Ridesharing in Adelaide: segmentation of users

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This is an Authors' Original Manuscript of an article whose final and definitive form, the Version of Record, has been published in ***Journal of Transport Geography,*** 2021, copyright Elsevier, available online at: https://doi.org/10.1016/j.jtrangeo.2021.103030

Abstract

Ridesharing and the tech companies that enable it have become household names. However, as research has focused on users rather than non-users, much less is known about the latter. Understanding the characteristics, behaviours, and motivations of non-users is quite important too, if the planning goal is to shift urban populations from private cars to ridesharing. This study examines both users and non-users in the context of Adelaide, an Australian metropolis of 1.3 million inhabitants. We segment (potential) ridesharers into three groups: (1) users, (2) interested non-users, and (3) non-interested non-users in order to investigate the determinants of their behaviours and preferences in more detail. Applying advanced statistical analyses, we find that neighbourhood density and quality, higher levels of education and income, causal work status, younger age, and access to smartphones are the key factors associated with higher ridesharing use and/or higher interest in ridesharing. Factors such as concern over safety and security, advanced age, digital illiteracy, and suburban living lead non-interested non-users to shun ridesharing. Socio-demographic factors such as car ownership, ethnic background; gender, and household size, are not associated with ridesharing behaviours or preferences. We conclude that the choice of ridesharing in Adelaide is driven by the notion of socio-economic status.

Figures and tables are at the end of this manuscript.

Introduction

Ridesharing and the tech companies that enable it have become household names; Uber (ubering/ubered) is now a verb.[1] Not only does ridesharing promise to make urban transportation more sustainable, but it also has the potential to boost the overall economic efficiency of cities by creating jobs, preventing unnecessary car-ownership costs, and monetising underutilised vehicles. Ridesharing offers a viable and attractive alternative to urbanites who, until recently, have been dependent on private cars either by choice or by circumstance.[2] Uber, the largest and most popular company, operates in more than 800 cities across 70 countries, and many competitors have entered the market (Mohamed et al., 2020).

As ridesharing services have expanded, so have academic studies on the topic (see, among others, Hampshire and Gaites 2011; Ballús-Armet et al. 2014; Chen and Kockelman 2016; Rode et al. 2017; Shaheen et al. 2017a; Chen et al. 2018; Middleton and Zhao 2019; Allan and Soltani 2019; Münzel et al. 2019; Jain et al. 2020; Julsrud and Farstad 2020; Ramos et al. 2020; Ramos et al. 2020; Becker et al. 2020). A fairly large body of knowledge has accumulated on the characteristics and behaviours of rideshare *users*. These differ from one city to another, even within the same country, but some general patterns can be discerned (see next section).

What about people who do *not* rideshare? Who are they, and why do they shun this novel mobility model? Because research has focused on users rather than non-users, much less is known about the latter. However, understanding the characteristics, behaviours, and motivations of non-users is quite important too, if the planning goal is to shift urban populations from private car ownership and use to ridesharing.

This study examines both ridesharing users and non-users (interested and non-interested) in the context of Adelaide, a city of 1.3 million inhabitants which serves as the capital of South Australia. The Australian setting is appropriate because car-dependency in this country is among the highest in the world (Soltani et al. 2018; Currie et al. 2018), with as many as 20 million registered private vehicles for a population of 25 million (Australian Bureau of Statistics 2020). As most of its Australian peers, Adelaide is a low-density, car-oriented city. However, its CBD area is relatively compact and comprises many middle-income families, students, and singles. Hence the potential for ridesharing uptake is high.

This is the first empirical study of ridesharing set in South Australia to employ survey data. Unlike other studies, we differentiate between CBD residents and outer-ring residents. Another novelty in this study is the segmentation of survey respondents into three groups: (1) users, (2) interested non-users, and (3) non-interested non-users in order to investigate the determinants of their behaviours and preferences in more detail. By contrast, most other studies simply compare users to non-users. Below we provide a brief history of ridesharing in Australia, and set forth the theoretical framework for this study, before proceeding to the empirical portion.

Brief history of ridesharing in Australia

Ridesharing arrived in Australia later than in North America and Europe: UberX did not start operating in Sydney and Melbourne until 2014 (Economics Deloitte Access 2016; Soltani et al. 2018). After launching, it became rapidly popular, spreading to 37 cities, including Adelaide, by 2020. Customers appreciated Uber's efficiency, reliability, comfort, and reasonable fares relative to public transport, especially along low-demand routes (Zhou 2019). In the mid-2010s, nearly a quarter of the Australian population had used UberX at least once

(Institute of Transport and Logistics Studies 2016). Some ridesharing use may have replaced taxi use.

