the inner-suburb, 0 otherwise) for DP	0.44	0.50	-1.073	0.458	-2.342	0.0150	0.0123	**-0.0628**	0.0356
Outer-suburb dwellers (1 if the respondent lives in the outer suburb, 0 otherwise) for BP	0.43	0.50	1.100	0.333	3.299	-0.1059	-0.0849	-0.0365	**0.2272**
Existing travel behaviour indicators									
Non-frequent household car user (1 if the respondent is an infrequent household car user, 0 otherwise) for DP	0.24	0.43	-1.826	0.747	-2.445	0.0256	0.0209	-0.1070	0.0605
Personality-traits indicators									
Open personality (1 if the respondent has a variety of experiences, diversity of interests, 0 otherwise) for RA	0.43	0.50	-0.657	0.295	-2.229	0.0324	-0.0906	0.0075	0.0507
Social-norm indicators									
The social expectation for preserving the environment (1 if the respondent has feelings for social expectation to preserve the environment, 0 otherwise) for BP	0.76	0.43	0.886	0.224	3.957	-0.0852	-0.0683	-0.0294	0.1830

Table 6-21: Multinomial logit model results concerning the likelihood of driverless taxi use and riding with a stranger in DC

Explanatory variables for the MNL model with four usage types concerning driverless taxi (DT) and riding with a stranger (RS)	**Model estimation**					**Average partial effects of parameters**			
	Mean	*St.dev*	*Coeff.*	*St. error*	*T-ratio*	No preference (NPS)	Ride with a stranger (RS)	Driverless taxi (DT)	Both preference (BPS)
Socio-demographic indicators									
Constant			0.521	0.214	2.437				
Masters or higher degree holder (1 if respondent hold a master's degree or higher, 0 otherwise) for RS	0.46	0.50	-0.896	0.403	-2.222	0.018	**-0.062**	0.021	0.023
Millennials (1 if the respondent's age is between 23 - 43, 0 otherwise) for NPS	0.29	0.46	-0.535	0.288	-1.862	**-0.101**	0.011	0.045	0.046
Baby boomer (1 if the respondent's age is between 56 -74, 0 otherwise) for BPS	0.37	0.48	0.425	0.250	1.698	-0.036	-0.011	-0.043	**0.090**
Lower-income earner (1 if the respondent is earning below £20000 per year, 0 otherwise) for NPS	0.12	0.32	0.725	0.370	1.962	**0.137**	-0.015	-0.061	-0.062
Higher-income earner (1 if the respondent is earning £50000 - £70000, 0 otherwise) for	0.45	0.50	-0.826	0.432	-1.910	0.017	**-0.057**	0.020	0.021
Zero car holder (1 if the respondent owns no car, 0 otherwise) for BPS	0.18	0.39	0.614	0.285	2.157	-0.052	-0.015	-0.062	**0.130**
Car owner (1 if the respondent owns at least one car, 0 otherwise) for RS	0.29	0.46	-1.276	0.614	-2.078	0.026	**-0.088**	0.030	0.032
City centre dwellers (1 if the respondent lives in the city centre, 0 otherwise) for NPS	0.34	0.47	-0.471	0.284	-1.659	**-0.089**	0.010	0.039	0.040
No-children household (1 if the respondent is from a household without children, 0 otherwise) for DT	0.42	0.49	0.489	0.212	2.308	-0.041	-0.012	**0.102**	-0.049
Existing travel behaviour indicators									
Frequent household car user (1 if the respondent is a frequent household car user, 0 otherwise) for DT	0.30	0.46	0.542	0.2309	2.3488	-0.0453	-0.0129	**0.1130**	-0.0547
Personality-traits indicators									
Agreeable personality (1 if the respondent is cooperative and trusting, 0 otherwise) for BPS	0.28	0.45	0.611	0.240	2.544	-0.0520	-0.0154	-0.0617	**0.1290**
Social-norm indicators									
The social expectation for sharing resources (1 if the respondent bare feelings to share resources with others, 0 otherwise) for BPS	0.09	0.29	0.606	0.367	1.650	-0.0515	-0.0153	-0.0612	**0.1280**

6.5.5 Conclusion on joint analysis of determinants towards non-shared and shared DC options through multinomial logit model

This section represents a comparative analysis of the respondents' attitudes toward accepting non-shared and shared DC use. The data set used in this section is the same as that collected through an online survey in Edinburgh, UK. The Multinomial-logit (MNL) modelling approach was applied to compare these results with common observable factors affecting the likelihood of DC shared and non-shared use for regular urban trips in a hypothetical market scenario.

In the first stage, four usage types concerning non-shared DC types (e.g., Private DC, Riding alone in DC) were extracted. In this process, 'Neutral', 'Likely', and 'Very Likely' responses are configured as '1', while other response categories are configured as '0'. The four (0,0; 1,0; 0,1;1,1) combinations of non-shared DC usage types are thus formed into four non-shared DC options (e.g., No preference, Riding alone in DC, Private DC, Both Private DC and Riding alone in DC preferences). A similar process was followed to extract four shared DC usage options (e.g., No preference, Riding with a stranger in DC, Driverless Taxi, Both Riding with a stranger in DC and Driverless taxi preferences). The modelled output data showed that 55% of the respondents preferred private DC and Riding alone in DC compared to 55% of observed data in the non-shared DC category. The percentage to prefer sharing a ride with a stranger in DC and Driverless taxi use is 34%, as initially observed by the raw data.

The MNL analysis was performed at the next stage, focusing on respondents' likelihood of non-shared and shared DC usage types for regular urban trips as dependent variables. Both models are assessed with explanatory (predictor) variables concerned with sharing behaviour, personality, social norm, and socio-demographic characteristics. MNL determines the probabilities of non-shared and shared DC usages (between 0 and 1), estimated through the log-likelihood and model parameters' significance tests.

For the non-shared DC model, respondents were heterogeneous primarily and influenced by their education level, age, income, car ownership, residential location, present travel-sharing behaviour, personality and social norm attitudes. Bachelor’s degree holding, higher-earning millennial respondents who belong to a household with at least one car in the outer suburbs dwelling, possess the social norm attitudes to preserve the environment and have distinctive experiences were most inclined to support both forms of non-shared (Private DC and riding alone in DC) DC use. Family size is not essential for respondents to define any direction for non-shared DC use.

For the shared DC model, it was evident that higher car ownership, postgraduate degrees and higher income are responsible for the disapproval of ridesharing with a stranger in DC. Driverless taxi use was highly linked to respondents who use household cars frequently and have no children. Besides, no car ownership and the age of the respondents (age over 55 years), personality, and social norm attitudes are essential factors that help people decide on shared DC car use. People incapable of driving, with a cooperative mentality and sharing attitudes, were inclined to use driverless taxis and ride with strangers in DC.

These factors influencing shared and non-shared DC choices were subject to location and technological changes. DC technology is flourishing; therefore, DC sharing facilities and use variations are not so apparent to radically change the ridesharing concept within a short timeframe (like 5 years). However, these models are location-specific (e.g., for Edinburgh) and based on the collected baseline DC choice responses without further error measures and compatibility analysis. So, using these model findings, the city variations and associated bias in the new questionnaire design and data collection techniques should be judged with precautions.

7. Chapter 7: Conclusions and recommendations for future research

7.1 Introduction

This chapter aims to summarise the findings of this study concerning the shared ownership and ridership of DC in an urban environment. Research findings, limitations, and scope for further study are discussed in this chapter. First, in this chapter, the survey results are summarised and presented. After the summary, the results are used to answer the relevant research questions. Implications for policy regarding sharing DC into the broader transport arena are then drawn. Limitations and scope of further research came after that. Finally, this chapter ends with some concluding remarks.

7.2 Summary of the findings

7.2.1 Reasons for this Research

In the DC research arena, discrete choice modelling applications are based on some assumptions with general choice data relevant to this emerging technology, where household use of DC use was not reflected. To this end, this research was conducted by applying a discrete choice modelling approach with household car-sharing data and socio-demographic factors to uncover the propensities of different DC-sharing options.

7.2.2 Main Findings

This study utilised discrete choice modelling methods/techniques to analyse data collected through an online questionnaire survey within Edinburgh postcode zones. The online survey data were analysed with several econometric and statistical methods. All the socioeconomic, personality and social-norm variables were transformed into binary variables. DC shared ownership and ridership preference levels were collected on a 5-point Likert scale and analysed through econometric methods. Binary Probit, Ordered Probit, Binary Logit, and Multinomial Logit were mentionable econometric analysis models applied for this research. For all these econometric methods, DC shared ownership and ridership choice preference levels were dependent variables, while socioeconomic, personality and social-norm variables were used as explanatory variables. Appendix G of this dissertation has a detailed list of relevant explanatory variables.

7.2.2 Sample Size and Population Representativeness

The survey aimed to collect samples within the range of 450 – 550 to appropriately capture the population variations in Edinburgh, as discussed in Chapter 4. After the survey, 500 samples were obtained, 475 of which were fully completed. A comparison was performed between the sample data and the Edinburgh population census data to establish the survey's representativeness. Due to the sampling and administration bias, there are some sociodemographic variations between the sample and the Scottish population, particularly an overrepresentation of male and older respondents. However, considering the exploratory nature of the research and its focus on the determinants of DC sharing preferences, we can consider having enough participants in each sociodemographic group. Therefore, the sample is deemed suitable to answer the research questions.

7.2.3 Propensity to share ownership and ridership of DC

Regarding shared ownership, most (43%) respondents are interested in using private DC for regular urban travel, with 41% being interested in driverless taxi use. For occasional travel, most (49%) respondents are inclined to driverless taxis, with a similar but smaller proportion (47%) likely to use private DC as well. The likelihood of using shared-owned cars for regular and occasional use is 8% and 16%, respectively.

For regular urban trips without family members, riding alone is the most (52%) preferred form of DC riding, while riding with a stranger is the least (15%) preferred. For occasional trips, these preferences are almost similar. Most (64%) respondents preferred riding only with family members for regular trips involving family members, while only a few (18%) preferred sharing with a stranger. For occasional travel, these preference levels are similar. For both ridesharing types with and without family members, sharing with a stranger is the least preferred option. Concerning ridesharing, respondents are mainly interested in sharing with family members and close contacts.

7.2.4 Answers to the Research Questions

Table 7-1 summarizes the methods employed to answer the research questions and the relevant Chapters where answers are discussed.

Table 7-1: Research questions, relevant methods, and Chapters where answers are discussed

Serial. No.	Research Questions	Method of Estimation	Related Chapters

1	**What are the current behaviours in terms of shared mobility?**		
	1a. What are the current shared ownership behaviours by different travel modes?	Descriptive Statistics; Cluster Analysis; Cross-classification analysis	4, 5
	1b. What are the current ridesharing behaviours by different travel modes?	Descriptive Statistics; Cluster Analysis; Cross-classification analysis	4, 5
	1c. What are the factors influencing present shared ownership and ridesharing behaviour?	Descriptive Statistics; Cluster Analysis; Cross-classification analysis	4, 5
2	**What are the expected behaviours and attitudes regarding shared mobility using DC?**		
	2a. How do sharing behaviours influence propensity towards shared DC?	Binary Probit	6: Sections 6.1
	2b. What are the attitudes determining weak propensities to accept shared DC use over non-shared DC options?	Binary Logit	6: Sections 6.3
	2c. What are the attitudes determining non-shared and shared DC use?	Multinomial Logit models	6: Sections 6.4
3	**How do personal characteristics influence the shared mobility choices with DC?**		
	3a. How do sociodemographic characteristics influence the sharing choices concerning DCs?	Ordered Probit Analysis; Cross-classification with Clusters	6: Section 6.2
	3b. How do personality traits influence the sharing choices concerning DCs?	Descriptive statistics; Ordered Probit Analysis	6: Section 6.2
	3c. How do social-norm characteristics influence the sharing choices concerning DCs?	Descriptive statistics; Ordered Probit Analysis	6: Section 6.2

Question 1. What is the current behaviour in terms of shared mobility?

The first research question seeks respondents' answers for shared car ownership and ridership usage frequencies. In terms of shared ownership, these options are 1) a household car, 2) a car of the people you know well, 3) a car of a car club, 4) a car of a car rental company, and 5) a Peer-to-peer car rental. For ridesharing or shared ridership, these options are: 1) Drive alone; 2) As a driver with people you know well; 3) As a passenger with people you know well; 4) As a driver with a stranger; 5) As a passenger with a stranger; 6) In a taxi. For both these travel-sharing options, trip frequency data was collected using the scale: 1) several times in a week, 2) a few days in a month, 3) a few times in a year, and 4) never.

Q1a. What are the current shared ownership behaviours by different travel modes?

Regarding carsharing, for trips made several times a week, most respondents (53.5%) are willing to use their household cars, with only a few willing to share cars with known people, whereas respondents are unwilling to share/rent cars from a car club, car rentals and peer-to-peer carsharing services. For trips occurring several times a month, respondents prefer to use their household car' (23.4%) and share cars with close contacts' (21.4%) rather than sharing cars from a car club, car rentals and peer-to-peer carsharing service. When travel demand is yearly, most respondents (41.2%) use to take/rent cars from their close contacts and car rentals (25.2%). When respondents travel rarely, this survey reveals that most (97.5%) prefer to share cars from peer-to-peer services, followed by car clubs and rentals. These findings indicated that for people who travel several times a week and a few days a month, their travel behaviours are associated with household car use or sharing a car with their close contacts.

As a result of the clustering with frequency and shared ownership types, these clusters broadly define the present shared car ownership behaviour among the survey participants. This exercise reflected that the survey sample is divided into frequent Household car users (30.2%), non-frequent household car users (33.4%), and frequent household car users who don't use car rentals (36.4%).

Q1b. What are the current ridesharing behaviours by different travel modes?

Respondents' answers related to rideshare demonstrated that most respondents (43.2%) used to drive alone on their journeys several times a week. However, a substantial number (35.4%) of them travel with known passengers, and 17.3% mentioned they share a car as a passenger. Only 1.3% are eager to share a ride with a stranger as a passenger, while only 0.6% diver with strangers. 3.3% of respondents said they travel by taxi for their weekly travel. These results imply that most respondents ride alone rather than share their car, and only a small fraction are ready to share a car with a stranger.

A cluster analysis method was employed in Chapter 5 to reflect the present ridesharing behaviour, which segmented the respondents into car divers (75.6%) and non-drivers (24.4%). Among them, drivers (53.3%) primarily rely on their cars and share (43.1%) cars with their close contacts for regular urban travel. Regarding occasional travel, 35.9 % of car users share their rides with known people as passengers, and 59.9% rarely use taxis. Regarding non-drivers, when they travel monthly, they mostly (34.3%) share their rides with known people. When travel demand is rare, they use taxi services (50%).

Q1c. What are the factors influencing present shared ownership and ridesharing behaviour?

This research collected data on five shared car ownership reasons on a five-point Likert scale, where reducing or eliminating insurance and tax expenses are highly important (39%) reasons, as well as reducing or eliminating the maintenance cost burden (38%).

On the other hand, the availability of shared car ownership and limited convenience are the two most important reasons (68% and 43%, respectively) for not choosing shared car ownership, with lack of familiarity with these services being the least (18%) important reason. Overall, cost and convenience are not the most noteworthy factors related to choosing and not choosing carsharing.

The two most important reasons for choosing ridesharing are the trip's lower cost (29%) and the possibility of getting rid of driving and parking hassles (29%). In contrast, the top reasons for not choosing ridesharing are possible unreliability to travel companions (70%) and less flexibility in departure time and route choice (63%).

Question 2. What are the expected behaviours and attitudes regarding shared mobility using DC?

Concentration was given on the findings to answer these research questions within Sections 6.1, 6.3 and 6.4 of Chapter 6, as mentioned in Table 7.1. Based on these findings, following points can be discussed to answer research question No.2, as shown below:

Q2a. How do sharing behaviours influence propensity towards shared DC?

Section 6.1 analysed the relative significance of present travel-sharing behaviours concerning DC-shared ownership and ridesharing by applying a Binary Probit model. The factors defining DC shared ownership are ownership types (driverless taxi use to private DC, shared DC use to private DC use), trip frequency (Occasional travel when regular travel as reference) and interaction terms (e.g., driverless taxi use for occasional trips when all other trip types are reference). The factors influencing DC ridesharing are DC shared ridership types (ridesharing with known people when ridesharing with a stranger is a reference), trip frequency (Occasional travel when regular travel as reference), family members' presence (with a family member when without family a member is a reference), and interaction terms (shared ridership with a stranger while a family member is there when all other trip types are reference).

The trip frequency estimates concerning DC-shared ownership are insignificant in explaining the likelihood of accepting DC-shared ownership. In contrast, the DC shared ridership model revealed that respondents are willing to accept DC shared ridership for their regular urban trips.

Shared driverless taxi use is more acceptable than DC shared ownership while riding with a known person is preferred in terms of DC ridesharing. These results implied that sharing partners are pivotal in deciding DC shared ridership. The propensity to share a ride with a stranger is unacceptable, with or without a family member. Following these current behavioural constraints, DC sharing will likely occur in the form of a driverless taxi and the presence of a known partner or close contacts.

Q2b. What are the attitudes determining weak propensities to accept shared DC use over non-shared DC options?

69.71% of the respondents are weakly inclined to use driverless taxis rather than own private DC or are indifferent in choosing their regular urban trips. The determinants for this choice are frequent household car users, highly educated, 56 -75 years old, not owning a car, and having a positive mental ability to handle stress.

53.4 % of the respondents showed a weak preference for sharing a ride with a stranger over riding alone in DC for regular urban trips. Positive determinants associated with such weak preferences were social norms favouring sharing resources, belonging to a family with at least one child, and being within the age bracket of 56 – 74. Two (or higher) car ownership was a negative determinant, indicating that people with more household cars are less inclined to share their ride with a stranger.

61.5% of the respondents were weakly inclined to share a DC ride with a stranger and a family member for regular urban trips. The positive influence of higher income and social norms favouring better quality of life determine such preferences. Besides, respondents living in the outer suburbs and bearing social norms to preserve the environment were less inclined to prefer DC sharing with strangers and family members for their regular urban trips.

The model results depicted in Table 6.3.2 revealed that respondents were heterogeneous in their behaviour and attitudes to adopt shared DC use over exclusive use, mainly influenced by their age, education, car ownership, household size, income, existing carsharing behaviour, personality and social norm status. No-car owners were inclined to use driverless taxis, while two or more car owners were less inclined to share DC with strangers. These results reflected that higher car ownership is unfavourable in deciding the DC sharing than private DC.

Other than age and car ownership, social-norm factors were essential in deciding the likelihood of sharing DC with a stranger. My findings suggested that respondents with social influence for sharing personal resources and better quality of life were more inclined to share their ride with a stranger, even in the presence of a family member.

Q2c. What are the attitudes determining non-shared and shared DC use?

In this part of the research, variations in the likelihood of non-shared and shared DC use were assessed and defined by a similar set of determinants concerning current sharing attitudes, personality, social norms and sociodemographic characteristics. Determinants of non-shared and shared DC options were jointly assessed to identify these variations. In Model 1, private DC and riding alone in DC were assessed as non-shared forms, and Model 2 relates to the assessment of driverless taxi use and riding with a stranger as shared DC usage. Therefore, these models are referred to as a joint non-shared assessment because private DC was taken from shared ownership, riding alone from shared ridership. Similarly, driverless taxi use and sharing a ride with a stranger in DC were jointly categorised as joined shared assessment.

Education, age, income, car ownership, personality and social norms are essential determinants for non-shared and shared DC models. Respondents with bachelor's level education support non-shared DC, and postgraduate degree-holding respondents are less inclined to share their trips with a stranger in driverless taxis.

Regarding age, millennials (age range 24 - 43) are likely to adopt shared DC in the city centre and are willing to share the ride with a stranger, while ageing seniors (over 55) support private DC use.

Higher-income households are inclined to use non-shared DC (private and riding alone), while an increase in income is associated with a lower propensity for shared use DC rides with strangers.

In terms of the impact of household location on DC choice, outer-suburban dwellers prefer the non-shared form of DC, while city-centre dwellers prefer driverless taxis and sharing rides with strangers.

People who cannot drive or don't have access to a car are highly likely to ride alone or have no preferences, while people who own two or more cars are more interested in owning a DC and riding alone in a DC than sharing their ride with others. While sharing the DC, people who do not own a car currently are interested in the driverless taxi and sharing with strangers, while owners of more than one car are less inclined to share the ride with strangers.

Respondents from households without children are inclined to use driverless taxis as a shared ride option, indicating that smaller families are likely adopters of shared DC use.

Model results related to present ridesharing tendency reflect that infrequent household car owners are reluctant to own a DC, as opposed to frequent household car users who are very interested in driverless taxi use (shared DC car use). These results proved that future DC sharing behaviour is linked with present ridesharing attitudes, which will likely advance as the DC sharing technology develops.

Regarding personality, respondents with diversified interests who are open to new things are less inclined to ride alone in DC. On the contrary, people with cooperative attitudes are more inclined to use driverless taxis (shared DC). So, personality-wise, openness and cooperative thinking are crucial attitudes in accepting DC sharing, which has promising potential to enhance DC sharing and thereby reduce car traffic on urban roads.

Societal influence on preserving the environment is vital in choosing the non-shared form of DC, while those influenced to share their resources are more open to accepting the shared DC. The effect of pro-environmentalism on non-shared DC choice should be studied further in controlled parameter conditions.

In choosing non-shared DC, existing travel behaviour, personality and social norms are not essential determinants. On the contrary, present zero-car ownership, personality, social norms, and existing travel behaviours are crucial determinants for shared DC use.

Question 3. How will personal characteristics influence the choices regarding DCs?

The respondent's socioeconomic status, personality and social norms determine the influences of personal characteristics in choosing DC options.

3a. How do sociodemographic characteristics influence the sharing choices concerning DCs?

Concerning the age of the respondents, millennials (age 24 – 43 years) are most interested in using a driverless taxi and riding with strangers in DC, even with their family members. On the other hand, baby boomers (age 56 -74 years) are not willing to use the non-shared form of DC (e.g., private DC, riding alone in DC).

Master's degree-holding respondents are not willing to use private DC or share their rides with strangers in the presence of their family members.

Families with at least one child are less inclined to driverless taxi use, nor do they tend to ride alone in DC. On the contrary, families without a child are not interested in sharing their ride with a stranger in DC.

Higher household income is a determinant of driverless taxi use. Except for this finding, the income influence on shared DC use was not proven.

In the case of household location, city-centre dwellers are willing to share their rides with strangers, while outer suburban dwellers are interested in sharing the ride with their families and close contacts in DC.

Car ownership and the present frequent household car use are two critical interdependent terms identifying determinants suggesting that car owners are not likely to use shared DC (e.g., driverless car, riding with strangers) of any form.

3b. How do personality traits influence the sharing choices concerning DCs?

My survey findings show that agreeableness and extraversion are two essential personality traits reflecting shared DC use tendencies. People with agreeableness and cooperative personalities are more inclined to use driverless taxis and share DC with strangers.

Highly energetic and active social life-maker extroverted respondents are not interested in sharing their rides with family members.

3c. How do social norms influence the sharing choices concerning DCs?

People with social influence to preserve the environment are primarily interested in non-shared (e.g., private DC, riding alone in DC, riding with a family member in DC) forms of DC, while people with social norm to preserve the environment are interested in driverless taxes, and to ride with strangers.

In response to Question No.3, the personal characteristics assessment proved that other than age, income and education, residential location, car ownership, present travel behaviour, personality and social norms are significant indicators of DC sharing choices.