Emboldened by Uber's success, six more ridesharing companies joined the Australian market: Ola, Shebah, GoCatch, Bolt, Rydo, and Ingogo. In addition, traditional taxi companies began introducing similar apps. The public sector is also seeking to mimic private tech companies by offering on-demand transport services to those who are ill-served by fixed-route, fixed-schedule public transport (Vij et al. 2020). These newer models are supplanting older forms of pre-booked transport services, which have existed since 2003 in Adelaide to serve elderly and/or mobility-impaired residents (Downer 2018). Overall, ridesharing is the most widespread form of shared mobility in Australia (Vij et al. 2020). However, local studies of ridesharing users and non-users are very limited. The available information to date is summarised below.

A recent study of on-demand transport users found that both demographic and economic factors drive this mode choice. The most frequent users are urban, younger, male, employed full-time, and well-educated. However, they also have lower-incomes and dependent children at home, and some are disabled. On-demand transport caters to all types of trips: work, leisure, shopping (Vij et al. 2020). A nation-wide study specific to Uber users found that they tend to be younger (25-49 years) and concentrated in Western Australia (Morgan 2019). Another nation-wide study, of UberX users, found that word-of-mouth advertising of this service has a large impact on the frequency of usage and users' pro-ridesharing attitudes. However, some users find the Uber app cumbersome, which may discourage adoption by people less adept at technology (Cheah et al. 2020). A study of ridesharing users, set in Adelaide, found that the "typical" ridesharing/Uber user is male, younger, well-educated, and poorer. Users like the cleanliness of Uber vehicles, the availability and reliability of the service, the quality of the mobile app, and the easy sign-up process. For the most part, ridesharing caters to social activities (Soltani et al. 2018).

Theoretical foundation

Based on the existing literature, three sets of interrelated factors appear to affect ridesharing. They include: (1) transport priorities; (2) socio-economic characteristics; and (3) built environment characteristics (see Appendix 1 for a full summary of available studies). We take a closer look at these factors below.

Transport priorities

Subjective transport priorities, which shape mode choices, include: comfort, convenience, safety, security, speed, time, and wellbeing (Mehdizadeh et al., 2019; Şimşekoğlu et al., 2015; Nordfjærn and Rundmo 2015; Rundmo et al., 2011; Egset and Nordfjærn 2019). Where people value travel comfort and safety above all else, they are more likely to opt for driving (Mehdizadeh et al. 2019). Women tend to be more wary of ridesharing as it involves riding in a car with strangers and drivers and often male (Sarriera et al. 2017; Zhen 2015; Ma et al. 2018; Wang et al. 2019; Alemi et al. 2019; Wang 2019; Alemi et al. 2019; Gilibert et al. 2020; Mohamed et al. 2020). People who value time and flexibility are more likely to adopt ridesharing (Şimşekoğlu et al. 2015). The latter is perceived as superior to public transport in terms of comfort and speed – especially among people with physical impairments (Rayle et al. 2014; Zhen 2015; Kumar and Joewono 2018; Gilibert et al. 2020; Mitra et al., 2019). Parking availability is another key transport priority: where parking for private cars is scarce or costly more people are likely to adopt ridesharing (Sarriera et al. 2017; Cohen and Shaheen 2018; Mohamed et al. 2020; Gilibert et al. 2020; Bansal et al. 2020). Some studies find that ridesharing encourages users to mix and match travel modes which results in a healthier lifestyle (Kent, 2014).

Socio-economic characteristics

The socio-economic characteristics that affect ridesharing vary by setting. For example, European users tend to be female, young or middle-aged, and well-educated (Caulfield 2009; Bruns and Farrokhikhiavi 2011; Gargiulo et al. 2015; Delhomme and Gheorghiu 2016; Shaheen et al. 2017b; Gheorghiu and Delhomme 2018; Gilibert et al. 2020; Mulley et al. 2020; Mohamed et al. 2020). In the Asia-Pacific region, users are also younger and well-educated, but most often male (Kumar and Joewono 2018; Ma et al. 2018; Soltani et al. 2018; Wang 2019; Wang et al. 2019; Morgan 2019; Vij et al. 2020; Cheah et al. 2020). North American findings are very diverse but here too, the younger and urban demographic dominates, whereas the prevailing gender of ridesharers varies by setting. Race, education, and income appear to be influential but results are bifurcated. In some cities, ethnic minorities are the leading user group owing to their lower incomes which preclude car ownership, whereas in other cities most users are higher-income, well-educated whites (Rayle et al. 2014; Zhen 2015; Sarriera et al. 2017; Alemi et al. 2018; Alemi et al. 2019; Mitra et al. 2019; Brown 2020; Bansal et al. 2020; Iqbal 2020; Young et al. 2020).

Built environment attributes

The impact of built environment variables (e.g., population density, land use patterns, street network design, transit access, etc.) on ridesharing is still unclear. Most existing studies suggest that people living in denser and more mixed urban areas (in terms of land use) are more likely to adopt ridesharing (Sarriera et al. 2017; Alemi et al. 2018; Gerte et al. 2018; Yu and Peng 2019; Mitra et al. 2019; Brown 2020; Sabouri et al. 2020; Bansal et al. 2020). Occasionally, however, studies find that finer grained land-use patterns deter ridesharing as they are more conducive to walking and cycling (Alemi et al. 2019). In the US, ridesharing is most popular in upscale regional centres such as San Francisco or Manhattan, in which car ownership is inconvenient (Jiang et al. 2018). Outside the US, some studies have found that ridesharing is more prevalent in suburbs with cheaper housing and poor public transport accessibility (Ma et al. 2018; Bruns and Farrokhikhiavi 2011).

Methodology

The City of Adelaide (included CBD of metropolitan Adelaide), our case study area, has a strategic vision of becoming one of the world's first carbon neutral cities (Nguyen et al. 2018; Allan and Soltani 2019; Soltani et al. 2018). To achieve this goal, ridesharing has been identified as a priority measure. As of now, the most popular form of ridesharing in Adelaide is UberX (Institute of Transport and Logistics Studies 2016). The City Council of Adelaide believes that there is high potential to increase ridesharing rates because inner-city residents are younger and their incomes are low to average. The City of Adelaide comprises large numbers of students and tourists. Public and non-motorised transport use is high by Australian standards, and parking restrictions apply (Soltani et al. 2018).

Based on the theoretical foundation laid out above, we hypothesised that the following factors affect ridesharing in Adelaide, and designed the study accordingly:

(1) *transport priorities*, including ease (comfort and convenience), safekeeping (safety and security), velocity (speed and time), and fitness (health and exercise);

(2) *socio-economic characteristics* including individual characteristics (age, gender, ethnicity, education, income, job status, smartphone access), and household characteristics (car ownership, number of people).

(3) *built environment attributes*, including population density; employment density; intersection density; distance to CBD; house prices, and land use mix.

To investigate *transport priorities* and *socio-economic characteristics*, we employed secondary data from a quantitative survey conducted in Adelaide during February-March 2018 with the support of the Australian CRC Research Node for Low Carbon Living (CRC-LCL).[3] The survey targeted people who had travelled from different parts of metropolitan Adelaide to one of six major landmarks in the City of Adelaide, including: Adelaide Oval; Royal Adelaide Hospital; Adelaide Railway Station; University of Adelaide; Rundle Mall, and Adelaide Central Market. All are well-known as major activity centres (trip attractors).[4] The survey sample size was 422, with about 70 questionnaires collected at each of the six Adelaide City trip attractors. Respondents came from all over metropolitan Adelaide. Those who lived more 60 km from the CBD were considered as outliers and eliminated, resulting in a full dataset of 408 data points.[5]

The study sample reflects the overall characteristics of the population in metropolitan Adelaide, South Australia, and Australia overall (see Table 1). Hence, we are confident that the findings are applicable beyond the case study setting. The home locations of sampled individuals aggregated at the postcode level are shown in Figure 1. As seen, respondents were well-distributed throughout the Adelaide metropolitan area.

The survey included 36 questions. Of these, 12 questions were intended to measure the respondent's *transport priorities* in relation to ridesharing. A slightly revised version of a 12-item validated survey instrument was used for this purpose (Mehdizadeh et al., 2019; Nordfjærn and Rundmo 2015; Şimşekoğlu et al., 2015). The survey respondents were asked to rank on a five-point Likert scale their transport priorities (comfort; convenience; safety; security; speed; time; travel distance; environmental concern; health; exercise; independence; and status/image) when deciding whether to use or shun ridesharing. Then they were asked to report the frequency of using ridesharing services within the last year on temporal scale (daily, fortnightly, monthly, yearly, never).

The remaining questions gathered information on the *socio-economic characteristics* of the respondents (age group, gender, ethnic background, job status, employment type, personal income, car ownership, household size, dwelling structure, and smartphone access). Participants were also asked to report their residential address. A few additional open-ended question inquired about respondent's experience with ridesharing.

The data on *built environment attributes* (population density; employment density; intersection density; distance to CBD; land use mix, and housing value) were retrieved from the Australian Bureau of Statistics (ABS) website, the Open Street Map website, and open-source state government data available on Data.SA.gov.au. At this stage, the study did not consider non-CBD trips, as in Adelaide the inner city tends to dominate the labour market. However, in the future, trips directed suburban employment centres (or intra-suburban trips) should be included as well.