7.3 Policy Implications

The implications of this research lie in the scope of this research in identifying the determinants of DC sharing for regular urban travel. The implications are given in the paragraphs below:

1. Shared car ownership with DC

The Joint DC shared ownership model and overall behavioural determinant assessment reflect that driverless taxi use is more likely than shared-owned DC use for regular urban trips. This result suggested that people's perception of shared-owned DC is not clear enough to judge its benefits compared to driverless taxi usage. Therefore, practically, the present car club model of sharing and peer-to-peer sharing options could be the best way to flourish DC's shared use. Besides, transport policymakers should carefully judge the propensities of DC use in driverless taxi forms to achieve confidence in shared-owned DC use. One research study supports this finding that forecasted replacing ten conventionally driven cars with one driverless taxi (Bischoff and Maciejewski, 2016). A driverless taxi can be synonymous with shared DC use discussed in recent findings (Liu *et al.*, 2020; Dandl and Bogenberger, 2019), with a profound aversion to sharing with a stranger (Clayton *et al.*, 2020) supporting the findings of this research. Therefore, to make DC shared ownership a viable concept, policymakers and carmakers can introduce schemes where several people can jointly own a DC with minimum/divided liabilities, which would otherwise be very expensive. For instance, General Motors's and Honda's joint venture Cruise (getcruise.com) project recently unveiled its first-ever DC prototype for shared use (Hitti, 2020). This prototype is designed to encourage more affordable and collaborative transport provision instead of private DC.

2. Shared ridership with DC

The propensity to DC shared ridership model reflected that riding with a known person is preferred to riding with a stranger. Millennials are more interested in sharing a ride in a driverless taxi with a stranger than any other age group.

Considering the above, Justification of ridesharing with DC requires proper policy measures considering sharing types and travel companions. These factors can enhance the tendency of DC sharing sustainably. The likely outcome could be shifting the propensity of privately-used DC to service use of DC (e.g., taxi, carpool) (Firnkorn and Müller, 2012). Service usage of DC can be introduced in many forms, with the standard type being the shared driverless taxi, driverless Uber, and driverless peer-to-peer sharing (Jaynes, 2016). So, from a policy perspective, proper ride matching (e.g., location, time of the day, companion) of DC sharing services will be crucial in determining the future success of shared DC use.

When several factors influence DC sharing, policy should be proposed for a dynamic performance-based regulatory system for shared DC use, as proposed by Grush & Niles (2018).

This system observes the nuances in the network performance matrices (e.g., car occupancy, private car use reduction) and helps the system operators address the market demand and its outwardness. In this vein, shared DC can be part of a MaaS system, where the gradual expansion reduces personal car use in the long run.

3. *Sharing a DC ride with a stranger and policies for designing the interior of driverless taxis and shuttles*

Substantive variations were found between the factors determining driverless taxi use and sharing DC with a stranger. Sharing with a stranger is the intrinsic feature of a shared driverless taxi with promising potential to remove traffic from the road network, but convincing people to share the ride with a stranger is a crucial barrier to overcome (Parkhurst and Seedhouse, 2019). For example, possible privacy issues in a shared driverless taxi may constitute an array of issues hampering this modal shift. Future policy interventions may encourage DC service providers to redesign DC interior space to attract private, concerned individuals to use shared driverless taxis with comfort. In this regard, policy should be prepared to turn the interior of shared DC into compartments, where the seating arrangements will be opposite-facing rather than face-to-face. To enhance privacy further, shared DC doors should be on both sides to allow passengers to get in and out without bothering the co-passengers. Privacy policies should also be straightened for long-distance DC sharing, where the passenger can come in contact with others for a longer time.

In the case of driverless shuttle service, the entryway into the vehicle should be more comprehensive than a typical car to allow entry and exit simultaneously. With extra legroom, each seat should be positioned single-facing and designed in two rows, keeping barriers between passengers to discourage conversation with other passengers. These doors should be sliding outwards and on both sides of the DC shuttle to ensure the safety of other road users and privacy-protective entry and exit.

4. *Sharing a car or ride with family or close contacts*

The frequent household car usage was observed in this research, which determines that DC sharing will flourish with close contacts and family members. These findings suggested that people are often attached to their private car use, influencing their likely adoption of private DC for household use. In such conditions, an average household with several working-class residents and trip demands with multiple present cars might give up their extra cars, allowing one shared DC based on their household trips. In support of this assumption, Menon et al. (2018) found that people are likely to renounce their present car use with the advent of shared DC. In this regard, the Government should impose policy measures to cap more than one DC use for household use. This measure will reduce car ownership as well as reduce congestion on roads.

5. Housing location choice influence on DC sharing

Econometric analysis results for household locations in choosing DC options reflect a clear distinction between city-centre dwellers and suburban residents. City-centre and inner-suburban dwellers are more interested in using shared DC but less interested in private DC. On the other hand, outer suburban residents are inclined to use DC ridesharing with their close contacts and family members. These results reflected the geographic variations of DC sharing choices and their possible modal share.

Spatial segregation of DC sharing possibilities can create some economic and land-use imbalances after DC is fully implemented. Higher-paying jobs are usually found in the central cities. Due to sharing possibilities with DC, city dwellers will always have access to better opportunities and services than low-income suburban dwellers who cannot afford private DC. This spatial mismatch will be greater in the regions where services are dispersed, and the absence of lower-cost shared DC provision may hinder further opportunities.

Focusing on the residential location choice, the policies should be prioritised for more economic provision of shared DC use to private DC use in the suburban areas to bridge gaps in the transport network and employment centres. In light of the shared DC use, when less parking provision is needed, the leftover spaces of parking areas can be utilized for further development. So, transport planners and urban designers should reuse these spaces for community facilities, small-unit housing, recreation, commerce, sustainability initiatives and groundwater recharging.

6. Policy Implications Associated with social-norm and personality traits

The objective of selecting social norms and personality traits used for this research was to analyse the societal and personal influence on DC systematically shared ownership and ridesharing behaviour. My research indicated that societies with a solid sharing culture are more inclined to adopt driverless taxis or the shared use of DC.

Both social norms and personality traits data are associated with behavioural psychology. These data can be valuable assets for profiling car users with correct sharing attitudes, which can help research organisations and policymakers create area profiles with high DC sharing tendencies to enable better infrastructure provision. To the ridesharing agencies, these data can be valuable resources to produce correct DC ride-matching according to users' needs. Besides, personality data can be a vital source of knowledge that helps identify how DC sharing possibilities vary in personal perspectives.

7. DC sharing in rural areas

Unlike many other DC studies, this study also didn't put any effort into analysing DC sharing in rural areas. But, as there is a lack of public transport in rural areas, and only limited availability of ride-sharing facilities (e.g., Uber, taxis), DC sharing integration in the rural landscape can be a true alternative to these services. Although, a low number of public transport in rural areas is the demand issue, DC can be used as a demand-responsive transport system as and when needed.

One way to combat the low demand share for public transport is to include the scheduled Driverless Bus with fixed route operation to serve the rural communities. These buses can be of 4-6 passenger capacity with a limited geographic range.

7.4 Limitations and Further Research

This study has a few limitations, as described in the following paragraphs. Addressing them could improve the understanding of how DC will be shared.

1. This research study mainly focused on household DC shared ownership and ridership propensity for regular and occasional urban trips, while determinants did not emphasise any particular trip purposes. Except this, all other types of DC, such as goods delivery, service delivery, and utility DC were not observed. Therefore, this research agenda doesn't truly reflect the impact of multimodal transport assessment.
2. Considering the ideology 'DC will be mainly attracted to the present car users'; this survey sample doesn't reflect the accurate view of present car users' opinions due to a low number of car users' responses compared to the number of Scottish car users. Therefore, this survey limits the scope of the present car users' perspective on how they will use DC. Considering this limitation, future studies should focus on collecting data from a balanced sample with all types of road users.
3. Active travel modes are part of overall travel behaviour, and people's perception of active mode use is associated with short travel distances with limited trip purposes. Shared DC integration may also reduce the need for some of this active travel behaviour. Therefore, in the model development, efforts are made to consider the variation between with and without active travel mode provision.

4. For this study, trip duration/length was not considered. Only urban trips were considered with limited geographic coverage. However, since DC can be an efficient transport mode to cover long distances within a short time, these modes should be considered in the stated choice survey to reflect peoples' true nature of DC demand within long distances. For instance, LaMondia et al. (2016) focused on the possible modal shift from personal cars to using DC and found that personal DC use is prominent for more than 500 miles of travel compared to airlines. Therefore, distance is a valuable factor of shared DC choice, which was not addressed in my research.
5. The results from this travel survey may be associated with perception bias due to the use of new DC technology. There are typical difficulties in stating something (new technology or service) without testing or using it (Sheela and Mannering, 2019). Therefore, when respondents were asked to express their interest in DC options based on their experience with their current carsharing and ridesharing options (e.g., taxi, hired car, car from car club), they always referred to present car use, although DC use is different from the conventional cars. Therefore, efforts were made to mitigate this issue by introducing DC-sharing and ridesharing possibilities through a video at the beginning of the online questionnaire. However, this may not compensate for the lack of knowledge and experience with the DC system.
6. This research only focused on the behavioural determinants of carsharing and ridesharing without quantifying the travel time value and monetary benefit DC types can bring.

In light of the aim, findings and limitations of the present research, further research ideas were identified, as given below:

1. This study reveals that ageing seniors are reluctant to use shared DC in exchange for their conventional cars, irrespective of technological innovation. Therefore, the insights relating to the impact of present car ownership and sharing behaviour on future DC sharing options should be further studied to understand how the switch from private to shared mode of transport can be facilitated with the emergence of shared DC.
2. This research introduced 'personality traits' and 'social norm', two behavioural psychology terms that contribute to explaining sharing attitudes with DC. Such factors should be evaluated in greater detail with stated choice experiments to understand the behavioural and psychological constraints in transforming the private use of DC to service use.

3. Simultaneous estimations of models concerning the likelihood of shared ownership and the likelihood of shared ridership could be a helpful approach to proceeding with a robust research agenda in future. This would allow assessing the existence and the influence of common unobserved determinants.

4. Focusing on the recent world pandemic due to COVID-19, a new study should include the factors concerning public health issues in sharing DC.

5. Young urban adults are the pioneers in using DC shared ridership, while ageing seniors are likely to accept DC for private and family use. Therefore, from an age perspective, DC shared ownership and ridership should be studied further through a longitudinal study to reflect on how attitudes towards sharing DC evolve. Also, sharing propensity with age variations and their likely impact on urban travel demand should be assessed for fully functional DC use.

6. Trip cost and travel time reduction are essential determinants for any transport investment decision-making project, and this research did not use time and cost factors to formulate hypothetical choice scenarios. Therefore, future studies can be deployed with discrete modelling scenarios with variations in the trip cost and travel time for any reference journeys and with shared DC ridership or ownership to observe the changes in demand compared to the present.

7. The challenge of privacy preservation in a shared driverless taxi may constitute an array of further issues that can hamper this modal shift. Future policy interventions may encourage DC service providers to redesign the DC interior with privacy-preservative space to attract privacy-concerned individuals to use shared driverless taxis.

7.5 Conclusions and Recommendations for Future Research

Although a large body of research exists on the shared use of DC, only a handful of studies discussed DC shared ownership, shared ridership and their determinants. This research discussed choice determinants such as respondents' present carsharing behaviour, socioeconomic characteristics, personality and social norms are determinants to assess the propensity of shared and non-shared DC ownership and ridership types. Therefore, this research study provides valuable insights for transport researchers and policymakers regarding DC shared ownership and ridership.

The model results reflect that the respondents' attitudes towards DC sharing are heterogeneous, especially regarding age, present car ownership, personality, and social norms.

Millennials are the likely adopters of shared-use DC in the first place, while most ageing seniors (baby boomers) are indifferent in their choices for non-shared DC. In addition, present car ownership and feelings for social expectation to preserve the environment increase the willingness for non-shared use of DC. Finally, shared DC use is enhanced by respondents' cooperative attitudes and the general tendency for sharing.

Even though age, personality, and social norm factors are prominent in explaining the likelihood of driverless taxis and sharing DC with a stranger, substantive variations were found between these two types of DC-sharing possibilities. Results reflected that higher-income society valued driverless taxis as a single-use DC option. The shared use possibilities of DC can be envisaged as a new challenge due to sharing a confined space with strangers. On the way forward, people should overcome this challenge with their cooperative attitudes of sharing guided by their environment-savvy behaviour.

These variations in choice determinants and associated DC choices set new challenges for transport planners and policymakers to formulate new policy measures facilitating the modal shift from single-use DC to shared-use driverless taxis. The insights obtained from this research can be utilised to understand demographic and socioeconomic variations in adopting shared DCs. This study reflects the relationship between current sharing behaviour and public willingness to use emerging DC technologies. However, it should be considered that people's perception of DC technology is evolving as the technology flourishes. Additionally, the media broadcast and information provision of DC can significantly rejuvenate people's perceptions about sharing with DC. Therefore, findings from this research should be considered cautiously. Future studies can test the behavioural determinants related to shared DC technology, taking the determinants from the present study as the baseline.

8. References

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9. Appendix A: Semi-structured interview questionnaire

1. What factors will influence the adoption of a full DC (Society of Automation Engineers' Level 5)? How important will be the possibility of carrying out in-vehicle activities for current drivers?
2. (a) What will be the most likely ownership model of Level 5 DC? (b) Will people buy their vehicle, or will they share a vehicle (within the household or with strangers)? (c) What factors affect the decision to buy a private DC or use a shared one? (d) Will there be any differences between different groups of the population (e.g., age, gender, income level, urban/rural) and/or type of trip (e.g. long/short distance, commuting/leisure)?
3. (a) What will be the most likely ridesharing model of Level 5 DC? (b) Will people share the vehicle for the same journey, or will it be for sole use (with another household member or with strangers)? (c) What factors will affect the decision to travel alone or with other people? (d) Will there be any differences between different groups of the population (e.g., age, gender, income level, urban/rural) and/or type of trip (e.g. long/short distance, commuting/leisure etc.)?
4. (a) How can the shared ownership of full DC be promoted? (b) How can the shared ridership of full DC be promoted?
5. Are you aware of other research or projects concerning the ownership and ridership of DC?

10. Appendix B: Semi-structured interview summary

Question number	Question theme	Responses
1a	Factors explaining DC adoption	The comfort of using, acceptance /trust, the utility of travel time, safety, efficiency, price, ease of access, connectivity, uniformity, convenience, availability, affordability, reliability
1b	In-vehicle activity preference	There will be no massive influence of in-vehicle time saving on preferring the DC service. But DC will offer a dedicated opportunity to ease mobile communication, With infotainment, seamless data transfer, and onboard control, DC can enhance the facility of in-vehicle activity
2a	Likely shared ownership model of the DC	The sustainable option of shared ownership will be primarily due to the cost of owning a Level 5 DC. But most push will come towards sharing the DC despite a high ownership cost. Tony Kenmuir proposed a Manufacturer, Distributor and Financial model of DC ownership where mobile apps will act as aggregators. Alongside, car club-type sharing of DC is anticipated by some respondent
2b	Private ownership Vs shared use of DC	DC ownership may be introduced as a shared pattern due to cost Shared and public transport type ridership may be the most common scenario People will make some trade-offs for the cost and convenience factors Shared ownership will not be possible due to time matching, cost-sharing, time management issues, equality and equity matters, maintenance and insurance burden etc. Sharing will happen first, which will help to develop different types of DC ownership at later stages as the concept get matured and reliability
2c	Factors explaining shared DC ownership	Cost, ease of access, willingness to share, legal matters, driving restrictions, parking restriction, geographic location, convenience, family size, access to a car, personal car space/ luggage carrier, user's flexibility, availability, knowledge/ communication/ information/ familiarity/ reliability of DC performance/ benefits and time-saving capacity of DC, necessity, age, education and socioeconomic status

2d	Variations of DC ownership among socioeconomic class	Ownership will be varied by comfort, level of privacy, willingness to share, sharing partner, and urban and rural variation. But some people will be sceptical about AV use due to their personal choice. But mostly tech-savvy, university-educated young adults with average income and middle-class people will be the first adopters of AV; several respondents support this. Alongside, urban preference, income level and size of the vehicle will be essential factors for owning and sharing 'High-density urban mix and commuter market will face the first implementation of DC in the form of a city bus or taxi service'. Variations among cities and cultures are also inevitable.
3a	Likely ridesharing model	Future MaaS (Mobility as a Service) option will include the shared AV Shared DC will mainly be applied for site-specific (e.g., music venue, football ground) or journey-specific and last-mile type solutions of the entire trip length The Ridesharing business will be run jointly by public transport body and a users consortium (e.g., a car club) The shuttle bus will be the most likely scenario for ridesharing since this will arrive in a predicted time and give the hop-on and hop-off opportunity Taxi service, City bus, School bus, campus-based service, company vehicle and any other specialised services
3b	Ridesharing behaviour with AV	Shared DC will get the preference when there is a common destination, carpooling, and the need for trip cost reduction Based on cost and convenience, some trade-offs will have happened among carsharing types Several Shared DC business models will be flourished for different use cases (e.g., station based; out of town shopping shuttle from several hubs of the city; airport link; dedicated shared DC lane) Several personal and ethical issues of the passengers may hinder ride sharing (e.g., time matching, privacy, personal space, predictability, luggage issues, and strangers) predictability and sharing with strangers will influence the oice decision

3c	Factors of ridesharing	Cost, trust of technology, social acceptance for sharing, pre-conception of journey sharing / negative stereotyping, car/ passenger security; cleanliness/comfort/interior of the vehicle/ income level/status symbol for sharing; the size of the DC vehicle/ premium users/trip duration/ waiting time; the value of time for the traveller/ flexibility to use and booking; environmental concern; DC function and capacity; ICT for the DC use; connectivity and control of the vehicle; Awareness of the AV use; willingness to take share; the decision to speed control; schedule of time use/ inefficiency of sharing; carrier space; time of the day; journey leg; reliability and acceptability of robots interacting with a human being
3d	Variation of ridership choices among socioeconomic class	Gender, age and income level variation will play a negative role in the decision to share a ride with shared DC Sharing will happen for short / leisure journeys The Shared DC option will be similar to the public transport/train/bus system Income level and willingness to share the vehicle in a confined space (e.g., higher income class will not use DC unless privacy and comfort will be ensured) Young, tech-savvy, highly educated urban people will be the first adopters of a shared ride with DC
4a	Promotion for shared ownership of DC	Community car/car club/carpooling options should come into legislation and policy implementation for shared use of the vehicle In-vehicle entertainment/ infotainment; premium for mobility; vehicle size; dedicated space for luggage Promotional membership; Competitive pricing concerning shared DC free trial; high-profile people's recommendation A congestion charge should be imposed for the single occupancy car at a higher amount to discourage single-car use and thereby promote the shared form of ownership. Like high occupancy vehicle lanes, Shared DC lanes should be implemented The opportunity for cost-sharing and enhancement of the comfort, safety terion and more in-vehicle activity opportunity Ownership can be promoted in a combination of ideas like safety; lower fuel cost, lower emission; the speed of the vehicle; technology (because they like it); cost; parking cost (but this is not a high cost) Financial incentive; generating trust of the consumer for new technology and demonstration for flexible use e insurance model should be restructured to adopt the new

		type of vehicle technology
4b	Promoting shared ridership of AV	New development sites must have a car-free zone Office and university campuses can be car-free Public vehicle rather than the private vehicle Easy and stress-free access for ridesharing and promotion to increase interest in new technology Promote the DC rideshare by considering the cost and time use Social media use to grow public awareness about the shared DC The taxi model/taxi adoption model can be followed to understand the adoption of DC Marketing of DC ridesharing option from the viewpoint of new technology promotion Transparency of the service/ flexibility of use/information provision for other sharing partners (strangers) Ridesharing should be promoted on the ground of environmental efficiency; fuel efficiency, cut congestion; cost-effective Trust in technology will be an issue with cost incentives and positive users' experience
5	Potential AV use and application	Site-specific use (e.g., music venue, football ground) or journey-specific use (e.g., last-mile type solution; train station to nearby town or city centre; city centre to suburbia; Airport link) Future mobility as a service option will include the shared DC Sharing will happen for short / leisure journeys The Shared DC option will be similar to the public transport/train/bus system The application area will be restricted (Geo-fenced) to a small section of highway and/or campus DC will be an on-demand service (e.g., taxi, Uber) with a shared facility or personal use For large-scale share, a driverless shuttle will be the possibility (e.g., airport link, train station to nearby town or city centre; city Centre to suburbia) Taxi or City bus with a limited sitting capacity

11. Appendix C: Ethical approval form

Edinburgh Napier University Research Consent Form
Ownership and ridership of driverless vehicles
Edinburgh Napier University requires that all persons who participate in research studies give their written consent to do so. Please read the following and sign it if you agree with what it says.

1. I freely and voluntarily consent to be a participant in the research project on the topic of ownership and ridership of autonomous vehicles to be conducted by Sayed Faruque, who is a PhD student at Edinburgh Napier University.
2. The broad goal of this research study is to explore whether fully autonomous vehicles will be privately owned or shared, and if they will be used by individual occupants or groups of people. Specifically, I have been asked to participate in an interview, which should take no longer than 45 minutes to complete.
3. I have been told that my responses will recorded and then used in anonymised form. My name will not be linked with the research materials, and I will not be identified or identifiable in any report subsequently produced by the researcher.
4. I also understand that if at any time during the interview, I feel unable or unwilling to continue, I am free to leave. That is, my participation in this study is completely voluntary, and I may withdraw from it without negative consequences. However, after data has been anonymised or after the publication of results, it will not be possible for my data to be removed as it would be untraceable at this point.
5. In addition, should I not wish to answer any particular question or questions, I am free to decline.
6. I have been given the opportunity to ask questions regarding the interview and my questions have been answered to my satisfaction.
7. I have read and understand the above and consent to participate in this study. My signature is not a waiver of any legal rights. Furthermore, I understand that I will be able to keep a copy of the informed consent form for my records.

Participant’s Signature Date

I have explained and defined in detail the research procedure in which the respondent has consented to participate. Furthermore, I will retain one copy of the informed consent form for my records.

Researcher’s Signature Date

12. Appendix D: Final Questionnaire

Transport Research Institute
Part of Edinburgh Napier University

Shared ownership and use of driverless vehicles (Extended until 15/12/2019)

1. Welcome to the survey on driverless vehicle use

Driverless vehicles are vehicles that can drive by themselves without any input from human beings. They are expected to be on our roads in 10 - 15 years. Please watch the video on the next page for more information about how they can be used.

At the Transport Research Institute of Edinburgh Napier University (https://blogs.napier.ac.uk/tri/) we are researching how driverless vehicles will change urban mobility. We would be grateful if you could help us by participating in this survey about how people will own and use driverless vehicles. Your answers will help us build more liveable and sustainable cities. And by completing the survey you could win one of three Amazon Fire HD 8 Tablets! You can participate in the survey only if you are 16 years old or older.

The survey will take around 15 minutes. There is no risk associated with the participation. You are free to withdraw at any time and to skip any question you do not want to answer.

To participate in the prize draw of the three tablets, you will have to give us your email address so that we can contact you in case you are among the winners. Your email will be used only for the prize draw. You do not have to provide your email address if you are not interested in the draw.

The data obtained from this survey will be used only for research purposes and will not be shared with any third party. No personally identifiable information will be used in the research. Data will be dealt with in accordance with the current data protection legislation, in particular with the EU General Data Protection Regulation (GDPR).

By participating in the survey, you confirm that you are 16 years old or older, have understood the above and consent to participate in the study. Participation is not a waiver of any legal rights.

If you have any questions, please email us at [redacted]

1 / 6 17%

Next

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Shared ownership and use of driverless vehicles (Extended until 15/12/2019)

2. How you can use driverless vehicles

A driverless vehicle is like a taxi without a taxi driver: they drive in a professional way, you do not need to know how to drive to use them, you do not need to spend time to park them, and you can tell them to come and pick you up when you need them. Being like taxis, they can be shared more easily than conventional vehicles. The video below illustrates the different ways to use a driverless vehicle. The video is taken from the webpage of CDM Smith (https://www.cdmsmith.com/en/Video/How-Will-Driverless-Vehicles-Change-the-Way-We-Travel).

Driverless vehicle sharing in urban areas

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3. Your current travel patterns

1. For trips **within urban areas**, how often do you travel by car in the following situations?

	Several times in a week	Few days in a month	Few times in a year	Never
Driving alone				
As a driver, with people you know well				
As a passenger, with people you know well				
As a driver, with strangers				
As a passenger, with strangers				
In a taxi				

2. For trips **within urban areas**, how often do you use the following means of transport?

	Several times in a week	Few days in a month	Few times in a year	Never
Household car				
Car of people you know well (e.g., friends, colleagues)				
Car of a car club (e.g., Enterprise car club)				
Car of a car rental company (e.g., Europe car)				
Peer-to-peer car rental (that is renting a car from a private owner, e.g. through a platform like 'Hiya car')"				

3. For each of the following trip purposes, what is your usual urban travel mode?

	Car as a driver	Car as a Passenger	Public transport	Walking/Cycling	Mixed modes
Commute to work/ study					
Commute from work/ study					
Shopping					
Leisure (e.g. gym, cinema, restaurant, etc.)					
Personal/family business (e.g.,Doctor, Bank, Post office, Government office, etc.)					

4. How important to you is the possibility of carrying out the following types of activities while you travel?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Work or study related activities (e.g., calling, email, internet use, etc.)					
Social interaction (e.g., social media, chatting with other passengers, calling to friends and family, etc.)					
Relaxing (e.g., music, window gazing, sleeping/snoozing, personal grooming, etc.)					
Enjoy driving					

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4. Reasons to share a car

5. What makes or could make a car from car clubs, car rentals, peer to peer sharing more attractive than a private car for you? Please assess the importance of the following factors.

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Replacing purchasing costs with subscription costs					
Reducing or eliminating maintenance burden					
Reducing or eliminating insurance and taxes expenses					
Reducing or eliminating parking costs					
Greater choice of vehicles					

6. What makes or could make a car from car clubs, car rentals, peer to peer sharing less attractive than a private car for you? Please assess the importance of the following factors.

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Car may not be available all the time you need					
Lack of familiarity with the shared car					
Limited comfort compared to private car (e.g., car condition, seating, infotainment)					
Limited convenience compared to private cars (e.g., luggage space, travel anytime)					
Cost of using a shared car					

7. What makes or could make sharing a ride (with somebody who is not part of your household) more attractive than travelling alone for you?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Lower cost of trip (including parking)					
Ability to work while someone else drives					
Ability to socialise while someone else drives					
Ability to relax while someone else drives					
You can get rid of driving and parking hassle					

8. What makes or could make sharing a ride (with somebody who is not part of your household) less attractive than travelling alone for you?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Extra journey time with picking up/dropping off/waiting for travel companions					
Less flexibility to choose (departure) time and route					
Possible unreliability of travel companions					
Lack of privacy when need to share space with strangers					
Lack of security when need to travel with strangers					
Lack of trust due to someone else driving					
Distraction when I am driving					
Problems in finding suitable travel companions					

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Shared ownership and use of driverless vehicles (Extended until 15/12/2019)

5. Use of driverless vehicle

9. For your **regular** personal **urban trips** (e.g. daily commute, taking children to school) **made by driverless vehicles**, how likely are you to choose the following options?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
Your private driverless vehicle					
Driverless vehicle owned with other 3-4 people not from your household. Purchase and maintenance costs are shared but the car may not be available when you need it.					
Driverless taxi service. You do not need to own a vehicle but must pay for the service and wait until the car arrives.					

10. For **occasional** personal **urban trips** (e.g. e.g. trips to reach a leisure destination or a shop) **made by driverless vehicles**, how likely are you to choose the following options?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
Your private driverless vehicle					
Driverless vehicle owned with other 3-4 people not from your household. Purchase and maintenance costs are shared but the car may not be available when you need it.					
Driverless taxi service. You do not need to own a vehicle but must pay for the service and wait until the car arrives.					

11. For **regular** personal **urban trips** (e.g. daily commute, taking children to school), **made by driverless vehicles** with no other member of your household, how likely are you to choose the following trip sharing options?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
To ride alone					
To ride with people you know if possible and thereby reduce the trip cost					
To ride with strangers if possible and thereby reduce the trip cost					

12. For **occasional** personal **urban trips** (e.g. trips to reach a leisure destination or a shop), **made by driverless vehicles** with no other member of your household, how likely are you to choose the following trip sharing options?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
To ride alone					
To ride with people you know if possible and thereby reduce the trip cost					
To ride with strangers if possible and thereby reduce the trip cost					

13. For **regular** personal **urban trips** (e.g., daily commute, take children to school), **made by driverless vehicles** with other members of your household, how likely are you to choose the following trip sharing options?

	Very unlikely	Unlikely	Neutral	Likely	Very likely
To ride only with other household members					
To ride with other household members and other people you know, if possible, and thereby reduce the trip cost					
To ride with other household members and strangers as well, if possible, and thereby reduce the trip cost					

14. For **occasional** personal **urban trips** (e.g., e.g. trips to reach a leisure destination or a shop), **made by driverless vehicles** with other members of your household, how likely are you to choose the following trip sharing options?

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Shared ownership and use of driverless vehicles (Extended until 15/12/2019)

6. About yourself

15. How much do you agree with the following statements? **I see myself as someone who …**

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Is reserved	○	○	○	○	○
Generally trusts	○	○	○	○	○
Tends to be lazy	○	○	○	○	○
Is relaxed, handles stress well	○	○	○	○	○
Has few artistic interests	○	○	○	○	○
Is outgoing, sociable	○	○	○	○	○
Tends to find fault with others	○	○	○	○	○
Does a thorough job	○	○	○	○	○
Gets nervous easily	○	○	○	○	○
Has an active imagination	○	○	○	○	○

16. How much do you agree with the following statements? **I believe that ...**

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Most of my acquaintances share or rent their resources (e.g. house or car) when possible	○	○	○	○	○
Society expects me to share or rent my resources (e.g. house or car) when possible	○	○	○	○	○
Most of my acquaintances make an effort to improve the quality of life where they live	○	○	○	○	○
Society expects me to make an effort to improve the quality of life where I live	○	○	○	○	○
Most of my acquaintances make an effort to protect the environment	○	○	○	○	○
Society expects me to make an effort to protect the environment	○	○	○	○	○

17. What is your gender?

- ☐ Female
- ☐ Male
- ☐ Prefer not to say

18. What is your age?

19. What is your highest educational qualification?

- ☐ Primary / elementary education
- ☐ Secondary / technical education
- ☐ Bachelor degree
- ☐ Master degree or higher

20. What is your annual average household income?

- ☐ Less than £20,000
- ☐ £50,000 to £70,000

- [ ] £20,000 to £30,000
- [ ] £30,000 to £50,000
- [ ] Over £70,000
- [ ] Prefer not to say

21. Do you have any physical disability which prevents you from driving?

- ( ) Yes
- ( ) No

22. How many vehicles do you have in your household?

23. Please indicate your household composition?

- [ ] Living alone
- [ ] Household with no children
- [ ] Household with children
- [ ] Other arrangements

24. Which of the following best describes the type of your residential location?

- [ ] City centre
- [ ] Inner suburb
- [ ] Outer suburb
- [ ] Rural

25. Please insert the first part of your POSTCODE (e.g. EH10) if you live in the UK or your Country of residence otherwise.

26. If you want to participate in the draw of the Amazon Fire tablets, please insert your email address.

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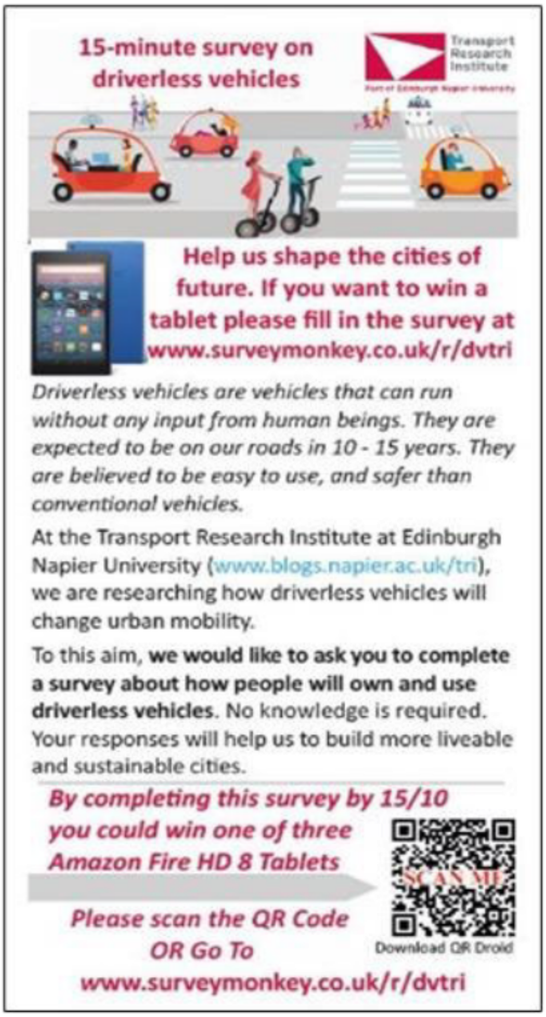
13. Appendix E: Relationship between research questions and the final questionnaire

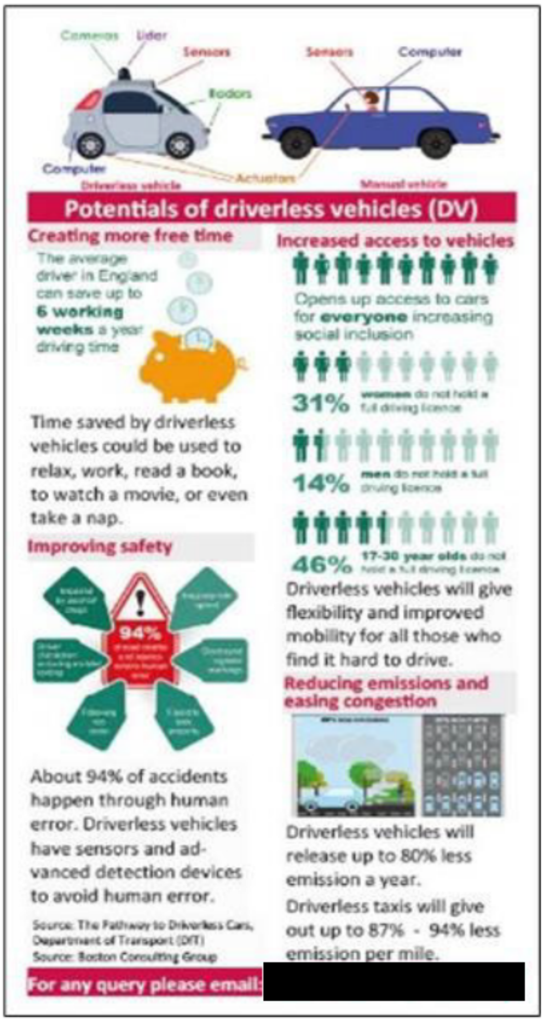
Serial No.	Research Questions	Relavent Factors	Questions of the questionnaire	Sr. No. from the Questionnaire	Variable Dependency	Method of Estimation	Related Chapters in the thesis
1	**What are the current behaviours in terms of shared mobility?** *1a. What are the current shared ownership behaviours by different travel modes? 1b. What are the current ridesharing behaviours by different travel modes? 1c. What are the factors influencing present shared ownership and ridesharing behaviour?*	Car sharing frequency	For trips within urban areas, how often do you travel by car in the following situations?	1	Independent	Descriptive Statistics; Cluster Analysis	Chapter 4, 5
		Ride sharing frequency	For trips within urban areas, how often do you use the following means of transport?	2	Independent	Descriptive Statistics; Cluster Analysis	Chapter 4, 5
		Trip Purposes	For each of the following trip purposes, what is your usual urban travel mode?	3	Independent	Descriptive Statistics	Chapter 4
		In-vehicle activity preferences	How important to you is the possibility of carrying out the following types of activities while you travel?	4	Independent	Descriptive Statistics	Chapter 4
		Car sharing reasons and their ranks	What makes or could make a car from car clubs, car rentals, peer to peer sharing more attractive than a private car for you? Please assess the importance of the following factors.	5	Independent	Descriptive Statistics; Cross-classification	Chapter 4, 5
		No-car sharing reasons and their ranks	What makes or could make a car from car clubs, car rentals, peer to peer sharing less attractive than a private car for you? Please assess the importance of the following factors.	6	Independent	Descriptive Statistics; Cross-classification	Chapter 4, 5
		Ride sharing reasons and their ranks	What makes or could make sharing a ride (with somebody who is not part of your household) more attractive than travelling alone for you?	7	Independent	Descriptive Statistics; Cross-classification	Chapter 4, 5
		No ridesharing reasons and their ranks	What makes or could make sharing a ride (with somebody who is not part of your household) less attractive than travelling alone for you?	8	Independent	Descriptive Statistics; Cross-classification	Chapter 4, 5
2	**What are the expected behaviours and attitudes regarding shared mobility using DC?** 2a. How do sharing behaviours influence propensity towards shared DC? 2b. What are the attitudes determining weak propensities to accept shared DC use over non-shared DC options? 2c. What are the	Preferences for Private Driverless car; Shared Owned DC; Driverless Taxi (in a five-point Likert scale)	For your **regular personal urban trips** (e.g. daily commute, taking children to school) made by driverless vehicles, how likely are you to choose the following options	9	Dependent	Binary Probit, Binary Logit, Multinomial Logit models	Chaptet 6, Section 6.1, Section 6.3, Section 6.4
		Preferences for Private Driverless car; Shared Owned DC; Driverless Taxi (in a five-point Likert scale)	How likely are you to choose the following options for occasional personal urban trips (e.g. e.g. trips to a leisure destination or a shop) made by driverless vehicles?	10	Dependent		Chaptet 6, Section 6.1, Section 6.3, Section 6.4
		Preferences for riding alone; ride with other known people; ride with stranger (in a five-point Likert scale)	For **regular personal urban trips** (e.g. daily commute, taking children to school), made by driverless vehicles with no other member of your household, how likely are you to choose the following trip-sharing options?	11	Dependent		Chaptet 6, Section 6.1, Section 6.3, Section 6.4
		Preferences for to ride alone; ride with other known people; ride with stranger (in a five-point Likert scale)	For **occasional personal urban trips** (e.g. trips to reach a leisure destination or a shop), made by driverless vehicles with no other member of your household, how likely are you to choose the following trip-sharing options?	12	Dependent		Chaptet 6, Section 6.1, Section 6.3, Section 6.4

	attitudes determining non-shared and shared DC use?	Preferences to ride only with other household members; to ride with other household members and other people you know; to ride with other household members and strangers (in a five-point Likert scale)	How likely are you to choose the following trip sharing options for regular personal urban trips (e.g., daily commute, take children to school), made by driverless vehicles with other members of your household?	13	Dependent		Chaptet 6, Section 6.1, Section 6.3, Section 6.4
		Preferences to ride only with other household members; to ride with other household members and other people you know; to ride with other household members and strangers (in a five-point Likert scale)	For **occasional personal urban trips** (e.g., e.g. trips to reach a leisure destination or a shop), made by driverless vehicles with other members of your household, how likely are you to choose the following trip sharing options?	14	Dependent		Chaptet 6, Section 6.1, Section 6.3, Section 6.4
3	**How do personal characteristics influence shared mobility choices with DC?** *3a. How do sociodemographic characteristics influence the sharing choices concerning DCs? 3b. How do personality traits influence the sharing choices concerning DCs? 3c. How do social-norm characteristics influence the sharing choices concerning DCs?*	Agreeableness; Conscientiousness; Extraversion; Neuroticism; Openness	How much do you agree with the following statements? I see myself as someone who (Personality traits….)	15	Independent	Descriptive statistics; Order Probit models	Chapter 6: Section 6.2
		The social expectation for sharing; better quality of life; preserving the environment	How much do you agree with the following statements? I believe that (Social norm…..)	16	Independent		Chapter 6: Section 6.2
		Male; Female	What is your Gender?	17	Independent		Chapter 6: Section 6.2
		Age groups: Centennials; Millennial; Generation X; Baby boomer; Traditionalist	What is you age?	18	Independent		Chapter 6: Section 6.2
		Lower education level; Bachelor's degree; Master's degree or higher	What is your highest educational qualification?	19	Independent		Chapter 6: Section 6.2
		Salary Bands: Less than £20,000 £20,000 to £30,000 £30,000 to £50,000 £50,000 to £70,000 Over £70,000	What is your annual average household income?	20	Independent		Chapter 6: Section 6.2
		Disability: Yes/No?	Do you have any physical disability which prevents you from driving?	21	Independent		Chapter 6: Section 6.2
		No Car, One Car, Two Cars, Three or more cars	How many vehicles do you have in your household?	22	Independent		Chapter 6: Section 6.2
		Living alone; A household without a child; Household with at least one child; Other arrangements	Please indicate your household composition?	23	Independent		Chapter 6: Section 6.2
		City centre dwellers; Inner suburban dwellers; Outer suburban dwellers; Rural dwellers	Which of the following best describes the type of your residential location?	24	Independent		Chapter 6: Section 6.2

14. Appendix F: Final leaflet design



Leaflet front



Leaflet back

15. Appendix G: List of variables with coding and their descriptions

Explanatory Variables (Determinants)	Code reported	Mean
Existing travel behaviour variables		
Car Driver (1 if the behaviour shows for car driver and who drives with other people, 0 otherwise)	Cd	0.76
Non-driver (1 if the behaviour shows for a non-driver, 0 otherwise)	Nd	0.24
Regular car user (1 if the behaviour shows frequent household car user who shares ride sometimes, 0 otherwise)	Vs_fhcr	0.3
Non-frequent car user (1 if the behaviour is oriented to infrequent household car user, 0 otherwise)	Vs_nhc	0.31
Frequent household car user (1 if behaviour shows for frequent household car user who doesn't use rideshare, 0 otherwise)	Vs_fhc	0.34
Social-norm variables		
The social expectation for sharing (1 if the social expectation for sharing is present, 0 other-wise)	SES_16	0.09
The social expectation for contribution to a better quality of life (1 if the respondent has a social expectation to contribute for a better quality of life, 0 otherwise)	SEQ16	0.55
The social expectation for preserving the environment (1 if the respondent has feelings for social expectation to preserve the environment, 0 otherwise)	SPE_16	0.76
Personality-traits variables		
Agreeableness (1 if the respondent is cooperative and trusting, 0 otherwise)	Agr	0.28
Conscientiousness (1 if the respondent is organised, dutiful, but less creative, 0 otherwise)	Cons	0.54
Extraversion (1 if the respondent is energetic and has an active social life, 0 otherwise)	Extra	0.23
Neuroticism (1 if the respondent has negative emotions, 0 otherwise)	Neu	0.35
Openness (1 if the respondent has a variety of experiences and diversity of interests, 0 otherwise)	Opn	0.43
Demographic variables		
Male (1 if the respondent is a male, 0 otherwise)	Me	0.67
Female (1 if the respondent is a female, 0 otherwise)	Fm	0.33
Centennials (1 if the respondent is 0-23 years old, 0 otherwise)	Cen	0.07
Millennial (1 if the respondent is 24 - 43 years old, 0 otherwise)	Mille	0.29
Generation X (1 if the respondent is 44 - 55 years old, 0 otherwise)	GenX	0.22
Baby boomer (1 if the respondent is 56 -74 years old, 0 otherwise)	Bboom	0.37
Traditionalist (1 if the respondent is over 74 years old, 0 otherwise)	Trad	0.06

Lower education level (1 if respondent have secondary level education, 0 otherwise)	He0	0.21
Bachelor's degree holder (1 if respondent holds a bachelor's degree, 0 otherwise)	He1	0.33
Masters or higher degree holder (1 if respondent hold a master's degree or higher, 0 other-wise)	He2	0.46
Socio-economic variables		
Lower-income earner (1 if the respondent earns below £20000 per year, 0 otherwise)	Hi1	0.12
Lower-income earner (1 if the respondent earns within £20001 - £30000 per year, 0 otherwise)	Hi2	0.19
Higher-income earner (1 if the respondent earns within £30001 - £50000 per year, 0 other-wise)	Hi3	0.26
Higher-income earner (1 if the respondent earns within £50001 - £70000 per year, 0 other-wise)	Hi4	0.18
Higher-income earner (1 if the respondent earns over £70000 per year, 0 otherwise)	Hi5	0.26
Living alone (1 if the respondent is living alone, 0 otherwise)	La	0.13
A household without a child (1 if the respondent lives in a household with no children, 0 oth-erwise)	Hwcn	0.42
Household with at least one child (1 if the respondent lives in a household with at least one child, 0 otherwise)	Hcn	0.37
Other arrangements (1 if the respondent below to a household with other arrangements, 0 oth-erwise)	Oa	0.08
City centre dwellers (1 if the respondent lives in the city centre, 0 otherwise)	Cc	0.34
Inner suburban dwellers (1 if the respondent lives in the inner suburb, 0 otherwise)	Is	0.44
Outer suburban dwellers (1 if the respondent lives in the outer suburb, 0 otherwise)	Os	0.21
Rural dwellers (1 if the household lives in a rural area, 0 otherwise)	Ru	0.01
Zero car ownership (1 if the respondent owns no car, 0 otherwise)	Cown0	0.18
One car ownership (1 if the respondent has one car, 0 otherwise)	Cown1	0.5
Two car ownership (1 if the respondent has two cars, 0 otherwise)	Cown2	0.26
Two and more car ownership (1 if the respondent has more than two cars, 0 otherwise)	Cown3	0.05

16. Appendix H: NLOGIT output relating to model influencing sharing characteristics on the overall propensity towards shared DC options.

JSHOP Model estimation summary with model development codes

```
O-----------------------------------------------------O
| NLOGIT 6  (tm)           Mar 22, 2021, 03:19:26PM
| Econometric Software, Inc.  Copyright 1986-2016
| Plainview, New York 11803   www.nlogit.com
| Registered to AA
| Registration Number:
O-----------------------------------------------------O
-------Initializing NLOGIT Version 6 (Sep 7, 2016)---------
-------------------------------------------------------
|->IMPORT;FILE="D:\PhD_Edinburgh_Napier\Reports\Data Analysis\Ordered_probit_JSHOP
and JSHARP\DV_180321_JSHOP_data_edit.csv"$
|-> Skip $
|-> OPEN ; Export = "D:\PhD_Edinburgh_Napier\Reports\Data Analysis\Ordered_probit_JSHOP
and JSHARP\JSHOP_results.csv" $
|-> Dstat ; Rhs = JSHOP,OCC,TY,INT;Export $
--------+------------------------------------------------------------------
        |              Standard                          Missing
Variable|       Mean   Deviation     Minimum     Maximum   Cases  Values
--------+------------------------------------------------------------------
   JSHOP|     .590811     .491817        0.0        1.0    1850     146
     OCC|          .5     .500125        0.0        1.0    1996       0
      TY|          .5     .500125        0.0        1.0    1996       0
     INT|         .25     .433121        0.0        1.0    1996       0
--------+------------------------------------------------------------------
Descriptive Statistics for   4 variables
DSTAT results are matrix LASTDSTA in the current project.
|-> Probit  ; Lhs = JSHOP
   ; Rhs = One, OCC, TY, INT
   ; Partials;Export $
------------------------------------------------------------
Deleted    146 observations with missing data. N is now  1850
------------------------------------------------------------
The iterative procedure has converged
Normal exit:   4 iterations. Status=0, F=    .1195659D+04
-----------------------------------------------------------------------
Binomial Probit Model
Dependent variable             JSHOP
Log-likelihood function     -1195.65878
Restricted log-likelihood   -1251.63985
Chi-squared [  3](P= .000)    111.96214
Significance level            .00000
McFadden Pseudo R-squared      .0447262
```

```
Estimation based on N =   1850, K =   4
Inf. Cr.AIC  =   2399.3 AIC/N =    1.297
--------+--------------------------------------------------------------------
        |               Standard            Prob.      95% Confidence
   JSHOP|  Coefficient      Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |Index function for probability......................................
Constant|    -.12511**      .05848    -2.14  .0324     -.23972   -.01050
     OCC|     .11164       .08245     1.35  .1757     -.04996    .27323
      TY|    .62846***     .08455     7.43  .0000      .46274    .79419
     INT|   -.01218        .12009     -.10  .9192     -.24755    .22319
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Mar 22, 2021, at 03:20:09 PM
```

JSHARP Model estimation summary with model development codes

```
O--------------------------------------------------------O
| NLOGIT 6  (tm)            Mar 22, 2021, 01:14:41PM
| Econometric Software, Inc.  Copyright 1986-2016
| Plainview, New York 11803   www.nlogit.com
| Registered to AA
| Registration Number:
O--------------------------------------------------------O
-------Initializing NLOGIT Version 6 (Sep 7, 2016)---------
------------------------------------------------------------
|-> IMPORT;FILE="D:\PhD_Edinburgh_Napier\Reports\Data Analysis\Ordered_probit_JSHOP
and JSHARP\DV_180321_JSHARP_data.csv"$
The last observation read from the data file was    3992
|-> Skip $
|-> OPEN ; Export = "D:\PhD_Edinburgh_Napier\Reports\Data Analysis\Ordered_probit_JSHOP
and JSHARP\JSHARP.csv" $
|-> Dstat; RHS = JSHARP, OCC, TYP, FAM, INT; Export $
--------+--------------------------------------------------------------------
        |               Standard                               Missing
Variable|        Mean    Deviation     Minimum      Maximum    Cases  Values
--------+--------------------------------------------------------------------
  JSHARP|     .553317     .497216        0.0         1.0     3723     269
     OCC|         .5     .500063         0.0         1.0     3992       0
     TYP|         .5     .500063         0.0         1.0     3992       0
     FAM|         .5     .500063         0.0         1.0     3992       0
     INT|        .25     .433067         0.0         1.0     3992       0
--------+--------------------------------------------------------------------

Descriptive Statistics for   5 variables
DSTAT results are matrix LASTDSTA in the current project.
|-> Probit  ; Lhs = JSHARP
   ; Rhs = One, OCC, TYP, FAM, INT
```

```
 ; Partials;Export $
-----------------------------------------------------------
Deleted   269 observations with missing data. N is now  3723
-----------------------------------------------------------
The iterative procedure has converged
Normal exit:  4 iterations. Status=0, F=   .2425594D+04
-----------------------------------------------------------------------
Binomial Probit Model
Dependent variable             JSHARP
Log-likelihood function     -2425.59386
Restricted log-likelihood   -2559.37972
Chi-squared [  4](P= .000)   267.57172
Significance level            .00000
McFadden Pseudo R-squared     .0522728
Estimation based on N =   3723, K =   5
Inf. Cr.AIC  =   4861.2 AIC/N =    1.306
--------+--------------------------------------------------------------
        |             Standard            Prob.      95% Confidence
  JSHARP|  Coefficient       Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------
        |Index function for probability....................................
Constant|     .52842***      .04793    11.03  .0000      .43448    .62236
     OCC|    -.10807**       .04211    -2.57  .0103     -.19062   -.02553
     TYP|    -.64090***      .05952   -10.77  .0000     -.75756   -.52424
     FAM|      .00864        .06055      .14  .8865     -.11003    .12732
     INT|    -.06718         .08426     -.80  .4253     -.23234    .09797
--------+--------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Mar 22, 2021, at 01:16:54 PM
     TYP|    -.24853***      .02243   -11.08  .0000     -.29250   -.20457  #
     FAM|      .00322        .02258      .14  .8865     -.04103    .04748  #
     INT|    -.02524         .03188     -.79  .4284     -.08772    .03724  #
--------+--------------------------------------------------------------
#  Partial effect for dummy variable is E[y|x,d=1] - E[y|x,d=0]
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Mar 22, 2021, at 01:16:54 PM
-----------------------------------------------------------------------
```

17. Appendix I: NLOGIT output relating to Ordered Probit model findings concerning mode-specific DC shared ownership and shared ridership intentions

Ordered Probit Model estimation results for the likelihood of Private DC (PV9)

```
|-> ORDERED; Lhs=PV9; Rhs=one,VS_FHC,SPE_16,He2,Bboom,CoweC;PartialEffect;List;Export $
-----------------------------------------------------------
Deleted    94 observations with missing data. N is now    405
-----------------------------------------------------------
Iterative procedure has converged
Normal exit:  13 iterations. Status=0, F=    .6057789D+03
+----------------------------------------------------------------+
|             CELL FREQUENCIES FOR ORDERED CHOICES              |
+----------------------------------------------------------------+
|           Frequency       Cumulative  < =    Cumulative  > =  |
|Outcome     Count   Percent   Count    Percent   Count    Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|PV9=00       111   27.4074     111   27.4074     405  100.0000 |
|PV9=01        50   12.5926     161   40.0000     294   72.5926 |
|PV9=02        68   16.7901     229   56.7901     244   60.0000 |
|PV9=03       106   26.1728     335   82.9630     176   43.2099 |
|PV9=04        69   17.0370     405  100.0000      69   17.0370 |
+----------------------------------------------------------------+
-----------------------------------------------------------------------
Ordered Probability Model
Dependent variable               PV9
Log-likelihood function      -605.77889
Restricted log-likelihood    -634.88889
Chi-squared [  5](P= .000)     58.22000
Significance level             .00000
McFadden Pseudo R-squared      .0458505
Estimation based on N =    405, K =   9
Inf.Cr.AIC  =   1229.6 AIC/N =    3.036
Underlying probabilities based on Normal
--------+--------------------------------------------------------------
        |              Standard          Prob.      95% Confidence
     PV9|  Coefficient      Error      z    |z|>Z*       Interval
--------+--------------------------------------------------------------
        |Index function for probability......................................
Constant|     .15727        .16265      .97  .3336     -.16152    .47606
  VS_FHC|     .19909*       .11775     1.69  .0909     -.03168    .42987
  SPE_16|    .29456**       .12730     2.31  .0207      .04506    .54406
     HE2|   -.22218**       .10785    -2.06  .0394     -.43356   -.01080
   BBOOM|   -.60728***      .11494    -5.28  .0000     -.83257   -.38199
   COWEC|    .63406***      .15069     4.21  .0000      .33871    .92942
        |Threshold parameters for index.....................................
  Mu(01)|    .38203***      .04506     8.48  .0000      .29372    .47034
```

```
 Mu(02)|    .85181***     .05633    15.12  .0000     .74140    .96222
 Mu(03)|   1.69314***     .07812    21.67  .0000    1.54002   1.84626
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jan 05, 2021, at 03:02:59 PM
-----------------------------------------------------------------------------
-----------------------------------------------------------------------------
Marginal effects for an ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+--------------------------------------------------------------------
        |     Partial                      Prob.      95% Confidence
    PV9|     Effect    Elasticity     z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *VS_FHC|    -.06284*      -.18881    -1.73  .0844     -.13419    .00852
 *SPE_16|    -.09919**     -.29807    -2.22  .0262     -.18665   -.01173
    *HE2|    .07191**      .21607     2.05  .0407      .00303    .14078
  *BBOOM|     .20474***     .61522     5.08  .0000      .12573    .28375
  *COWEC|    -.22514***    -.67653    -3.94  .0001     -.33713   -.11316
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *VS_FHC|    -.01295       -.09268    -1.61  .1070     -.02871    .00280
 *SPE_16|    -.01568***    -.11221    -2.67  .0075     -.02718   -.00418
    *HE2|    .01356**      .09699     2.07  .0381      .00075    .02637
  *BBOOM|     .03015***     .21569     5.27  .0000      .01893    .04136
  *COWEC|    -.02301***    -.16462    -4.80  .0000     -.03241   -.01361
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *VS_FHC|    -.00239       -.01369     -.82  .4141     -.00813    .00335
 *SPE_16|     .00206        .01182      .50  .6175     -.00604    .01017
    *HE2|    .00113        .00646      .47  .6383     -.00358    .00584
  *BBOOM|    -.00582       -.03333     -.83  .4074     -.01960    .00795
  *COWEC|     .01766        .10107     1.57  .1165     -.00439    .03971
        |--------------[Partial effects on Prob[Y=03] at means]--------------
 *VS_FHC|     .03048*       .13047     1.73  .0831     -.00399    .06496
 *SPE_16|     .04965**      .21254     2.17  .0304      .00471    .09460
    *HE2|   -.03541**     -.15156    -2.00  .0460     -.07018   -.00063
  *BBOOM|    -.10079***    -.43143    -4.65  .0000     -.14327   -.05831
  *COWEC|     .11203***     .47956     3.79  .0002      .05411    .16996
        |--------------[Partial effects on Prob[Y=04] at means]--------------
 *VS_FHC|     .04770        .40047     1.62  .1043     -.00986    .10526
 *SPE_16|     .06316**      .53025     2.45  .0141      .01271    .11361
    *HE2|   -.05118**     -.42971    -2.06  .0397     -.09995   -.00242
  *BBOOM|    -.12828***   -1.07691    -5.15  .0000     -.17706   -.07949
  *COWEC|     .11846***     .99453     4.85  .0000      .07063    .16629
--------+--------------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
```

The model was estimated on Jan 05, 2021, at 03:03:00 PM

Ordered Probit Model estimation results for the likelihood of Driverless Taxi (DT9)

```
|-> ORDERED; Lhs=DT9; Rhs=one, SES_16, Agr, Hri, Mille, GenX, Hwc, Cc; Partials; Export $
-----------------------------------------------------------
Deleted    129 observations with missing data. N is now    370
-----------------------------------------------------------
The iterative procedure has converged
Normal exit:  14 iterations. Status=0, F=    .5587928D+03
+----------------------------------------------------------------+
|             CELL FREQUENCIES FOR ORDERED CHOICES               |
+----------------------------------------------------------------+
|            Frequency       Cumulative  < =    Cumulative  > =  |
|Outcome     Count   Percent   Count   Percent   Count   Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|DT9=00        73   19.7297      73   19.7297     370  100.0000 |
|DT9=01        60   16.2162     133   35.9459     297   80.2703 |
|DT9=02        80   21.6216     213   57.5676     237   64.0541 |
|DT9=03       116   31.3514     329   88.9189     157   42.4324 |
|DT9=04        41   11.0811     370  100.0000      41   11.0811 |
+----------------------------------------------------------------+
-----------------------------------------------------------------------
Ordered Probability Model
Dependent variable               DT9
Log-likelihood function      -558.79277
Restricted log-likelihood    -574.89685
Chi-squared [  7](P= .000)    32.20816
Significance level            .00004
McFadden Pseudo R-squared     .0280121
Estimation based on N =    370, K =  11
Inf. Cr.AIC  =   1139.6 AIC/N =    3.080
Underlying probabilities based on Normal
--------+--------------------------------------------------------------
        |              Standard          Prob.     95% Confidence
     DT9|  Coefficient      Error      z    |z|>Z*       Interval
--------+--------------------------------------------------------------
        |Index function for probability....................................
Constant|     .47137***     .10683    4.41  .0000     .26199    .68075
  SES_16|     .31136*       .18695    1.67  .0958    -.05506    .67778
     AGR|     .27408**      .12183    2.25  .0245     .03530    .51286
     HRI|     .28991**      .12001    2.42  .0157     .05469    .52513
   MILLE|     .33874**      .13467    2.52  .0119     .07479    .60269
    GENX|     .37032**      .15632    2.37  .0178     .06394    .67671
     HWC|    -.28064**      .13088   -2.14  .0320    -.53717   -.02411
      CC|     .30710**      .11924    2.58  .0100     .07340    .54080
        |Threshold parameters for index....................................
  Mu(01)|     .50838***     .05164    9.84  .0000     .40716    .60960
```

```
 Mu(02)|   1.08425***     .06153    17.62  .0000     .96365   1.20485
 Mu(03)|   2.18107***     .09296    23.46  .0000    1.99887   2.36327
--------+----------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Feb 07, 2021, at 01:38:38 PM
-------------------------------------------------------------------------
-------------------------------------------------------------------------
Marginal effects for an ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+----------------------------------------------------------------
        |   Partial                     Prob.     95% Confidence
     DT9|    Effect   Elasticity    z   |z|>Z*        Interval
--------+----------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *SES_16|   -.07407*      -.42271   -1.90  .0579    -.15060    .00247
    *AGR|   -.06974**     -.39802   -2.36  .0183    -.12766   -.01182
    *HRI|   -.07642**     -.43614   -2.44  .0148    -.13787   -.01497
  *MILLE|   -.08556***    -.48831   -2.65  .0079    -.14872   -.02240
   *GENX|   -.09017***    -.51465   -2.61  .0091    -.15793   -.02242
    *HWC|    .07709**      .43998    2.08  .0372     .00459    .14959
     *CC|   -.07837***    -.44730   -2.69  .0071    -.13547   -.02128
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *SES_16|   -.03475       -.22006   -1.58  .1143    -.07788    .00838
    *AGR|   -.02928**     -.18542   -2.18  .0296    -.05565   -.00290
    *HRI|   -.02998**     -.18984   -2.40  .0164    -.05446   -.00550
  *MILLE|   -.03625**     -.22955   -2.44  .0148    -.06539   -.00711
   *GENX|   -.04059**     -.25702   -2.27  .0231    -.07560   -.00557
    *HWC|    .02775**      .17572    2.23  .0259     .00334    .05215
     *CC|   -.03266**     -.20682   -2.50  .0125    -.05829   -.00703
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *SES_16|   -.01462       -.06596   -1.05  .2932    -.04189    .01264
    *AGR|   -.00898       -.04052   -1.40  .1623    -.02158    .00362
    *HRI|   -.00713       -.03216   -1.42  .1560    -.01698    .00272
  *MILLE|   -.01159       -.05228   -1.52  .1291    -.02656    .00338
   *GENX|   -.01554       -.07011   -1.46  .1456    -.03648    .00539
    *HWC|    .00407        .01837    1.05  .2939    -.00353    .01168
     *CC|   -.00983       -.04434   -1.52  .1280    -.02249    .00283
        |--------------[Partial effects on Prob[Y=03] at means]--------------
 *SES_16|    .06026*       .18025    1.93  .0532    -.00083    .12136
    *AGR|    .05679**      .16987    2.36  .0184     .00958    .10400
    *HRI|    .06187**      .18506    2.45  .0144     .01230    .11143
  *MILLE|    .06946***     .20778    2.67  .0076     .01847    .12046
   *GENX|    .07314***     .21878    2.66  .0078     .01928    .12700
    *HWC|   -.06183**     -.18496   -2.11  .0346    -.11918   -.00449
     *CC|    .06369***     .19051    2.68  .0073     .01719    .11019
        |--------------[Partial effects on Prob[Y=04] at means]--------------
```

```
 *SES_16|   .06318       .56980    1.44  .1502    -.02288   .14924
   *AGR|   .05121**     .46186    2.05  .0406     .00219   .10023
   *HRI|   .05166**     .46590    2.28  .0225     .00728   .09603
 *MILLE|   .06393**     .57663    2.25  .0242     .00834   .11953
  *GENX|   .07316**     .65985    2.05  .0402     .00329   .14304
   *HWC|  -.04708**    -.42459   -2.15  .0312    -.08990  -.00425
    *CC|   .05717**     .51565    2.33  .0196     .00915   .10520
--------+--------------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Feb 07, 2021, at 01:38:39 PM
```

Ordered Probit Model estimation results for the likelihood of Riding Alone in DC (RA11)

```
-> ORDERED; Lhs = RA11; Rhs = one,VS_FHC,SPE_16,Bboom,Mille,Hwc,CoweC;Export $
------------------------------------------------------------
Deleted    91 observations with missing data. N is now    408
------------------------------------------------------------
The iterative procedure has converged
Normal exit:  14 iterations. Status=0, F=    .6115460D+03
+----------------------------------------------------------------+
|              CELL FREQUENCIES FOR ORDERED CHOICES               |
+----------------------------------------------------------------+
|            Frequency       Cumulative  < =    Cumulative  > =  |
|Outcome     Count   Percent   Count   Percent   Count   Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|RA11=00       76   18.6275      76   18.6275     408  100.0000 |
|RA11=01       39    9.5588     115   28.1863     332   81.3725 |
|RA11=02       84   20.5882     199   48.7745     293   71.8137 |
|RA11=03      137   33.5784     336   82.3529     209   51.2255 |
|RA11=04       72   17.6471     408  100.0000      72   17.6471 |
+----------------------------------------------------------------+
--------------------------------------------------------------------------
Ordered Probability Model
Dependent variable               RA11
Log-likelihood function      -612.27936
Restricted log-likelihood    -626.43641
Chi-squared [  6](P= .000)    28.31411
Significance level             .00008
McFadden Pseudo R-squared      .0225993
Estimation based on N =    408, K =  10
Inf. Cr.AIC  =   1244.6 AIC/N =    3.050
Underlying probabilities based on Normal
--------+--------------------------------------------------------------------
        |              Standard          Prob.     95% Confidence
    RA11|  Coefficient      Error      z   |z|>Z*       Interval
--------+--------------------------------------------------------------------
        |Index function for probability....................................
```

```
Constant|    .51882***     .17058     3.04  .0024     .18449    .85314
  VS_FHC|    .27425**      .11707     2.34  .0191     .04480    .50370
  SPE_16|    .33385***     .12431     2.69  .0072     .09021    .57750
   BBOOM|   -.25554*       .13174    -1.94  .0524    -.51376    .00267
   MILLE|    .25565*       .13224     1.93  .0532    -.00353    .51483
     HWC|   -.26203**      .11623    -2.25  .0242    -.48983   -.03423
   COWEC|    .21095        .15054     1.40  .1611    -.08410    .50600
        |Threshold parameters for index....................................
  Mu(01)|    .32385***     .04382     7.39  .0000     .23797    .40972
  Mu(02)|    .89601***     .05598    16.01  .0000     .78630   1.00572
  Mu(03)|   1.89889***     .07758    24.48  .0000    1.74684   2.05095
--------+-----------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Mar 03, 2021, at 01:30:48 AM
--------------------------------------------------------------------------
--------------------------------------------------------------------------
Marginal effects for an ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+-----------------------------------------------------------------
        |    Partial                        Prob.     95% Confidence
    RA11|     Effect    Elasticity     z    |z|>Z*        Interval
--------+-----------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *VS_FHC|   -.06848**     -.34982    -2.42  .0155     -.12392   -.01304
 *SPE_16|   -.09317**     -.47597    -2.50  .0123     -.16609   -.02025
  *BBOOM|    .06856*       .35027     1.87  .0613     -.00326    .14038
  *MILLE|   -.06327**     -.32321    -2.02  .0434     -.12465   -.00188
    *HWC|    .06960**      .35558     2.19  .0283      .00740    .13181
  *COWEC|   -.05803       -.29645    -1.32  .1858     -.14399    .02794
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *VS_FHC|   -.02028**     -.20151    -2.33  .0199     -.03735   -.00321
 *SPE_16|   -.02279***    -.22644    -2.92  .0035     -.03810   -.00747
  *BBOOM|    .01812**      .18009     2.01  .0444      .00045    .03579
  *MILLE|   -.01900*      -.18879    -1.91  .0555     -.03844    .00045
    *HWC|    .01871**      .18593     2.31  .0206      .00287    .03455
  *COWEC|   -.01470       -.14607    -1.49  .1373     -.03409    .00469
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *VS_FHC|   -.02003**     -.09222    -2.06  .0394     -.03909   -.00098
 *SPE_16|   -.01644***    -.07567    -2.97  .0030     -.02729   -.00559
  *BBOOM|    .01498**      .06897     2.07  .0387      .00078    .02918
  *MILLE|   -.01912*      -.08801    -1.70  .0890     -.04115    .00291
    *HWC|    .01592**      .07329     2.27  .0234      .00215    .02969
  *COWEC|   -.01122*      -.05167    -1.76  .0791     -.02375    .00131
        |--------------[Partial effects on Prob[Y=03] at means]--------------
 *VS_FHC|    .03789**      .11302     2.45  .0142      .00759    .06818
 *SPE_16|    .05602**      .16710     2.41  .0159      .01050    .10153
```

```
 *BBOOM|   -.04038*     -.12045   -1.82  .0684    -.08380   .00304
 *MILLE|    .03472**     .10356    2.09  .0364     .00219   .06724
   *HWC|   -.04068**    -.12135   -2.14  .0324    -.07794  -.00342
 *COWEC|    .03480       .10381    1.28  .2010    -.01854   .08814
       |-------------[Partial effects on Prob[Y=04] at means]-------------
*VS_FHC|    .07090**     .46904    2.23  .0259     .00851   .13330
*SPE_16|    .07638***    .50526    2.84  .0045     .02370   .12905
 *BBOOM|   -.06129**    -.40546   -1.99  .0467    -.12169  -.00089
 *MILLE|    .06666*      .44101    1.83  .0668    -.00462   .13795
   *HWC|   -.06355**    -.42043   -2.27  .0232    -.11842  -.00869
 *COWEC|    .04915       .32516    1.50  .1344    -.01519   .11350
--------+-----------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model were estimated on Mar 03, 2021, at 01:30:48 AM
```

Ordered Probit Model estimation results for the likelihood of Riding with a Stranger in DC (RS11)

```
-> IMPORT;FILE="D:\PhD_Edinburgh_Napier\Reports\Data Analysis\RS11_msel\DV.csv"$
The last observation read from the data file was     499
|-> skip $
|-> Open; Export="D:\PhD_Edinburgh_Napier\Reports\Data Analysis\RS11_msel\RS11_2.csv"$
|-> ORDERED; Lhs=RS11; Rhs = one,SES_16,Mille,Agr,Hwcn,Cc;Partial;Export $
-----------------------------------------------------------
Deleted     60 observations with missing data. N is now    439
-----------------------------------------------------------
The iterative procedure has converged
Normal exit:  12 iterations. Status=0, F=    .6078423D+03
+----------------------------------------------------------------+
|              CELL FREQUENCIES FOR ORDERED CHOICES              |
+----------------------------------------------------------------+
|           Frequency       Cumulative  < =    Cumulative  > =   |
|Outcome     Count    Percent   Count    Percent   Count    Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|RS11=00       139   31.6629     139   31.6629     439  100.0000 |
|RS11=01       129   29.3850     268   61.0478     300   68.3371 |
|RS11=02       103   23.4624     371   84.5103     171   38.9522 |
|RS11=03        57   12.9841     428   97.4943      68   15.4897 |
|RS11=04        11    2.5057     439  100.0000      11    2.5057 |
Ordered Probability Model
Dependent variable               RS11
Log-likelihood function      -607.84225
Restricted log-likelihood    -624.07971
Chi-squared [  5](P= .000)    32.47492
Significance level            .00000
McFadden Pseudo R-squared     .0260182
```

```
Estimation based on N =    439, K =   9
Inf.Cr.AIC  =   1233.7 AIC/N =    2.810
Underlying probabilities based on Normal
--------+--------------------------------------------------------------------
        |               Standard            Prob.      95% Confidence
    RS11|  Coefficient       Error       z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |Index function for probability.....................................
Constant|     .28901***      .09474     3.05  .0023      .10333     .47470
  SES_16|     .49450***      .17596     2.81  .0049      .14963     .83938
   MILLE|     .33356***      .11333     2.94  .0032      .11143     .55569
     AGR|     .24430**       .11388     2.15  .0319      .02109     .46750
    HWCN|    -.17658*        .10553    -1.67  .0943     -.38341     .03025
      CC|     .20642*        .10843     1.90  .0570     -.00610     .41895
        |Threshold parameters for index.....................................
  Mu(01)|     .78050***      .05341    14.61  .0000      .67581     .88518
  Mu(02)|    1.54964***      .07174    21.60  .0000     1.40902    1.69025
  Mu(03)|    2.57318***      .13682    18.81  .0000     2.30500    2.84135
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 12, 2023 at 01:37:10 AM
-----------------------------------------------------------------------------
-----------------------------------------------------------------------------
Marginal effects for ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+--------------------------------------------------------------------
        |     Partial                         Prob.      95% Confidence
    RS11|      Effect    Elasticity     z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *SES_16|    -.15374***     -.51463    -3.28  .0011     -.24573    -.06175
  *MILLE|    -.11299***     -.37823    -3.07  .0022     -.18522    -.04076
    *AGR|    -.08357**      -.27975    -2.21  .0269     -.15760    -.00954
   *HWCN|     .06261*        .20960     1.66  .0963     -.01118     .13641
     *CC|    -.07144*       -.23913    -1.94  .0525     -.14364     .00077
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *SES_16|    -.04091*       -.13668    -1.75  .0797     -.08667     .00485
  *MILLE|    -.01650*       -.05511    -1.83  .0674     -.03417     .00118
    *AGR|    -.01114        -.03723    -1.44  .1486     -.02626     .00398
   *HWCN|     .00471         .01574     1.31  .1903     -.00234     .01176
     *CC|    -.00826        -.02758    -1.35  .1786     -.02029     .00377
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *SES_16|     .05767***      .23397     4.06  .0000      .02983     .08552
  *MILLE|     .04743***      .19240     3.11  .0019      .01752     .07733
    *AGR|     .03550**       .14400     2.26  .0236      .00475     .06624
   *HWCN|    -.02742*       -.11121    -1.65  .0997     -.06005     .00522
```

```
    *CC|    .03068*       .12445    1.95  .0509    -.00012    .06147
       |--------------[Partial effects on Prob[Y=03] at means]--------------
 *SES_16|    .10205**      .75967    2.54  .0110     .02344    .18067
  *MILLE|    .06404***     .47669    2.74  .0061     .01828    .10980
   *AGR|    .04649**      .34609    2.02  .0434     .00138    .09160
  *HWCN|   -.03194*      -.23775   -1.67  .0939    -.06931    .00544
    *CC|    .03872*       .28826    1.83  .0668    -.00268    .08013
       |--------------[Partial effects on Prob[Y=04] at means]--------------
 *SES_16|    .03492*      1.65495    1.89  .0593    -.00137    .07121
  *MILLE|    .01802**      .85394    2.32  .0203     .00280    .03324
   *AGR|    .01272*       .60293    1.84  .0659    -.00084    .02628
  *HWCN|   -.00797       -.37773   -1.63  .1021    -.01752    .00158
    *CC|    .01029*       .48763    1.69  .0903    -.00162    .02219
--------+--------------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 12, 2023 at 01:37:10 AM
-----------------------------------------------------------------------------
|-> Dstat;Rhs = one,RS11,SES_16,Mille,Agr,Hwcn,Cc;Export $
--------+--------------------------------------------------------------------
       |              Standard                          Missing
Variable|       Mean    Deviation     Minimum      Maximum    Cases  Values
--------+--------------------------------------------------------------------
   RS11|    1.215054    1.106889        0.0         4.0     465     34
 SES_16|     .089936     .286397        0.0         1.0     467     32
  MILLE|     .292035     .455202        0.0         1.0     452     47
   AGR|     .277056     .44803         0.0         1.0     462     37
  HWCN|      .417749     .493723        0.0         1.0     462     37
    CC|     .337634     .473412        0.0         1.0     465     34
--------+--------------------------------------------------------------------
Descriptive Statistics for   6 variables
DSTAT results are matrix LASTDSTA in current project.
|-> Correlation ; Rhs = SES_16,Mille,Agr,Hwcn,Cc;Export $
--------+--------------------------------------------------------------------
Descriptive Statistics for   6 variables

Correlations computed for   5 variables.
Used    447 observations.
Covariances and/or Correlations Using Listwise Deletion
Missing values removed    499 of     52 observations.
--------+--------------------------------------------
Cor.Mat.|  SES_16    MILLE     AGR    HWCN      CC
--------+--------------------------------------------
 SES_16| 1.00000   .06957   .04377  -.03240   .11717
  MILLE|  .06957  1.00000  -.03681  -.16084   .04255
   AGR|  .04377  -.03681  1.00000  -.04058   .03977
  HWCN| -.03240  -.16084  -.04058  1.00000   .00161
```

```
    CC|  .11717   .04255   .03977   .00161  1.00000
|-> Close ; Export $
```

Ordered Probit Model estimation results for the likelihood of riding with a family member in DC (RM13)

```
-> IMPORT;FILE="D:\PhD_Edinburgh_Napier\Reports\Data Analysis\RM13_msel\DV.csv"$
The last observation read from the data file was     499
|-> skip $
|-> Create ; If(Rl > 0) Sb = 1;(Else) Sb = 0 $
|-> Create ; If(Rl =-999) Sb = -999 $
|-> Create ; If(Ag > 55) Ol = 1;(Else) Ol = 0 $
|-> Create ; If(Ag =-999) Ol = -999 $
|-> Open; Export="D:\PhD_Edinburgh_Napier\Reports\Data
Analysis\RM13_msel\RM13_3.csv"$
|-> ORDERED; Lhs=RM13; Rhs= one,Vs_fhc,SPE_16,Extra,Ol,Os;Partial;Export $
-----------------------------------------------------------
Deleted     87 observations with missing data. N is now    412
-----------------------------------------------------------
The iterative procedure has converged
Normal exit:  12 iterations. Status=0, F=    .5717160D+03
+----------------------------------------------------------------+
|              CELL FREQUENCIES FOR ORDERED CHOICES              |
+----------------------------------------------------------------+
|             Frequency       Cumulative  < =    Cumulative  > =  |
|Outcome     Count   Percent   Count   Percent   Count   Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|RM13=00        55   13.3495      55   13.3495     412  100.0000 |
|RM13=01        17    4.1262      72   17.4757     357   86.6505 |
|RM13=02        70   16.9903     142   34.4660     340   82.5243 |
|RM13=03       157   38.1068     299   72.5728     270   65.5340 |
|RM13=04       113   27.4272     412  100.0000     113   27.4272 |
+----------------------------------------------------------------+
-----------------------------------------------------------------------
Ordered Probability Model
Dependent variable               RM13
Log likelihood function      -571.71599
Restricted log likelihood    -586.67359
Chi squared [  5](P= .000)     29.91519
Significance level             .00002
McFadden Pseudo R-squared      .0254956
Estimation based on N =    412, K =   9
Inf.Cr.AIC  =   1161.4 AIC/N =    2.819
Underlying probabilities based on Normal
--------+--------------------------------------------------------------
        |               Standard          Prob.      95% Confidence
    RM13|  Coefficient       Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------
```

```
        |Index function for probability.....................................
Constant|     .88174***      .12260     7.19  .0000      .64145   1.12202
  VS_FHC|     .18865*       .11340     1.66  .0962     -.03361    .41090
  SPE_16|     .46119***      .12508     3.69  .0002      .21603    .70635
   EXTRA|    -.29771**      .12640    -2.36  .0185     -.54545   -.04997
      OL|    -.32580***      .11090    -2.94  .0033     -.54316   -.10844
      OS|     .29719**      .13606     2.18  .0289      .03053    .56386
        |Threshold parameters for index.....................................
  Mu(01)|     .18129***      .03930     4.61  .0000      .10426    .25832
  Mu(02)|     .74250***      .05551    13.38  .0000      .63371    .85129
  Mu(03)|    1.78682***      .07345    24.33  .0000     1.64286   1.93077
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jan 12, 2023, at 01:54:55 AM
-----------------------------------------------------------------------------
-----------------------------------------------------------------------------
Marginal effects for an ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+--------------------------------------------------------------------
        |     Partial                          Prob.      95% Confidence
    RM13|      Effect    Elasticity      z     |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *VS_FHC|    -.03723*       -.34358    -1.71  .0876     -.07994    .00549
 *SPE_16|    -.10711***      -.98851    -3.25  .0011     -.17162   -.04260
  *EXTRA|     .06632**       .61210     2.16  .0311      .00604    .12661
     *OL|     .06913***      .63800     2.79  .0053      .02058    .11768
     *OS|    -.05446**      -.50264    -2.42  .0155     -.09858   -.01035
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *VS_FHC|    -.00816*       -.21975    -1.68  .0927     -.01767    .00135
 *SPE_16|    -.01975***      -.53197    -3.88  .0001     -.02973   -.00977
  *EXTRA|     .01293**       .34811     2.40  .0165      .00235    .02350
     *OL|     .01412***      .38019     2.98  .0028      .00484    .02339
     *OS|    -.01262**      -.33997    -2.27  .0231     -.02352   -.00173
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *VS_FHC|    -.02271        -.13956    -1.63  .1029     -.05000    .00458
 *SPE_16|    -.04771***      -.29315    -4.16  .0000     -.07018   -.02523
  *EXTRA|     .03258**       .20019     2.55  .0108      .00752    .05763
     *OL|     .03712***      .22808     3.00  .0027      .01287    .06137
     *OS|    -.03692**      -.22687    -2.10  .0358     -.07139   -.00245
        |--------------[Partial effects on Prob[Y=03] at means]--------------
 *VS_FHC|     .00529         .01341     1.11  .2678     -.00407    .01465
 *SPE_16|     .03581**       .09080     2.13  .0334      .00282    .06881
  *EXTRA|    -.01948        -.04939    -1.49  .1374     -.04518    .00622
     *OL|    -.01623*       -.04115    -1.66  .0962     -.03535    .00289
     *OS|     .00168         .00426      .21  .8314     -.01377    .01713
```

```
       |--------------[Partial effects on Prob[Y=04] at means]--------------
 *VS_FHC|     .06281        .21121     1.63  .1028     -.01265    .13827
 *SPE_16|     .13875***      .46659     3.91  .0001      .06920    .20830
  *EXTRA|    -.09235**      -.31054    -2.47  .0137     -.16574   -.01895
     *OL|    -.10413***     -.35017    -2.96  .0031     -.17308   -.03518
     *OS|     .10233**       .34410     2.08  .0375      .00589    .19876
--------+-----------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jan 12, 2023, at 01:54:55 AM
--------------------------------------------------------------------------
|-> Close ; Export $
```

Ordered Probit Model estimation results for the likelihood of riding with a family member in the presence of a stranger in a DC (RMS13)

```
|-> skip $
|-> Create; if (He > 0) Ed = 1; (Else) Ed = 0 $
|-> Create; if (He = -999) Ed = -999 $
|-> Open; Export="D:\PhD_Edinburgh_Napier\Reports\Data
Analysis\RMS13_msel\RMS13_3.csv"$
|-> ORDERED; Lhs=RMS13; Rhs= one,SES_16,Agr,Mille,Hwan,ED,Cc;Partials;Export$
-----------------------------------------------------------------
Deleted     59 observations with missing data. N is now    440
-----------------------------------------------------------------
The iterative procedure has converged
Normal exit:  13 iterations. Status=0, F=    .6318251D+03
+----------------------------------------------------------------+
|             CELL FREQUENCIES FOR ORDERED CHOICES                |
+----------------------------------------------------------------+
|            Frequency       Cumulative  < =    Cumulative  > =  |
|Outcome     Count   Percent  Count   Percent  Count   Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|RMS13=00      119   27.2727     119   27.2727     440  100.0000 |
|RMS13=01      128   29.0909     247   56.3636     321   72.7273 |
|RMS13=02      110   25.0000     357   81.3636     193   43.6364 |
|RMS13=03       65   14.7727     422   96.1364      83   18.6364 |
|RMS13=04       17    3.8636     440  100.0000      17    3.8636 |
+----------------------------------------------------------------+
--------------------------------------------------------------------------
Ordered Probability Model
Dependent variable              RMS13
Log-likelihood function      -631.82510
Restricted log-likelihood    -646.06936
Chi-squared [  6](P= .000)     28.48851
Significance level              .00008
McFadden Pseudo R-squared      .0220476
Estimation based on N =    440, K =  10
```

```
Inf. Cr.AIC  =   1283.7 AIC/N =    2.917
Underlying probabilities based on Normal
--------+--------------------------------------------------------------------
        |               Standard            Prob.      95% Confidence
   RMS13|  Coefficient       Error      z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Index function for probability......................................
Constant|      .63539***       .13036     4.87  .0000      .37988    .89090
 SES_16|      .31082*         .17459     1.78  .0750     -.03138    .65301
   AGR|      .24255**        .11295     2.15  .0318      .02117    .46393
  MILLE|      .28463**        .11367     2.50  .0123      .06184    .50743
   HWCN|     -.18270*         .10460    -1.75  .0807     -.38772    .02232
     ED|     -.26094**        .12851    -2.03  .0423     -.51281   -.00906
     CC|      .27910**        .10932     2.55  .0107      .06483    .49337
        |Threshold parameters for index.....................................
 Mu(01)|      .78924***       .05316    14.85  .0000      .68505    .89342
 Mu(02)|     1.55127***       .06801    22.81  .0000     1.41797   1.68456
 Mu(03)|     2.46751***       .11358    21.73  .0000     2.24490   2.69011
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jan 12, 2023, at 02:26:59 AM
-----------------------------------------------------------------------------
-----------------------------------------------------------------------------
Marginal effects for an ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+--------------------------------------------------------------------
        |     Partial                       Prob.      95% Confidence
   RMS13|      Effect    Elasticity     z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
 *SES_16|     -.09317**      -.36893    -1.97  .0491     -.18596   -.00037
    *AGR|     -.07664**      -.30349    -2.23  .0260     -.14411   -.00918
  *MILLE|     -.08961***     -.35483    -2.61  .0092     -.15703   -.02219
   *HWCN|      .06037*        .23905     1.73  .0837     -.00804    .12878
     *ED|      .08118**       .32143     2.14  .0321      .00695    .15540
     *CC|     -.08862***     -.35092    -2.63  .0086     -.15468   -.02257
        |--------------[Partial effects on Prob[Y=01] at means]--------------
 *SES_16|     -.03025        -.10316    -1.36  .1739     -.07386    .01335
    *AGR|     -.01932*       -.06587    -1.76  .0777     -.04078    .00215
  *MILLE|     -.02296**      -.07828    -2.02  .0437     -.04527   -.00065
   *HWCN|      .01129*        .03849     1.73  .0835     -.00150    .02407
     *ED|      .02225         .07586     1.62  .1044     -.00460    .04910
     *CC|     -.02162**      -.07372    -2.09  .0364     -.04188   -.00136
        |--------------[Partial effects on Prob[Y=02] at means]--------------
 *SES_16|      .03333**       .12724     2.33  .0196      .00535    .06131
    *AGR|      .02975**       .11357     2.30  .0214      .00441    .05510
```

```
 *MILLE|    .03457***     .13195     2.68  .0074     .00928    .05985
  *HWCN|   -.02476*      -.09451    -1.69  .0909    -.05346    .00394
    *ED|   -.03082**     -.11765    -2.29  .0219    -.05718   -.00447
    *CC|    .03458***     .13201     2.67  .0076     .00919    .05998
       |-------------[Partial effects on Prob[Y=03] at means]-------------
*SES_16|    .06131*       .39696     1.69  .0903    -.00964    .13227
   *AGR|    .04649**      .30101     2.05  .0402     .00208    .09091
 *MILLE|    .05462**      .35362     2.38  .0172     .00969    .09955
  *HWCN|   -.03381*      -.21892    -1.75  .0810    -.07179    .00416
    *ED|   -.05051*      -.32704    -1.93  .0536    -.10180    .00078
    *CC|    .05324**      .34472     2.43  .0151     .01029    .09619
       |-------------[Partial effects on Prob[Y=04] at means]-------------
*SES_16|    .02878        .76208     1.42  .1560    -.01098    .06854
   *AGR|    .01972*       .52214     1.88  .0607    -.00088    .04032
 *MILLE|    .02338**      .61916     2.13  .0332     .00186    .04490
  *HWCN|   -.01309*      -.34655    -1.73  .0844    -.02795    .00178
    *ED|   -.02209*      -.58492    -1.72  .0846    -.04719    .00302
    *CC|    .02241**      .59358     2.22  .0266     .00260    .04223
--------+----------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jan 12, 2023, at 02:26:59 AM
-------------------------------------------------------------------------
|-> Close ; Export $
```

18. Appendix J: SPSS output for Binary Logistic Regression model findings concerning the weak propensity to accept shared over non-shared DC use

Model estimation result assessment concerning the weak preferences concerning driverless taxi use than private DC (DVT)

For this model, overall, 307 responses are taken into consideration (Table 6.16a1). Without any variables, the null model estimation result shows that the constant is positive, indicating that the number of choice responses for choosing driverless taxis to private DC is significant (Table 6.16a2).

Table 6.16a1: Responses used in the analysis

Observation		Number	Percentage
Driverless taxi use over Private Driverless Car	Included in Analysis	307	61.52
	Missing Cases	192	38.48
	Total	499	100

Table 6.16a2: The null model estimation result

No variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step	Constant	0.83	0.12	45.02	1.00	0.00	2.30

Besides, the Omnibus tests of model coefficients predict whether a model including the complete set of predictors significantly improves model fit over the null (intercept-only) model. Effectively, an omnibus test of the null hypothesis proves that the regression slopes with all predictors in the model are equal to zero (Pituch & Stevens, 2016). The results indicated that data fit significantly better for the final modelling step than a null model, $\chi^2(5)=42.101$, $p<.001$, as in Table 6.16a3.

Table 6.16a3: Omnibus test result of model coefficient

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	12.091	1	0.001
	Block	12.091	1	0.001
	Model	12.091	1	0.001
Step 2	Step	10.821	1	0.001
	Block	22.912	2	0.000
	Model	22.912	2	0.000
Step 3	Step	7.412	1	0.006
	Block	30.324	3	0.000
	Model	30.324	3	0.000
Step 4	Step	6.967	1	0.008
	Block	37.291	4	0.000
	Model	37.291	4	0.000
Step 5	Step	4.810	1	0.028
	Block	42.101	5	0.000
	Model	42.101	5	0.000

The Model Summary Table 6.16a4 contains the log-likelihood and two “pseudo-R-square” measures. The log-likelihood is most useful for comparing competing models when distributed as chi-square to indicate the model deviance. Here in this model, the log-likelihood values improved with the number of steps it took to terminate. Except for the Log-likelihood result, the other two R-square results followed here are unconventional, and there is not enough evidence of how these can be used, as shown in Table 6.16a4.

Table 6.16a4: Log-likelihood and 'Pseudo R-square' measures

Modelling Steps	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	364.492[a]	0.039	0.055
2	353.671[a]	0.072	0.102
3	346.259[a]	0.094	0.133
4	339.292[a]	0.114	0.162
5	334.483[b]	0.128	0.181

Along with the tests for model fitness above, the Hosmer & Lemeshow test in Table 6.16a5 can be used to evaluate global fit by non-significant test results. As seen here, $p < 1.00$ for all the modelling steps indicates a good model fit.

Table 6.16a5: Hosmer & Lemeshow test measures

Step	Chi-square	df	Significance
1	0.00	0	
2	0.03	1	0.87
3	1.78	4	0.78
4	5.04	6	0.54
5	6.59	7	0.47

Based on the modelling results, the classification in Table 6.16a6 provides the frequencies and percentages reflecting the degree to which the BLR model correctly and incorrectly predicts category membership on the dependent variable. This table shows that the BLR model correctly predicts that 72.96% of the data sample can relate to the outcome variable (Higher or Equal likelihood of Driverless taxi use than Private DC).

Table 6.16a6: Classification results indicating category membership on the dependent variable

Observed			Predicted DT9 >= PV9 Else	Predicted DT9 >= PV9 Diff	Percentage Correct
Step 1	DT9 >= PV9	Else	0	93	0.00
		Diff	0	214	100.00
Overall Percentage					69.71
Step 2	DT9 >= PV9	Else	0	93	0.00
		Diff	0	214	100.00
Overall Percentage					69.71
Step 3	DT9 >= PV9	Else	0	93	0.00
		Diff	0	214	100.00
Overall Percentage					69.71
Step 4	DT9 >= PV9	Else	28	65	30.11
		Diff	20	194	90.65
Overall Percentage					72.31
Step 5	DT9 >= PV9	Else	22	71	23.66
		Diff	12	202	94.39
Overall Percentage					72.96

After the classification result, the model variable estimation results are given as shown in the following Tabel 6.16a7.

Table 6.16a7: Variables in the Equation concerning the weak preferences concerning driverless taxi use than private DC (DVT)

Step	Determinants	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Bboom(1)	1.015	0.309	10.775	1	0.001	2.760
	Constant	0.569	0.143	15.909	1	0.000	1.766
Step 2[b]	Cowe0(1)	1.194	0.395	9.127	1	0.003	3.299
	Bboom(1)	1.172	0.315	13.855	1	0.000	3.229
	Constant	0.343	0.157	4.755	1	0.029	1.409
Step 3[c]	He2(1)	0.709	0.263	7.255	1	0.007	2.032
	Cowe0(1)	1.181	0.398	8.798	1	0.003	3.259
	Bboom(1)	1.192	0.318	14.039	1	0.000	3.295
	Constant	0.004	0.200	0.000	1	0.984	1.004
Step 4[d]	He2(1)	0.757	0.268	7.976	1	0.005	2.132
	Cowe0(1)	1.262	0.403	9.795	1	0.002	3.531
	Bboom(1)	1.299	0.325	15.963	1	0.000	3.666
	RHS15 > 2 & Nu15 < 2;RHS15 <= 2 & Nu15 >= 2(1)	0.751	0.292	6.613	1	0.010	2.119
	Constant	-0.301	0.235	1.645	1	0.200	0.740
Step 5[e]	He2(1)	0.764	0.270	8.005	1	0.005	2.146
	Cowe0(1)	1.242	0.407	9.300	1	0.002	3.463
	Bboom(1)	1.346	0.328	16.850	1	0.000	3.842
	Vs_fhcr(1)	0.644	0.300	4.604	1	0.032	1.904
	RHS15 > 2 & Nu15 < 2;RHS15 <= 2 & Nu15 >= 2(1)	0.727	0.295	6.077	1	0.014	2.069
	Constant	-0.497	0.254	3.834	1	0.050	0.608
a. Variable(s) entered on step 1: Bboom.							
b. Variable(s) entered on step 2: Cowe0.							
c. Variable(s) entered on step 3: He2.							
d. Variable(s) entered on step 4: RHS15 > 2 & Nu15 < 2;RHS15 <= 2 & Nu15 >= 2.							
e. Variable(s) entered on step 5: Vs_fhcr.							

Model estimation results concerning the weak preferences for sharing a DC with a stranger to riding alone in a DC (RST)

Overall, 307 responses are considered for this model (Table 6.16b1). Without any variables, the null model estimation result shows that the constant is negative, indicating that the number of choice responses from choosing shared DC with a stranger to riding alone is insignificant (Table 6.16b2).

Table 6.16b1: Responses used in the analysis

Observation		Number	Percentage
Sharing a DC with Stranger to riding alone in DC	Included in Analysis	307	61.52
	Missing Cases	192	38.48
	Total	499	100

Table 6.16b2: The null model estimation result

No variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-0.137	0.114	1.434	1	0.231	0.872

Besides, the Omnibus tests of model coefficients predict whether a model including the complete set of predictors significantly improves model fit over the null (intercept-only) model. The results indicated that data fit significantly better for the final modelling step than a null model, $\chi^2(4)=23.16$, $p<.001$, as in Table 6.16b3.

Table 6.16b3: Omnibus test result of model coefficient

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	4.34	1	0.037
	Block	4.34	1	0.037
	Model	4.34	1	0.037
Step 2	Step	4.367	1	0.037
	Block	8.706	2	0.013
	Model	8.706	2	0.013
Step 3	Step	5.538	1	0.019
	Block	14.244	3	0.003
	Model	14.244	3	0.003
Step 4	Step	8.911	1	0.003
	Block	23.155	4	0.000
	Model	23.155	4	0.000

The Model Summary Table 6.16b4 contains the log-likelihood and two “pseudo-R-square” measures. The log-likelihood is most useful for comparing competing models when distributed as chi-square to indicate the model deviance. Here in this model, the log-likelihood values improved with the number of steps it took to terminate. Except for the Log-likelihood result, the other two R-square results followed here are unconventional, and there is not enough evidence of how these can be used.

Table 6.16b4: Log-likelihood and ‘Pseudo R-square’ measures

Modelling Steps	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	419.815a	0.014	0.019
2	415.449a	0.028	0.037
3	409.910a	0.045	0.061
4	401.000b	0.073	0.097

Along with the tests for model fitness above, the Hosmer & Lemeshow test in Table 6.16b5 can be used to evaluate global fit by non-significant test results. As seen here, $p < 1.00$ for all the modelling steps indicates a good model fit.

Table 6.16b5: Hosmer & Lemeshow test measures

Step	Chi-square	df	Significance
1	0.000	0	0.000
2	0.006	1	0.936
3	0.211	4	0.995
4	0.734	5	0.981

Based on the modelling results, the classification in Table 6.16b6 provides the frequencies and percentages reflecting the degree to which the BLR model correctly and incorrectly predicts category membership on the dependent variable. As seen in this table, the BLR model correctly predicts that 59.9% of the data sample belongs to the outcome variable (Higher or Equal likelihood of DC sharing with a stranger than riding alone in DC).

Table 6.16b6: Classification results indicating category membership on the dependent variable

Observed			Predicted		Percentage Correct
			RS11 >= RA11		
			Else	Diff	
Step 1	DT9 >= PV9	Else	152	12	92.7
		Diff	122	21	14.7
Overall Percentage					56.4
Step 2	DT9 >= PV9	Else	152	12	92.7
		Diff	122	21	14.7
Overall Percentage					56.4
Step 3	DT9 >= PV9	Else	121	43	73.8
		Diff	80	63	44.1
Overall Percentage					59.9
Step 4	DT9 >= PV9	Else	88	76	53.7
		Diff	47	96	67.1
Overall Percentage					59.9

After the classification reault, the model variable estimation results are given as shown in the following Tabel 6.16b7.

Table 6.16b7: Variables in the Equation concerning the weak preferences for riding with a stranger to riding alone in DC (RST)

Step	Determinants	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	SES_16(1)	0.779	0.382	4.169	1	0.041	2.18
	Constant	-0.22	0.122	3.271	1	0.07	0.803
Step 2b	Cowe2(1)	-0.564	0.273	4.262	1	0.039	0.569
	SES_16(1)	0.786	0.385	4.172	1	0.041	2.194
	Constant	-0.082	0.138	0.357	1	0.55	0.921
Step 3c	Hwc(1)	0.569	0.244	5.456	1	0.02	1.766
	Cowe2(1)	-0.701	0.283	6.127	1	0.013	0.496
	SES_16(1)	0.814	0.388	4.408	1	0.036	2.257
	Constant	-0.293	0.166	3.115	1	0.078	0.746
Step 4d	Hwc(1)	0.819	0.263	9.693	1	0.002	2.268
	Cowe2(1)	-0.882	0.295	8.91	1	0.003	0.414
	Bboom(1)	0.809	0.275	8.644	1	0.003	2.247
	SES_16(1)	0.914	0.395	5.358	1	0.021	2.494
	Constant	-0.624	0.205	9.301	1	0.002	0.536
a Variable(s) entered on step 1: SES_16.							
b Variable(s) entered on step 2: Cowe2.							
c Variable(s) entered on step 3: Hwc.							

d Variable(s) entered on step 4: Bboom.

Model estimation results concerning the weak preferences for DC shared ridership with a family member in the presence of a stranger than to share the DC with family alone (RSF)

Overall, 312 responses are considered for this model (Table 6.16c1). Without any variables, the null model estimation result shows that the constant is negative, indicating that the number of choice responses relating DC shared ridership with a stranger and family members to riding only with a family member is significant (Table 6.16c2) result.

Table 6.16c1: Responses used in the analysis

Observation		Number	Percentage
Sharing a DC with Stranger to riding alone in DC	Included in Analysis	312	62.5
	Missing Cases	187	37.5
	Total	499	100

Table 6.16c2: The null model estimation result

No variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step	Constant	-0.47	0.116	16.313	1	0	0.625

Besides, the Omnibus tests of model coefficients predict whether a model including the complete set of predictors significantly improves model fit over the null (intercept-only) model. The results indicated that data fit significantly better for the final modelling step than a null model, $\chi^2(4)=23.53$, $p<.001$, as in Table 6.16c3.

Table 6.16c3: Omnibus test result of model coefficient

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	8.576	1	0.00
	Block	8.576	1	0.00
	Model	8.576	1	0.00
Step 2	Step	6.846	1	0.01
	Block	15.422	2	0.00
	Model	15.422	2	0.00
Step 3	Step	4.315	1	0.04
	Block	19.737	3	0.00
	Model	19.737	3	0.00
Step 4	Step	3.795	1	0.05
	Block	23.532	4	0.00
	Model	23.532	4	0.00

The Model Summary Table 6.17c4 contains the model's log-likelihood and two “pseudo-R-square” measures. Here in this model, the log-likelihood values improved with the number of steps it took to terminate. Except for the Log-likelihood result, the other two R-square results followed here are unconventional, and there is not enough evidence of how these can be used.

Table 6.16c4: Log-likelihood and ‘Pseudo R-square’ measures

Modelling Steps	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	407.181a	0.027	0.037
2	400.336b	0.048	0.066

3	396.021b	0.061	0.083
4	392.226b	0.073	0.099

Along with the tests for model fitness above, the Hosmer & Lemeshow test in Table 6.16c5 can be used to evaluate global fit by non-significant test results. As seen here, $p < 1.00$ for all the modelling steps indicates a good model fit.

Table 6.16c5: Hosmer & Lemeshow test measures

Step	Chi-square	df	Significance
1	0.00	0	0.00
2	2.955	2	0.228
3	4.618	3	0.202
4	5.538	6	0.477

Based on the modelling results, the classification in Table 6.16c6 provides the frequencies and percentages reflecting the degree to which the BLR model correctly and incorrectly predicts category membership on the dependent variable. As seen in this table, the BLR model correctly predicts that 67% of the data sample belongs to the outcome variable (Higher or Equal likelihood of DC shared ridership with a stranger and a family member to share the DC with a family member-only).

Table 6.16c6: Classification results indicating category membership on the dependent variable

Observed			Predicted		Percentage Correct
			RMS13 >= RM13		
			Else	Diff	
Step 1	DT9 >= PV9	Else	155	37	80.7
		Diff	79	41	34.2
Overall Percentage					62.8
Step 2	DT9 >= PV9	Else	167	25	87
		Diff	82	38	31.7
Overall Percentage					65.7
Step 3	DT9 >= PV9	Else	167	25	87
		Diff	82	38	31.7
Overall Percentage					65.7
Step 4	DT9 >= PV9	Else	159	33	82.8
		Diff	70	50	41.7
Overall Percentage					67.0

After the classification result, the model variable estimation results are given as shown in the following Tabel 6.16c7.

Table 6.16c7: Variables in the Equation concerning the weak preference for DC shared ridership with a family member in the presence of a stranger than to share the DC with family alone (RSF)

Step	Determinants	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	SPE_16(1)	-0.777	0.266	8.552	1	0.003	0.46
	Constant	0.103	0.227	0.205	1	0.651	1.108
Step 2b	Os(1)	-0.845	0.337	6.268	1	0.012	0.43
	SPE_16(1)	-0.802	0.269	8.862	1	0.003	0.448
	Constant	0.263	0.238	1.223	1	0.269	1.301
Step 3c	Os(1)	-0.838	0.34	6.06	1	0.014	0.433

	SEQ_16(1)	0.561	0.274	4.177	1	0.041	1.752
	SPE_16(1)	-1.08	0.307	12.402	1	0	0.34
	Constant	0.157	0.244	0.412	1	0.521	1.17
Step 4d	Hi2(1)	0.618	0.317	3.801	1	0.051	1.855
	Os(1)	-0.854	0.342	6.250	1	0.012	0.426
	SEQ_16(1)	0.572	0.276	4.303	1	0.038	1.772
	SPE_16(1)	-1.053	0.308	11.651	1	0.001	0.349
	Constant	0.025	0.254	0.010	1	0.921	1.026
a Variable(s) entered on step 1: SPE_16.							
b Variable(s) entered on step 2: Os.							
c Variable(s) entered on step 3: SEQ_16.							
d Variable(s) entered on step 4: Hi2.							

Table 6.16b7: Variables in the Equation concerning the weak preferences for riding with a stranger to riding alone in DC (RST)

Step	Determinants	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	SES_16(1)	0.779	0.382	4.169	1	0.041	2.18
	Constant	-0.22	0.122	3.271	1	0.07	0.803
Step 2b	Cowe2(1)	-0.564	0.273	4.262	1	0.039	0.569
	SES_16(1)	0.786	0.385	4.172	1	0.041	2.194
	Constant	-0.082	0.138	0.357	1	0.55	0.921
Step 3c	Hwc(1)	0.569	0.244	5.456	1	0.02	1.766
	Cowe2(1)	-0.701	0.283	6.127	1	0.013	0.496
	SES_16(1)	0.814	0.388	4.408	1	0.036	2.257
	Constant	-0.293	0.166	3.115	1	0.078	0.746
Step 4d	Hwc(1)	0.819	0.263	9.693	1	0.002	2.268
	Cowe2(1)	-0.882	0.295	8.91	1	0.003	0.414
	Bboom(1)	0.809	0.275	8.644	1	0.003	2.247
	SES_16(1)	0.914	0.395	5.358	1	0.021	2.494
	Constant	-0.624	0.205	9.301	1	0.002	0.536
a Variable(s) entered on step 1: SES_16.							
b Variable(s) entered on step 2: Cowe2.							
c Variable(s) entered on step 3: Hwc.							
d Variable(s) entered on step 4: Bboom.							

Model estimation results concerning the weak preferences for DC shared ridership with a family member in the presence of a stranger than to share the DC with family alone (RSF)

Overall, 312 responses are considered for this model (Table 6.16c1). Without any variables, the null model estimation result shows that the constant is negative, indicating that the number of choice responses relating DC shared ridership with a stranger and family members to riding only with a family member is significant (Table 6.16c2) result.

Table 6.16c1: Responses used in the analysis

Observation		Number	Percentage
Sharing a DC with Stranger to riding alone in DC	Included in Analysis	312	62.5
	Missing Cases	187	37.5
	Total	499	100

Table 6.16c2: The null model estimation result

No variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step	Constant	-0.47	0.116	16.313	1	0	0.625

Besides, the Omnibus tests of model coefficients predict whether a model including the complete set of predictors significantly improves model fit over the null (intercept-only) model. The results indicated that data fit significantly better for the final modelling step than a null model, $\chi^2(4)=23.53$, $p<.001$, as in Table 6.16c3.

Table 6.16c3: Omnibus test result of model coefficient

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	8.576	1	0.00
	Block	8.576	1	0.00
	Model	8.576	1	0.00
Step 2	Step	6.846	1	0.01
	Block	15.422	2	0.00
	Model	15.422	2	0.00
Step 3	Step	4.315	1	0.04
	Block	19.737	3	0.00
	Model	19.737	3	0.00
Step 4	Step	3.795	1	0.05
	Block	23.532	4	0.00
	Model	23.532	4	0.00

The Model Summary Table 6.17c4 contains the model's log-likelihood and two “pseudo-R-square” measures. Here in this model, the log-likelihood values improved with the number of steps it took to terminate. Except for the Log-likelihood result, the other two R-square results followed here are unconventional, and there is not enough evidence of how these can be used.

Table 6.16c4: Log-likelihood and ‘Pseudo R-square’ measures

Modelling Steps	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	407.181a	0.027	0.037
2	400.336b	0.048	0.066
3	396.021b	0.061	0.083
4	392.226b	0.073	0.099

Along with the tests for model fitness above, the Hosmer & Lemeshow test in Table 6.16c5 can be used to evaluate global fit by non-significant test results. As seen here, $p < 1.00$ for all the modelling steps indicates a good model fit.

Table 6.16c5: Hosmer & Lemeshow test measures

Step	Chi-square	df	Significance
1	0.00	0	0.00
2	2.955	2	0.228
3	4.618	3	0.202
4	5.538	6	0.477

Based on the modelling results, the classification in Table 6.16c6 provides the frequencies and percentages reflecting the degree to which the BLR model correctly and incorrectly predicts category membership on the dependent variable. As seen in this table, the BLR model correctly predicts that 67% of the data sample belongs to the outcome variable (Higher or Equal likelihood of DC shared ridership with a stranger and a family member to share the DC with a family member-only).

Table 6.16c6: Classification results indicating category membership on the dependent variable

Observed			Predicted		Percentage Correct
			RMS13 >= RM13		
			Else	Diff	
Step 1	DT9 >= PV9	Else	155	37	80.7
		Diff	79	41	34.2
Overall Percentage					62.8
Step 2	DT9 >= PV9	Else	167	25	87
		Diff	82	38	31.7
Overall Percentage					65.7
Step 3	DT9 >= PV9	Else	167	25	87
		Diff	82	38	31.7
Overall Percentage					65.7
Step 4	DT9 >= PV9	Else	159	33	82.8
		Diff	70	50	41.7
Overall Percentage					67.0

After the classification result, the model variable estimation results are given, as shown in the following Tabel 6.16c7.

Table 6.16c7: Variables in the Equation concerning the weak preference for DC shared ridership with a family member in the presence of a stranger than to share the DC with family alone (RSF)

Step	Determinants	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	SPE_16(1)	-0.777	0.266	8.552	1	0.003	0.46
	Constant	0.103	0.227	0.205	1	0.651	1.108
Step 2b	Os(1)	-0.845	0.337	6.268	1	0.012	0.43
	SPE_16(1)	-0.802	0.269	8.862	1	0.003	0.448
	Constant	0.263	0.238	1.223	1	0.269	1.301
Step 3c	Os(1)	-0.838	0.34	6.06	1	0.014	0.433
	SEQ_16(1)	0.561	0.274	4.177	1	0.041	1.752
	SPE_16(1)	-1.08	0.307	12.402	1	0	0.34
	Constant	0.157	0.244	0.412	1	0.521	1.17
Step 4d	Hi2(1)	0.618	0.317	3.801	1	0.051	1.855
	Os(1)	-0.854	0.342	6.250	1	0.012	0.426
	SEQ_16(1)	0.572	0.276	4.303	1	0.038	1.772
	SPE_16(1)	-1.053	0.308	11.651	1	0.001	0.349
	Constant	0.025	0.254	0.010	1	0.921	1.026
a Variable(s) entered on step 1: SPE_16.							
b Variable(s) entered on step 2: Os.							
c Variable(s) entered on step 3: SEQ_16.							
d Variable(s) entered on step 4: Hi2.							

The rest of the model estimation results are described in Table 6-16 .

19. Appendix K: NLOGIT output concerning joint Multinomial logit model findings concerning the determinants of shared and non-shared modes of DC

Multinomial Logit model estimation considering the determinants of non-shared DC options (private DC, riding alone)_PVRA

```
|-> skip $
|-> Create; if(Vs=3) Vs_fhc = 1; (Else) Vs_fhc= 0 $
|-> Create; if(Vs=-999) Vs_fhc = -999 $
|-> Create; if(Vs=2) Vs_nhc = 1; (Else) Vs_nhc= 0 $
|-> Create; if(Vs=-999) Vs_nhc = -999 $
|-> Create; if(Vs=1) Vs_fhcr = 1; (Else) Vs_fhcr= 0 $
|-> Create; if(Vs=-999) Vs_fhcr = -999 $
|-> Create; if(He = 0) He0 = 1; (Else) He0 = 0 $
|-> Create; if(He = -999) He0 = -999 $
|-> Create; if(He = 1) He1 = 1; (Else) He1 = 0 $
|-> Create; if(He = -999) He1 = -999 $
|-> Create; if(He = 2) He2 = 1; (Else) He2 = 0 $
|-> Create; if(He = -999) He2 = -999 $
|-> Create; if(Gen = 1) Mille = 1; (Else) Mille = 0 $
|-> Create; if(Gen = -999) Mille = -999 $
|-> Create; if(Gen = 2) GenX = 1; (Else) GenX = 0 $
|-> Create; if(Gen = -999) GenX = -999 $
|-> Create; if(Gen = 3 ) Bboom = 1; (Else) Bboom = 0 $
|-> Create; if(Gen = -999) Bboom = -999 $
|-> Create; if(Hc = 1) Hwcn = 1; (Else) Hwcn = 0 $
|-> Create; if(Hc = -999) Hwcn = -999 $
|-> Create; if(Hc = 2) Hwc = 1; (Else) Hwc = 0 $
|-> Create; if(Hc = -999) Hwc = -999 $
|-> Create; if(Rl = 0) CC = 1; (Else) CC = 0 $
|-> Create; if(Rl = -999) CC = -999 $
|-> Create; if(Rl = 1) Is = 1; (Else) Is = 0 $
|-> Create; if(Rl = -999) Is = -999 $
|-> Create; if(Rl = 2) Os = 1; (Else) Os = 0 $
|-> Create; if(Rl = -999) Os = -999 $
|-> Create; if(Cowe = 0) Cowe0 = 1; (Else) Cowe0 = 0 $
|-> Create; if(Cowe = -999) Cowe0 = -999 $
|-> Create; if(Cowe = 2) Cowe2 = 1; (Else) Cowe2 = 0 $
|-> Create; if(Cowe = -999) Cowe2 = -999 $
|-> Create; if(Cowe = 1) Cowe1 = 1; (Else) Cowe1 = 0 $
|-> Create; if(Cowe = -999) Cowe1 = -999 $
|-> Create; if(Hi = 1) Hi1 = 1; (Else) Hi1 = 0 $
|-> Create; if(Hi = -999) Hi1 = -999 $
|-> Create; if(Hi = 2) Hi2 = 1; (Else) Hi2 = 0 $
|-> Create; if(Hi = -999) Hi2 = -999 $
|-> Create; if(Hi = 3) Hi3 = 1; (Else) Hi3 = 0 $
```

```
|-> Create; if(Hi = -999) Hi3 = -999 $
|-> Create; if(Hi = 4) Hi4 = 1; (Else) Hi4 = 0 $
|-> Create; if(Hi = -999) Hi4 = -999 $
|-> Create; if(Hi = 5) Hi5 = 1; (Else) Hi5 = 0 $
|-> Create; if(Hi = -999) Hi5 = -999 $
|-> Create; if(Hi < 3) Hri = 1; (Else) Hri = 0 $
|-> Create; if(Hi = -999) Hri = -999 $
|->    OPEN    ;    Export    =    "D:\PhD_Edinburgh_Napier\Reports\Data
Analysis\Multinomial_Logit/PVRA_1.csv" $
|-> Nlogit ; lhs = Choice
   ; choices = NP,RA,DP,BP
   ; Model:
   U(NP) = One*One + Bboom1*Bboom + Cowe01*Cowe0 + He0*He0 /
   U(RA) = Bboom2*Bboom + Cowe02*Cowe0 + Opn*Opn /
   U(DP) = Vs_nhc*Vs_nhc + Is*Is + Hi1*Hi1 /
   U(BP) = SPE_16 * SPE_16 + He1*He1 + Cowe2*Cowe2 + Mille*Mille + Os*Os + Hi4*Hi4
   ;Show
   ;describe
   ;Export output
   ;Export = Table

;Effects:Bboom[NP]/Cowe0[NP]/He0[NP]/Bboom[RA]/Cowe0[RA]/Opn[RA]/Vs_nhc[DP]/Is[DP]/
Hi1[DP]/SPE_16[BP]/He1[BP]/Cowe2[BP]/Mille[BP]/Os[BP]/Hi4[BP]
   ;Full
   $
+-----------------------------------------------------+
|WARNING:   Bad observations were found in the sample. |
|Found  172 bad observations among    499 individuals. |
|You can use ;CheckData to get a list of these points. |
+-----------------------------------------------------+
Sample proportions are marginal, not conditional.
Choices marked with * are excluded for the IIA test.
+----------------+------+
|Choice   (prop.)| Count|
+----------------+------+
|NP       .22324|   111|
|RA       .17431|    87|
|DP       .05505|    27|
|BP       .54740|   273|
+----------------+------+
+-------------------------------------------------------------+
| Model Specification:  Table entry is the attribute that       |
| multiplies the indicated parameter.                          |
+--------+------+---------------------------------------------+
| Choice |******| Parameter                                  |
|        |Row  1| ONE      BBOOM1   COWE01   HE0      BBOOM2    |
|        |Row  2| COWE02   OPN      VS_NHC   IS       HI1       |
```

```
|       |Row  3| SPE_16   HE1     COWE2    MILLE    OS       |
|       |Row  4| HI4                                |
+--------+------+--------------------------------------------+
|NP      |     1| ONE      BBOOM    COWE0    HE0      none      |
|        |     2| none     none     none     none     none      |
|        |     3| none     none     none     none     none      |
|        |     4| none                                |
|RA      |     1| none     none     none     none     BBOOM     |
|        |     2| COWE0    OPN      none     none     none      |
|        |     3| none     none     none     none     none      |
|        |     4| none                                |
|DP      |     1| none     none     none     none     none      |
|        |     2| none     none     VS_NHC   IS       HI1       |
|        |     3| none     none     none     none     none      |
|        |     4| none                                |
|BP      |     1| none     none     none     none     none      |
|        |     2| none     none     none     none     none      |
|        |     3| SPE_16   HE1      COWE2    MILLE    OS        |
|        |     4| HI4                                |
+------------------------------------------------------------+
The iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .3371296D+03
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable              Choice
Log-likelihood function      -337.12962
Estimation based on N =    327, K =  16
Inf.Cr.AIC  =    706.3 AIC/N =    2.160
---------------------------------------
           Log-likelihood R-sqrd R2Adj
Constants only   -369.0908  .0866 .0714
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   499, skipped  172 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
Constant|     .21545        .25386      .85  .3961     -.28211    .71300
  BBOOM1|     .82665**      .33561     2.46  .0138      .16886   1.48445
  COWE01|     .87986**      .37093     2.37  .0177      .15285   1.60687
     HE0|    -.73044*       .42315    -1.73  .0843    -1.55980    .09893
  BBOOM2|    1.16181***     .32763     3.55  .0004      .51967   1.80396
```

```
 COWE02|   1.10132***     .36923    2.98  .0029     .37765   1.82500
    OPN|   -.65676**      .29470   -2.23  .0258   -1.23435  -.07916
 VS_NHC|  -1.82622**      .74695   -2.44  .0145   -3.29020  -.36223
     IS|  -1.07269**      .45808   -2.34  .0192   -1.97051  -.17486
    HI1|    .96079*       .55366    1.74  .0827    -.12437   2.04595
 SPE_16|    .88579***     .22387    3.96  .0001     .44701   1.32457
    HE1|    .46641*       .26100    1.79  .0739    -.04513   .97795
  COWE2|    .59321**      .29212    2.03  .0423     .02067   1.16575
  MILLE|    .47554*       .27159    1.75  .0800    -.05678   1.00785
     OS|   1.10011***     .33348    3.30  .0010     .44651   1.75371
    HI4|    .68017**      .33829    2.01  .0444     .01714   1.34319
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:00 PM
---------------------------------------------------------------------------
+------------------------------------------------------------------------+
|          Descriptive Statistics for Alternative NP               |
|    Utility Function         | (CBS wt = 1.00000) |     73.0 observs.  |
|    Coefficient              | All     327.0 obs.|that chose NP      |
| Name        Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | -------------------+------------------- |
| ONE         .2154  ONE      |   1.000      .000|   1.000     .000 |
| BBOOM1      .8267  BBOOM    |    .321      .468|    .411     .495 |
| COWE01      .8799  COWE0    |    .193      .395|    .288     .456 |
| HE0        -.7304  HE0      |    .183      .388|    .110     .315 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
|          Descriptive Statistics for Alternative RA               |
|    Utility Function         | (CBS wt = 1.00000) |     57.0 observs.  |
|    Coefficient              | All     327.0 obs.|that chose RA      |
| Name        Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | -------------------+------------------- |
| BBOOM2     1.1618  BBOOM    |    .321      .468|    .474     .504 |
| COWE02     1.1013  COWE0    |    .193      .395|    .316     .469 |
| OPN        -.6568  OPN      |    .474      .500|    .404     .495 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
|          Descriptive Statistics for Alternative DP               |
|    Utility Function         | (CBS wt = 1.00000) |     18.0 observs.  |
|    Coefficient              | All     327.0 obs.|that chose DP      |
| Name        Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | -------------------+------------------- |
| VS_NHC    -1.8262  VS_NHC   |    .333      .472|    .111     .323 |
| IS        -1.0727  IS       |    .456      .499|    .333     .485 |
| HI1         .9608  HI1      |    .119      .325|    .278     .461 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
```

```
|          Descriptive Statistics for Alternative BP              |
|    Utility Function        | (CBS wt = 1.00000) |    179.0 observs.  |
|    Coefficient             | All     327.0 obs.|that chose BP      |
| Name        Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | -------------------+------------------- |
| SPE_16      .8858  SPE_16   |   .749      .434|    .782     .414 |
| HE1        .4664  HE1      |   .321      .468|    .346     .477 |
| COWE2       .5932  COWE2    |   .242      .429|    .291     .455 |
| MILLE       .4755  MILLE    |   .343      .475|    .385     .488 |
| OS        1.1001  OS       |   .187      .390|    .251     .435 |
| HI4        .6802  HI4      |   .171      .377|    .218     .414 |
+---------------------------------------------------------------------+
+-----------------------------------------------+
| Derivative averaged over observations.|
| Effects on probabilities of all choices in the model: |
| * = Direct Derivative effect of the attribute.    |
+-----------------------------------------------+
-----------------------------------------------------------------------
Average partial effect  on prob(alt) wrt BBOOM    in NP
--------+--------------------------------------------------------------
        |              Standard          Prob.      95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------
     NP|    .13191***     .00275    48.05  .0000     .12653    .13729
     RA|   -.04079***     .00206   -19.75  .0000    -.04483   -.03674
     DP|   -.01157***     .00068   -16.96  .0000    -.01290   -.01023
     BP|   -.07956***     .00146   -54.35  .0000    -.08242   -.07669
--------+--------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:00 PM
-----------------------------------------------------------------------
-----------------------------------------------------------------------
Average partial effect  on prob(alt) wrt BBOOM    in NP
--------+--------------------------------------------------------------
        |    Average      Sample Standard     Sample      Sample
  Choice|  Elasticity       Deviation       Minimum     Maximum
--------+--------------------------------------------------------------
     NP|    .13191         .00275         .022283      .20666
     RA|   -.04079         .00206        -.160653     -.00040
     DP|   -.01157         .00068        -.092847     -.00013
     BP|   -.07956         .00146        -.138380     -.02126
--------+--------------------------------------------------------------
-----------------------------------------------------------------------
Average partial effect  on prob(alt) wrt COWE0    in NP
--------+--------------------------------------------------------------
        |              Standard          Prob.      95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
```

--------+--

NP	.14040***	.00292	48.05	.0000	.13467	.14612
RA	-.04341***	.00220	-19.75	.0000	-.04772	-.03910
DP	-.01231***	.00073	-16.96	.0000	-.01373	-.01089
BP	-.08468***	.00156	-54.35	.0000	-.08773	-.08162

--------+--

***, **, * ==> Significance at 1%, 5%, 10% level.
Model was estimated on Jul 11, 2021 at 05:22:00 PM

Average partial effect on prob(alt) wrt COWE0 in NP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	.14040	.00292	.023718	.21996
RA	-.04341	.00220	-.170994	-.00042
DP	-.01231	.00073	-.098824	-.00013
BP	-.08468	.00156	-.147286	-.02263

Average partial effect on prob(alt) wrt HE0 in NP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.11656***	.00243	-48.05	.0000	-.12131	-.11180
RA	.03604***	.00182	19.75	.0000	.03246	.03961
DP	.01022***	.00060	16.96	.0000	.00904	.01140
BP	.07030***	.00129	54.35	.0000	.06776	.07283

--------+--

***, **, * ==> Significance at 1%, 5%, 10% level.
Model was estimated on Jul 11, 2021 at 05:22:00 PM

Average partial effect on prob(alt) wrt HE0 in NP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.11656	.00243	-.182609	-.01969
RA	.03604	.00182	.000351	.14195
DP	.01022	.00060	.000111	.08204
BP	.07030	.00129	.018785	.12227

Average partial effect on prob(alt) wrt BBOOM in RA

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.05732***	.00290	-19.75	.0000	-.06301	-.05163
RA	.16025***	.00408	39.28	.0000	.15226	.16825
DP	-.01328***	.00086	-15.44	.0000	-.01497	-.01160
BP	-.08965***	.00198	-45.20	.0000	-.09354	-.08576

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:00 PM

Average partial effect on prob(alt) wrt BBOOM in RA

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.05732	.00290	-.225789	-.00056
RA	.16025	.00408	.016236	.29045
DP	-.01328	.00086	-.121493	-.00014
BP	-.08965	.00198	-.200934	-.01523

Average partial effect on prob(alt) wrt COWE0 in RA

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.05434***	.00275	-19.75	.0000	-.05973	-.04895
RA	.15191***	.00387	39.28	.0000	.14433	.15949
DP	-.01259***	.00082	-15.44	.0000	-.01419	-.01099
BP	-.08498***	.00188	-45.20	.0000	-.08867	-.08130

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:00 PM

Average partial effect on prob(alt) wrt COWE0 in RA

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.05434	.00275	-.214033	-.00053
RA	.15191	.00387	.015391	.27533
DP	-.01259	.00082	-.115168	-.00014
BP	-.08498	.00188	-.190473	-.01443

Average partial effect on prob(alt) wrt OPN in RA

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	.03240***	.00164	19.75	.0000	.02919	.03562
RA	-.09059***	.00231	-39.28	.0000	-.09511	-.08607
DP	.00751***	.00049	15.44	.0000	.00655	.00846
BP	.05068***	.00112	45.20	.0000	.04848	.05287

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:00 PM

Average partial effect on prob(alt) wrt OPN in RA

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	.03240	.00164	.000316	.12764
RA	-.09059	.00231	-.164188	-.00918
DP	.00751	.00049	.000081	.06868
BP	.05068	.00112	.008608	.11359

Average partial effect on prob(alt) wrt VS_NHC in DP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	.02555***	.00151	16.96	.0000	.02260	.02851
RA	.02088***	.00135	15.44	.0000	.01823	.02353
DP	-.10698***	.00495	-21.62	.0000	-.11668	-.09728
BP	.06055***	.00292	20.72	.0000	.05482	.06628

***, **, * ==> Significance at 1%, 5%, 10% level.
Model was estimated on Jul 11, 2021 at 05:22:00 PM

Average partial effect on prob(alt) wrt VS_NHC in DP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	.02555	.00151	.000278	.20512

RA	.02088	.00135	.000224	.19097
DP	-.10698	.00495	-.456221	-.00701
BP	.06055	.00292	.001193	.27202

Average partial effect on prob(alt) wrt IS in DP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	.01501***	.00089	16.96	.0000	.01327	.01674
RA	.01226***	.00079	15.44	.0000	.01071	.01382
DP	-.06284***	.00291	-21.62	.0000	-.06854	-.05714
BP	.03557***	.00172	20.72	.0000	.03220	.03893

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM

Average partial effect on prob(alt) wrt IS in DP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	.01501	.00089	.000163	.12048
RA	.01226	.00079	.000132	.11217
DP	-.06284	.00291	-.267976	-.00412
BP	.03557	.00172	.000701	.15978

Average partial effect on prob(alt) wrt HI1 in DP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.01344***	.00079	-16.96	.0000	-.01500	-.01189
RA	-.01098***	.00071	-15.44	.0000	-.01238	-.00959
DP	.05628***	.00260	21.62	.0000	.05118	.06139
BP	-.03186***	.00154	-20.72	.0000	-.03487	-.02884

***, **, * ==> Significance at 1%, 5%, 10% level.
Model was estimated on Jul 11, 2021 at 05:22:01 PM
Average partial effect on prob(alt) wrt HI1 in DP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum

```
    NP|   -.01344        .00079       -.107914     -.00015
    RA|   -.01098        .00071       -.100472     -.00012
    DP|    .05628        .00260        .003687      .24002
    BP|   -.03186        .00154       -.143111     -.00063
--------+------------------------------------------------------------------
---------------------------------------------------------------------------
Average partial effect  on prob(alt) wrt SPE_16   in BP
--------+------------------------------------------------------------------
        |              Standard          Prob.      95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
--------+------------------------------------------------------------------
    NP|   -.08525***     .00157  -54.35  .0000    -.08832   -.08217
    RA|   -.06835***     .00151  -45.20  .0000    -.07131   -.06539
    DP|   -.02937***     .00142  -20.72  .0000    -.03215   -.02659
    BP|    .18297***     .00227   80.66  .0000     .17852    .18741
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM
Average partial effect  on prob(alt) wrt SPE_16   in BP
--------+------------------------------------------------------------------
        |   Average      Sample Standard     Sample      Sample
  Choice|  Elasticity       Deviation       Minimum     Maximum
--------+------------------------------------------------------------------
    NP|   -.08525        .00157       -.148279     -.02278
    RA|   -.06835        .00151       -.153197     -.01161
    DP|   -.02937        .00142       -.131940     -.00058
    BP|    .18297        .00227        .054833      .22144
--------+------------------------------------------------------------------
---------------------------------------------------------------------------
Average partial effect  on prob(alt) wrt HE1      in BP
--------+------------------------------------------------------------------
        |              Standard          Prob.      95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
--------+------------------------------------------------------------------
    NP|   -.04489***     .00083  -54.35  .0000    -.04651   -.04327
    RA|   -.03599***     .00080  -45.20  .0000    -.03755   -.03443
    DP|   -.01546***     .00075  -20.72  .0000    -.01693   -.01400
    BP|    .09634***     .00119   80.66  .0000     .09400    .09868
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM
---------------------------------------------------------------------------
---------------------------------------------------------------------------
Average partial effect  on prob(alt) wrt HE1      in BP
--------+------------------------------------------------------------------
        |   Average      Sample Standard     Sample      Sample
  Choice|  Elasticity       Deviation       Minimum     Maximum
```

NP	-.04489	.00083	-.078076	-.01199
RA	-.03599	.00080	-.080665	-.00611
DP	-.01546	.00075	-.069473	-.00030
BP	.09634	.00119	.028872	.11660

Average partial effect on prob(alt) wrt COWE2 in BP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.05709***	.00105	-54.35	.0000	-.05915	-.05503
RA	-.04577***	.00101	-45.20	.0000	-.04776	-.04379
DP	-.01967***	.00095	-20.72	.0000	-.02153	-.01781
BP	.12253***	.00152	80.65	.0000	.11955	.12551

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM

Average partial effect on prob(alt) wrt COWE2 in BP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.05709	.00105	-.099301	-.01526
RA	-.04577	.00101	-.102595	-.00777
DP	-.01967	.00095	-.088359	-.00039
BP	.12253	.00152	.036721	.14830

Average partial effect on prob(alt) wrt MILLE in BP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.04576***	.00084	-54.35	.0000	-.04742	-.04411
RA	-.03669***	.00081	-45.20	.0000	-.03828	-.03510
DP	-.01577***	.00076	-20.72	.0000	-.01726	-.01428
BP	.09823***	.00122	80.66	.0000	.09584	.10061

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM

Average partial effect on prob(alt) wrt MILLE in BP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.04576	.00084	-.079604	-.01223
RA	-.03669	.00081	-.082244	-.00623
DP	-.01577	.00076	-.070832	-.00031
BP	.09823	.00122	.029437	.11888

Average partial effect on prob(alt) wrt OS in BP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.10587***	.00195	-54.35	.0000	-.10969	-.10205
RA	-.08489***	.00188	-45.20	.0000	-.08857	-.08121
DP	-.03648***	.00176	-20.72	.0000	-.03993	-.03302
BP	.22723***	.00282	80.66	.0000	.22171	.23276

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM
Average partial effect on prob(alt) wrt OS in BP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NP	-.10587	.00195	-.184156	-.02829
RA	-.08489	.00188	-.190263	-.01442
DP	-.03648	.00176	-.163863	-.00072
BP	.22723	.00282	.068100	.27502

Average partial effect on prob(alt) wrt HI4 in BP

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NP	-.06546***	.00120	-54.35	.0000	-.06782	-.06310
RA	-.05248***	.00116	-45.20	.0000	-.05476	-.05021
DP	-.02255***	.00109	-20.72	.0000	-.02468	-.02042
BP	.14049***	.00174	80.65	.0000	.13708	.14391

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 05:22:01 PM

Average partial effect on prob(alt) wrt HI4 in BP

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum

NP	-.06546	.00120	-.113858	-.01749
RA	-.05248	.00116	-.117634	-.00891
DP	-.02255	.00109	-.101312	-.00044
BP	.14049	.00174	.042104	.17004

Derivative wrt change of X in row choice on Prob[column choice]

BBOOM	NP	RA	DP	BP
NP	.1319	-.0408	-.0116	-.0796

Derivative wrt change of X in row choice on Prob[column choice]

COWE0	NP	RA	DP	BP
NP	.1404	-.0434	-.0123	-.0847

Derivative wrt change of X in row choice on Prob[column choice]

HE0	NP	RA	DP	BP
NP	-.1166	.0360	.0102	.0703

Derivative wrt change of X in row choice on Prob[column choice]

BBOOM	NP	RA	DP	BP
RA	-.0573	.1603	-.0133	-.0896

Derivative wrt change of X in row choice on Prob[column choice]

COWE0	NP	RA	DP	BP
RA	-.0543	.1519	-.0126	-.0850

Derivative wrt change of X in row choice on Prob[column choice]

OPN	NP	RA	DP	BP
RA	.0324	-.0906	.0075	.0507

Derivative wrt change of X in row choice on Prob[column choice]

VS_NHC	NP	RA	DP	BP
DP	.0256	.0209	-.1070	.0605

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
IS      |     NP      RA      DP      BP
--------+----------------------------------
      DP|  .0150   .0123  -.0628   .0356

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
HI1     |     NP      RA      DP      BP
--------+----------------------------------
      DP| -.0134  -.0110   .0563  -.0319

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
SPE_16  |     NP      RA      DP      BP
--------+----------------------------------
      BP| -.0852  -.0683  -.0294   .1830

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
HE1     |     NP      RA      DP      BP
--------+----------------------------------
      BP| -.0449  -.0360  -.0155   .0963

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
COWE2   |     NP      RA      DP      BP
--------+----------------------------------
      BP| -.0571  -.0458  -.0197   .1225

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
MILLE   |     NP      RA      DP      BP
--------+----------------------------------
      BP| -.0458  -.0367  -.0158   .0982

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
OS      |     NP      RA      DP      BP
--------+----------------------------------
      BP| -.1059  -.0849  -.0365   .2272

Derivative wrt change of X in row choice on Prob[column choice]
--------+----------------------------------
HI4     |     NP      RA      DP      BP
--------+----------------------------------
```

BP| -.0655 -.0525 -.0226 .1405

Multinomial Logit model estimation considering the determinants of shared DC options (Driverless Taxi, riding with a stranger)_DTRS

```
|-> Create; if(Vs=3) Vs_fhc = 1; (Else) Vs_fhc= 0 $
|-> Create; if(Vs=-999) Vs_fhc = -999 $
|-> Create; if(Vs=2) Vs_nhc = 1; (Else) Vs_nhc= 0 $
|-> Create; if(Vs=-999) Vs_nhc = -999 $
|-> Create; if(Vs=1) Vs_fhcr = 1; (Else) Vs_fhcr= 0 $
|-> Create; if(Vs=-999) Vs_fhcr = -999 $
|-> Create; if(He = 0) He0 = 1; (Else) He0 = 0 $
|-> Create; if(He = -999) He0 = -999 $
|-> Create; if(He = 1) He1 = 1; (Else) He1 = 0 $
|-> Create; if(He = -999) He1 = -999 $
|-> Create; if(He = 2) He2 = 1; (Else) He2 = 0 $
|-> Create; if(He = -999) He2 = -999 $
|-> Create; if(Gen < 2) Cen = 1; (Else) Cen = 0 $
|-> Create; if(Gen = -999) Cen = -999 $
|-> Create; if(Gen = 0) Cent = 1; (Else) Cent = 0 $
|-> Create; if(Gen = -999) Cent = -999 $
|-> Create; if(Gen = 1) Mille = 1; (Else) Mille = 0 $
|-> Create; if(Gen = -999) Mille = -999 $
|-> Create; if(Gen = 2) GenX = 1; (Else) GenX = 0 $
|-> Create; if(Gen = -999) GenX = -999 $
|-> Create; if(Gen = 3 ) Bboom = 1; (Else) Bboom = 0 $
|-> Create; if(Gen = -999) Bboom = -999 $
|-> Create; if(Gen = 4 ) Trad = 1; (Else) Trad = 0 $
|-> Create; if(Gen = -999) Trad = -999 $
|-> Create; if(Hc = 0) La = 1; (Else) La = 0 $
|-> Create; if(Hc = -999) La = -999 $
|-> Create; if(Hc < 2) Hwcn = 1; (Else) Hwcn = 0 $
|-> Create; if(Hc = -999) Hwcn = -999 $
|-> Create; if(Hc = 2) Hwc = 1; (Else) Hwc = 0 $
|-> Create; if(Hc = -999) Hwc = -999 $
|-> Create; if(Rl > 0) Sl = 1; (Else) Sl = 0 $
|-> Create; if(Rl = -999) Sl = -999 $
|-> Create; if(Rl = 0) CC = 1; (Else) CC = 0 $
|-> Create; if(Rl = -999) CC = -999 $
|-> Create; if(Rl = 1) Is = 1; (Else) Is = 0 $
|-> Create; if(Rl = -999) Is = -999 $
|-> Create; if(Rl = 2) Os = 1; (Else) Os = 0 $
|-> Create; if(Rl = -999) Os = -999 $
|-> Create; if(Cr = 0) Cowe0 = 1; (Else) Cowe0 = 0 $
|-> Create; if(Cr = -999) Cowe0 = -999 $
|-> Create; if(Cr < 2) Cowe1 = 1; (Else) Cowe2 = 0 $
|-> Create; if(Cr = -999) Cowe2 = -999 $
```

```
|-> Create; if(Cr > 1) CoweR = 1; (Else) CoweR = 0 $
|-> Create; if(Cr = -999) CoweR = -999 $
|-> Create; if(Hi = 1) Hi1 = 1; (Else) Hi1 = 0 $
|-> Create; if(Hi = -999) Hi1 = -999 $
|-> Create; if(Hi = 2) Hi2 = 1; (Else) Hi2 = 0 $
|-> Create; if(Hi = -999) Hi2 = -999 $
|-> Create; if(Hi = 3) Hi3 = 1; (Else) Hi3 = 0 $
|-> Create; if(Hi = -999) Hi3 = -999 $
|-> Create; if(Hi = 4) Hi4 = 1; (Else) Hi4 = 0 $
|-> Create; if(Hi = -999) Hi4 = -999 $
|-> Create; if(Hi = 5) Hi5 = 1; (Else) Hi5 = 0 $
|-> Create; if(Hi = -999) Hi5 = -999 $
|-> Create; if(Hi < 2 ) Hrl = 1; (Else) Hrl = 0 $
|-> Create; if(Hi = -999) Hrl = -999 $
|-> Create; if(Hi > 3) Hri = 1; (Else) Hri = 0 $
|-> Create; if(Hi = -999) Hri = -999 $
|-> OPEN ; Export = "D:\PhD_Edinburgh_Napier\Reports\Data
Analysis\Multinomial_Logit/DTRS_1.csv" $
|-> Nlogit ; lhs = Choice
   ; choices = NPS,RS,DT,BPS
   ; Model:
   U(NPS) = One*One + Cc*Cc + Hi1*Hi1 + Mille1*Mille /
   U(RS) = He2*He2 + Hri*Hri + CoweR * CoweR /
   U(DT) = Vs_fhc*Vs_fhc + Hwcn*Hwcn /
   U(BPS) = SES_16*SES_16 + Agr*Agr + Cowe0*Cowe0 + Bboom1*Bboom
   ;Show
   ;describe
   ;Export output
   ;Export = Table
;Effects:Cc[NPS]/Hi1[NPS]/Mille[NPS]/He2[RS]/Hri[RS]/CoweR[RS]/Vs_fhc[DT]/Hwcn[DT]/SES_1
6[BPS]/Agr[BPS]/Cowe0[BPS]/Bboom[BPS]
   ;Full
   $
+------------------------------------------------------+
|WARNING:   Bad observations were found in the sample. |
|Found  171 bad observations among    499 individuals. |
|You can use; CheckData to get a list of these points. |
+------------------------------------------------------+
Sample proportions are marginal, not conditional.
Choices marked with * are excluded for the IIA test.
+----------------+------+
|Choice   (prop.)| Count|
+----------------+------+
|NPS      .26829|   134|
|RS       .07317|    37|
|DT       .32317|   161|
|BPS      .33537|   167|
```

```
+----------------+------+
+------------------------------------------------------------+
| Model Specification:  Table entry is the attribute that      |
| multiplies the indicated parameter.                    |
+--------+------+--------------------------------------------+
| Choice |******| Parameter                              |
|        |Row  1| ONE     CC      HI1     MILLE1   HE2      |
|        |Row  2| HRI     COWER    VS_FHC   HWCN    SES_16    |
|        |Row  3| AGR     COWE0    BBOOM1                  |
+--------+------+--------------------------------------------+
|NPS     |     1| ONE     CC      HI1     MILLE    none     |
|        |     2| none    none    none    none    none      |
|        |     3| none    none    none                    |
|RS      |     1| none    none    none    none    HE2      |
|        |     2| HRI     COWER   none    none    none      |
|        |     3| none    none    none                    |
|DT      |     1| none    none    none    none    none      |
|        |     2| none    none    VS_FHC   HWCN    none      |
|        |     3| none    none    none                    |
|BPS     |     1| none    none    none    none    none      |
|        |     2| none    none    none    none    SES_16    |
|        |     3| AGR     COWE0    BBOOM                   |
+------------------------------------------------------------+
Iterative procedure has converged
Normal exit:   7 iterations. Status=0, F=    .4004694D+03
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable              Choice
Log likelihood function      -400.46945
Estimation based on N =    328, K =  13
Inf.Cr.AIC  =    826.9 AIC/N =    2.521
--------------------------------------
          Log likelihood R-sqrd R2Adj
Constants only   -418.4521  .0430 .0302
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=   499, skipped  171 obs
--------+--------------------------------------------------------------------
        |               Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
Constant|     .52084**       .21374     2.44  .0148      .10193     .93975
      CC|    -.47059*        .28359    -1.66  .0970    -1.02642     .08524
```

```
     HI1|    .72502**       .36958     1.96  .0498      .00066   1.44939
  MILLE1|   -.53540*        .28750    -1.86  .0626    -1.09890    .02809
     HE2|   -.89571**       .40319    -2.22  .0263    -1.68595   -.10547
     HRI|   -.82585*        .43244    -1.91  .0562    -1.67342    .02171
   COWER|  -1.27563**       .61390    -2.08  .0377    -2.47885   -.07241
  VS_FHC|    .54232**       .23089     2.35  .0188      .08979    .99485
    HWCN|    .48935**       .21202     2.31  .0210      .07379    .90491
  SES_16|    .60594*        .36721     1.65  .0989     -.11379   1.32567
     AGR|    .61094**       .24011     2.54  .0109      .14033   1.08155
   COWE0|    .61427**       .28478     2.16  .0310      .05611   1.17244
  BBOOM1|    .42456*        .25007     1.70  .0895     -.06556    .91469
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:32 AM
-----------------------------------------------------------------------------
|           Descriptive Statistics for Alternative NPS               |
|    Utility Function          | (CBS wt = 1.00000) |    88.0 observs.  |
|    Coefficient               | All     328.0 obs.|that chose NPS      |
| Name         Value  Variable | Mean     Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | ------------------+------------------ |
| ONE          .5208  ONE      |  1.000      .000|   1.000      .000 |
| CC          -.4706  CC       |   .338      .474|    .261      .442 |
| HI1          .7250  HI1      |   .119      .324|    .159      .368 |
| MILLE1      -.5354  MILLE    |   .338      .474|    .273      .448 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
|           Descriptive Statistics for Alternative RS                |
|    Utility Function          | (CBS wt = 1.00000) |    24.0 observs.  |
|    Coefficient               | All     328.0 obs.|that chose RS       |
| Name         Value  Variable | Mean     Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | ------------------+------------------ |
| HE2         -.8957  HE2      |   .488      .501|    .333      .482 |
| HRI         -.8259  HRI      |   .445      .498|    .292      .464 |
| COWER      -1.2756  COWER    |   .293      .456|    .125      .338 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
|           Descriptive Statistics for Alternative DT                |
|    Utility Function          | (CBS wt = 1.00000) |   106.0 observs.  |
|    Coefficient               | All     328.0 obs.|that chose DT       |
| Name         Value  Variable | Mean     Std. Dev.|Mean      Std. Dev. |
| ------------------  -------- | ------------------+------------------ |
| VS_FHC       .5423  VS_FHC   |   .348      .477|    .425      .497 |
| HWCN         .4894  HWCN     |   .530      .500|    .566      .498 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
|           Descriptive Statistics for Alternative BPS               |
|    Utility Function          | (CBS wt = 1.00000) |   110.0 observs.  |
```

```
|    Coefficient           | All     328.0 obs.|that chose BPS     |
| Name        Value  Variable | Mean     Std. Dev.|Mean     Std. Dev. |
| ------------------  -------- | ------------------+------------------ |
| SES_16      .6059  SES_16   |    .104      .305|    .145     .354 |
| AGR         .6109  AGR      |    .290      .454|    .373     .486 |
| COWE0       .6143  COWE0    |    .195      .397|    .255     .438 |
| BBOOM1      .4246  BBOOM    |    .323      .468|    .336     .475 |
+---------------------------------------------------------------------+
+----------------------------------------------+
| Derivative averaged over observations.|
| Effects on probabilities of all choices in the model: |
| * = Direct Derivative effect of the attribute.    |
+----------------------------------------------+
Average partial effect  on prob(alt) wrt CC      in NPS
--------+--------------------------------------------------------------------
        |              Standard          Prob.     95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
     NPS|   -.08890***      .00102   -87.32  .0000    -.09089   -.08690
      RS|    .00953***      .00038    24.98  .0000     .00878    .01028
      DT|    .03934***      .00077    50.86  .0000     .03782    .04085
     BPS|    .04003***      .00067    59.69  .0000     .03872    .04135
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:33 AM
-----------------------------------------------------------------------------
Average partial effect  on prob(alt) wrt CC      in NPS
--------+--------------------------------------------------------------------
        |   Average      Sample Standard     Sample      Sample
  Choice|  Elasticity       Deviation       Minimum      Maximum
--------+--------------------------------------------------------------------
     NPS|   -.08890         .00102        -.117590     -.03105
      RS|    .00953         .00038         .000690      .03777
      DT|    .03934         .00077         .004241      .07761
     BPS|    .04003         .00067         .012269      .07408
--------+--------------------------------------------------------------------
Average partial effect  on prob(alt) wrt HI1     in NPS
--------+--------------------------------------------------------------------
        |              Standard          Prob.     95% Confidence
  Choice|  Coefficient      Error      z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
     NPS|    .13696***      .00157    87.32  .0000     .13389    .14004
      RS|   -.01468***      .00059   -24.98  .0000    -.01584   -.01353
      DT|   -.06060***      .00119   -50.86  .0000    -.06294   -.05827
     BPS|   -.06167***      .00103   -59.69  .0000    -.06370   -.05965
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
```

The model was estimated on Jul 11, 2021, at 01:34:33 AM

Average partial effect on prob(alt) wrt HI1 in NPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	.13696	.00157	.047841	.18117
RS	-.01468	.00059	-.058199	-.00106
DT	-.06060	.00119	-.119569	-.00653
BPS	-.06167	.00103	-.114134	-.01890

Average partial effect on prob(alt) wrt MILLE in NPS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.10114***	.00116	-87.32	.0000	-.10341	-.09887
RS	.01084***	.00043	24.98	.0000	.00999	.01169
DT	.04475***	.00088	50.86	.0000	.04303	.04648
BPS	.04554***	.00076	59.69	.0000	.04405	.04704

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:33 AM

Average partial effect on prob(alt) wrt MILLE in NPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.10114	.00116	-.133787	-.03533
RS	.01084	.00043	.000785	.04298
DT	.04475	.00088	.004825	.08830
BPS	.04554	.00076	.013959	.08428

Average partial effect on prob(alt) wrt HE2 in RS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	.01814***	.00073	24.98	.0000	.01672	.01956
RS	-.06198***	.00210	-29.49	.0000	-.06610	-.05786
DT	.02129***	.00082	26.07	.0000	.01969	.02290
BPS	.02255***	.00089	25.34	.0000	.02080	.02429

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:34 AM

Average partial effect on prob(alt) wrt HE2 in RS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	.01814	.00073	.001312	.07190
RS	-.06198	.00210	-.179217	-.00604
DT	.02129	.00082	.001452	.07325
BPS	.02255	.00089	.001458	.08308

Average partial effect on prob(alt) wrt HRI in RS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	.01673***	.00067	24.98	.0000	.01541	.01804
RS	-.05715***	.00194	-29.49	.0000	-.06094	-.05335
DT	.01963***	.00075	26.07	.0000	.01816	.02111
BPS	.02079***	.00082	25.34	.0000	.01918	.02240

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:34 AM

Average partial effect on prob(alt) wrt HRI in RS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	.01673	.00067	.001210	.06629
RS	-.05715	.00194	-.165239	-.00557
DT	.01963	.00075	.001339	.06754
BPS	.02079	.00082	.001344	.07660

Average partial effect on prob(alt) wrt COWER in RS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	.02583***	.00103	24.98	.0000	.02381	.02786
RS	-.08827***	.00299	-29.49	.0000	-.09414	-.08240
DT	.03033***	.00116	26.07	.0000	.02805	.03261
BPS	.03211***	.00127	25.34	.0000	.02963	.03459

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:34 AM

Average partial effect on prob(alt) wrt COWER in RS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	.02583	.00103	.001869	.10240
RS	-.08827	.00299	-.255232	-.00860
DT	.03033	.00116	.002068	.10432
BPS	.03211	.00127	.002076	.11832

Average partial effect on prob(alt) wrt VS_FHC in DT

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.04533***	.00089	-50.86	.0000	-.04708	-.04358
RS	-.01289***	.00049	-26.07	.0000	-.01386	-.01192
DT	.11297***	.00094	120.50	.0000	.11113	.11481
BPS	-.05474***	.00080	-68.82	.0000	-.05630	-.05318

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:34 AM

Average partial effect on prob(alt) wrt VS_FHC in DT

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.04533	.00089	-.089438	-.00489
RS	-.01289	.00049	-.044352	-.00088
DT	.11297	.00094	.057677	.13558
BPS	-.05474	.00080	-.085446	-.01751

Average partial effect on prob(alt) wrt HWCN in DT

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.04090***	.00080	-50.86	.0000	-.04248	-.03933
RS	-.01163***	.00045	-26.07	.0000	-.01251	-.01076
DT	.10193***	.00085	120.50	.0000	.10028	.10359
BPS	-.04940***	.00072	-68.82	.0000	-.05080	-.04799

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:35 AM

Average partial effect on prob(alt) wrt HWCN in DT

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.04090	.00080	-.080703	-.00441
RS	-.01163	.00045	-.040020	-.00079
DT	.10193	.00085	.052044	.12234
BPS	-.04940	.00072	-.077100	-.01580

Average partial effect on prob(alt) wrt SES_16 in BPS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.05154***	.00086	-59.69	.0000	-.05324	-.04985
RS	-.01525***	.00060	-25.34	.0000	-.01643	-.01407
DT	-.06117***	.00089	-68.82	.0000	-.06291	-.05942
BPS	.12796***	.00106	120.42	.0000	.12588	.13004

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:35 AM

Average partial effect on prob(alt) wrt SES_16 in BPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.05154	.00086	-.095388	-.01580
RS	-.01525	.00060	-.056205	-.00099
DT	-.06117	.00089	-.095469	-.01957
BPS	.12796	.00106	.064331	.15148

Average partial effect on prob(alt) wrt AGR in BPS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.05197***	.00087	-59.69	.0000	-.05368	-.05026
RS	-.01538***	.00061	-25.34	.0000	-.01657	-.01419
DT	-.06167***	.00090	-68.82	.0000	-.06343	-.05991
BPS	.12902***	.00107	120.42	.0000	.12692	.13112

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:35 AM

Average partial effect on prob(alt) wrt AGR in BPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.05197	.00087	-.096175	-.01593
RS	-.01538	.00061	-.056668	-.00099
DT	-.06167	.00090	-.096257	-.01973
BPS	.12902	.00107	.064862	.15273

Average partial effect on prob(alt) wrt COWE0 in BPS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.05225***	.00088	-59.69	.0000	-.05397	-.05054
RS	-.01546***	.00061	-25.34	.0000	-.01666	-.01427
DT	-.06201***	.00090	-68.82	.0000	-.06377	-.06024
BPS	.12972***	.00108	120.42	.0000	.12761	.13183

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:35 AM

Average partial effect on prob(alt) wrt COWE0 in BPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum
NPS	-.05225	.00088	-.096700	-.01602
RS	-.01546	.00061	-.056978	-.00100
DT	-.06201	.00090	-.096782	-.01984
BPS	.12972	.00108	.065216	.15356

Average partial effect on prob(alt) wrt BBOOM in BPS

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
NPS	-.03612***	.00061	-59.69	.0000	-.03730	-.03493
RS	-.01069***	.00042	-25.34	.0000	-.01151	-.00986
DT	-.04286***	.00062	-68.82	.0000	-.04408	-.04164
BPS	.08966***	.00074	120.42	.0000	.08820	.09112

***, **, * ==> Significance at 1%, 5%, 10% level.
The model was estimated on Jul 11, 2021, at 01:34:36 AM
Average partial effect on prob(alt) wrt BBOOM in BPS

Choice	Average Elasticity	Sample Standard Deviation	Sample Minimum	Sample Maximum

```
--------+---------------------------------------------------------------
    NPS|    -.03612         .00061         -.066835      -.01107
     RS|   -.01069         .00042         -.039381      -.00069
     DT|   -.04286         .00062         -.066892      -.01371
    BPS|    .08966         .00074          .045075      .10614
--------+---------------------------------------------------------------
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
CC      |    NPS      RS      DT     BPS
--------+---------------------------------
    NPS|  -.0889   .0095   .0393   .0400
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
HI1     |    NPS      RS      DT     BPS
--------+---------------------------------
    NPS|   .1370  -.0147  -.0606  -.0617
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
MILLE   |    NPS      RS      DT     BPS
--------+---------------------------------
    NPS|  -.1011   .0108   .0448   .0455
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
HE2     |    NPS      RS      DT     BPS
--------+---------------------------------
     RS|   .0181  -.0620   .0213   .0225
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
HRI     |    NPS      RS      DT     BPS
--------+---------------------------------
     RS|   .0167  -.0571   .0196   .0208
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
COWER   |    NPS      RS      DT     BPS
--------+---------------------------------
     RS|   .0258  -.0883   .0303   .0321
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
VS_FHC  |    NPS      RS      DT     BPS
--------+---------------------------------
     DT|  -.0453  -.0129   .1130  -.0547
Derivative wrt change of X in row choice on Prob[column choice]
--------+---------------------------------
HWCN    |    NPS      RS      DT     BPS
--------+---------------------------------
     DT|  -.0409  -.0116   .1019  -.0494
Derivative wrt change of X in row choice on Prob[column choice]
```

```
--------+----------------------------------
SES_16  |     NPS      RS      DT     BPS
--------+----------------------------------
     BPS|  -.0515   -.0153   -.0612    .1280
```

Derivative wrt change of X in row choice on Prob[column choice]

```
--------+----------------------------------
AGR     |     NPS      RS      DT     BPS
--------+----------------------------------
     BPS|  -.0520   -.0154   -.0617    .1290
```

Derivative wrt change of X in row choice on Prob[column choice]

```
--------+----------------------------------
COWE0   |     NPS      RS      DT     BPS
--------+----------------------------------
     BPS|  -.0523   -.0155   -.0620    .1297
```

Derivative wrt change of X in row choice on Prob[column choice]

```
--------+----------------------------------
BBOOM   |     NPS      RS      DT     BPS
--------+----------------------------------
     BPS|  -.0361   -.0107   -.0429    .0897
```

20. Appendix L: Literature review findings concerning DC shared ownership

Serial No.	Study Reference	Paper Title	Journal	Method used	Shared ownership/sharing types	Impacts	Impact/Ownership Change Possibilities	Determinants of DC shared ownership	Type of Intervention
1	(Mourad et al., 2019)	Owning or sharing autonomous vehicles: comparing different ownership and usage scenarios	European Transport Research Review	A generalised matching algorithm was used to choose the right match between the owner and rider of the DC	On-demand DC taxi service, private DC operating in P2P sharing	If a higher matching rate can be ensured, the overall travel distances can be reduced by up to 25%, and fewer number of DC are needed, with shorter travel time	If on-demand driverless shared taxis are fully used, better performance can be expected than individually-owned	Lower execution time, higher fleet size, right matching between DC owners and riders, use of meeting	Ownership
2	(Xu et al., 2019)	Privately Owned Autonomous Vehicle Optimization Model Development and Integration with Activity-Based Modeling	Transportation Research Record	Integrated activity-based modelling and dynamic traffic assignment (ABM-DTA) framework	Private DC and enhanced use of private DC to share within a family	One shared DC for all household members could replace four conventional cars and can reduce vehicle miles travelled	One DC can replace four conventional cars	Different household sizes; travel mode choice decisions, and travel behaviour	Ownership
3	(Allahviranloo & Chow, 2019)	A shared owned autonomous vehicle fleet sizing problem with time slot demand substitution effects	Transportation Research Part C journal	A bilevel fleet-sizing, vehicle routing time-slot pricing model that is sensitive to users' activity scheduling decisions in the lower level by equilibrium, and an Upper-level model of willingness to pay by the population under different pricing mechanisms	Driverless Car club model	DC car-club system requires a pricing mechanism for trading vehicles at different time slots impacted by users' activity scheduling and fleet size. Based on the available fleet size and activity scheduling demand, trip prices will vary for times of the day	Under the pricing substitution mechanism, shared owned DC usage is supposed to be reduced by 20%, with a 4% higher trip cost	Fleet capacity, Activity scheduling, pricing mechanism	Ownership
4	(Masoud & Jayakrishnan, 2016)	Autonomous or driver-less vehicles: Implementation strategies and operational concerns	Transportation Research Part E	Formulated two optimization problems, the first of which finds the minimum number of DC in a cluster, and the second problem uses DC's idle times to serve	shared Ownership of a DC in terms of cost and liabilities	The program's shared ownership component considerably impacts the reduction of vehicle ownership. And more households interested in participating in the program, the efficiency is going to increase at a higher rate	shared DC sharing can reduce car ownership by 33%	Number of DC in the cluster, pricing	Ownership

				the maximum number of on-demand carsharing requests					
5	(Haboucha et al., 2017)	User preferences regarding autonomous vehicles	Transportation Research Part C journal	This study utilised some latent factors and quantified DC acceptance through the use of logit kernel method with panel effect	This research experiments on the choices among the use of a regular car, private DC, shared DC	44% of the respondents are indifferent to using regular cars, while cost is the most important variable in determining shared DC use. This helped to gain a better understanding in private DC and shared DC utilisation	In case when shared DC is offered completely free of cost, only 75% of the respondents are willing to use shared DC	Enjoy driving, environmental concern, and Pro-AV attitude	Behaviour + Environment
6	(Yoo et al., 2021)	Willingness to Buy and / or Pay Disparity : Evidence from Fully Autonomous Vehicles	Munich Personal RePEc Archive; MPRA Paper No. 108882, posted 03 Aug 2021 00:43 UTC	Analysis of latent attitudes for willingness to buy and willingness to pay through structural equation modelling method	The study tried to differentiate between the willingness to buy and willingness to pay behaviour of DC in terms of environmental consciousness	Environmentally conscious people are more willing to buy DC than willing to pay for it on the ground that DC can reduce pollution levels and reduce congestion. On the contrary, considering natural preservation and accident mitigation, people's willingness to pay for DC is less, as these factors do not help identify DCs benefits	Factors for willingness to purchase DC and willingness to pay for DC service are not identical and therefore are not applicable for the same class of people.	Four latent attitudes related to natural environmental preservation, pollution reduction, possible accident preservation and convenience	Behaviour + Environment
7	(Stoiber et al., 2019)	Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households	Transportation Research Part D	An ordinal logistic model with proportional odds and quasi-likelihood was applied with Likert-scale responses	This study tested the difference among the likelihood of pooled-use DC, privately owned DC, and driverless public transport shuttles	Based on the earlier presumption, people are more aligned to choose pooled use of DC than privately used DC.	61% of the respondents showed their interest in the pooled use of DC and driverless shuttles	Socioeconomic status, car ownership, public transport subscription, and combined factor concerning comfort, cost and time	Behaviour and ownership
8	(Nazari et al., 2018)	Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes	Transportation Research Part C	Multivariate ordered outcome models with latent variables are employed	a found the	Model assessment reveals that people are reluctant to use both forms of DC on safety concerns, while green travel pattern and MOD savviness factor indicate the interest in shared DCs	Present car owners from multi-member households are more inclined to private DC, while individuals with larger inter-trip VMT variations are more inclined toward SAVs	Latent factors are traveller safety concerns about DC, green travel patterns, and mobility-on-demand savviness	Behaviour + Environment

9	(Lavieri, 2017)	Modelling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies	Transportation Research Record	A generalized, A heterogeneous data model system was estimated	This paper identifies the factors of different DC ownership and sharing paradigms based on surveyed data	Individuals who prefer a green lifestyle and are technologically aware are more likely to choose shared DC in future.	The outcome of this research shows 5% and 8% preference for DC sharing and ownership.	The propensity towards a green lifestyle and technological savviness	Behaviour + Environment
10	(Hao & Yamamoto, 2018)	Analysis of supply and demand of shared autonomous vehicles considering household vehicle ownership and shared use	IEEE Conference on Intelligent Transportation Systems, Proceedings	Multinomial logit model development with Stated Preference data	This research assessed relative preferences among privately owned DC, privately owned but shared DC, and on-demand shared DC	Having a high interest in DC, having low revenue expectations and having low car ownership are essential considerations in choosing shared DC use. In contrast, people only willing to use shared DC have high-interest DC and part-time jobs, which will make them eliminate their cars in the future.	20% - Shared DC can attract 30% of trips; 50 to 70% of the vehicles provided by households are sufficient to serve the demand Without significant waiting time.	High interest in shared DC use, socioeconomic status, car ownership and trip purposes	Behaviour
11	(Wadud & Kumar, 2021)	To own or not to own – That is the question: The value of owning a (fully automated) vehicle	Transportation Research Part C	Multinomial and Mixed logit model on choice experimentation data	The experiment described in this research considered privately owned DC, on-demand exclusive-use DC with ride services, and on-demand pooled/shared DC	This research proved a significant willingness to pay for DC ownership with a high heterogeneity among people in terms of gender, income, and car ownership	Without considering the convenience of ownership values, 60% of people choose DC ownership, while 20% prefer pooled ride service. But considering heterogeneous convenience values, these shares will be 50% and 26%	Cost per mile, journey time, waiting time, reliability, gender variations, car ownership	Behaviour