The collected dataset was first cleaned and cross-tabulated to reveal the basic characteristics of trip-makers. Then, the data were modelled. The respondents' opinions and perceptions around ridesharing (*transport priorities*) were reduced, and factors were extracted in Gnu Regression, Econometrics and Time-series Library (GRETL) package version 2020b through Principal Component Analysis (PCA). Following, a Multinomial Logit (MNL) model was applied in

NLOGIT 6.0 (LIMDEP) to determine the characteristics, behaviours, and preferences of users and non-users of ridesharing services. For readers unfamiliar with logit models, an explanation is provided in Appendix 2.

For modelling purposes, the survey respondents were divided into three groups, which capture both the ridesharing behaviour and the attitudes toward ridesharing:

- ridesharing users (U);
- non-users interested in ridesharing (I);
- uninterested non-users (H).[6]

In the model, the explanatory variables included *built environment attributes* at the neighbourhood level, *socio-economic characteristics* of trip-makers at the individual and household level, and *transport priorities*. These are listed in Table 2, along with definitions and abbreviations. Their conceptual relationships are illustrated in Figure 2. The MNL model had the following specifications:

- The utility function of *ridesharing users* (U) consisted of following parameters:

  Utility(U) = I0+I1*Age1724+I2*Age2539+I3*SmartxAge+I4*Fitness+I5*Welledu

- The utility function of *non-users interested in ridesharing* (I) consisted of following parameters:

  Utility(I)=H0+H1*Age1724+H2*Age2539+H3*Smart+H4*Safekeeping+H5*PrPrice10+H6*Income+H7*Ease+H8*Casual*Age+H9*Dens10

- The category of *uninterested non-users* (H) was considered as the referent.
- Two alternative-specific constants for U and I were considered.
- Two behavioural measures: elasticities (for continuous variables) and share difference (for dummy variables) were calculated to identify policy implications.

The key findings are discussed below. First descriptive statistics and cross-tabulations are provided, followed by the results of Principal Component Analysis (PCA) and Multinomial Logit (MNL) modelling.

Findings and discussion

Descriptive statistics and cross-tabulations

The descriptive statistics for the entire dataset (408 data points) are presented in Table 2. The table lists four dimensions (factors) which were extracted through PCA from the 12 original variables (see later). It also shows that incomes, house prices, and car ownership levels are high relative to the rest of the world, whereas densities and households sizes are low.

Overall, the sample comprises 29% ridesharing users (U); 30% non-users interested in ridesharing (I); and 41% uninterested non-users (H). The graphs in Figure 3 illustrate the relationships between the three groups (U, I, H) and some key variables, including the distance of respondent's home from the CBD; the average price of housing in the respondent's neighbourhood; the population density of the respondent's neighbourhood, and the respondent's age group. The graphs suggest that one's ridesharing behaviour depends a great deal on one's age and the neighbourhood in which one lives.

Consistent with the literature (Bruns and Farrokhikhiavi 2011; Mitra et al. 2019; Brown 2020), denser Adelaide metropolitan neighbourhoods contain more ridesharing users, likely because of smaller housing and more limited parking space which lead residents to give up private cars.

Older respondents, particularly those over 40, are less likely to rideshare, possibly because of lower digital literacy. This finding is also consistent with the literature (Mitra et al. 2019; Wang 2019; Bansal et al. 2020). The neighbourhood quality (represented by average housing price) is associated with ridesharing behaviour too: fancier neighbourhoods (i.e., those with costlier houses) have more ridesharers. One previous study has also found a positive association between neighbourhood quality and ridesharing, but in that study "quality" was defined as better urban design and greater pedestrian friendliness (Mitra et al. 2019). Proximity to the CBD does not necessarily lead to more ridesharing; on the other hand, living farther than 25 km from the CBD reduces ridesharing to a minimum. Existing studies in the US and Australia have similarly observed that suburbanites tend to shun ridesharing as they own and use private cars en masse (Brown 2020; Vij et al. 2020).

PCA and MNL modelling

In order to examine the dimensional structure of transport priorities, a principal component analysis (PCA) with varimax rotation and iteration was carried out (Table 3). The Kaizer criterion (an eigenvalue above 1.00) was used as the criterion for factor extraction. Further, visual inspection of the Scree plot was undertaken to determine the number of extracted components. A factor loading above 0.40 was used as a criterion for items to be retained in the dimensions (Hair, Black, Babin, Anderson, & Tatham, 1998). Twelve subjectively measured transport priorities were first reduced to eight. Four items (independence, environmental concerns, travel distance and status/image) were removed due to low factor loadings (<0.4) (Hair, Black, Babin, Anderson, & Tatham, 1998).[7] Then, the remaining eight items were grouped into four dimensions: Factor 1 (comfort and convenience); Factor 2 (safety and security); Factor 3 (speed and time) and Factor 4 (health and exercise). These four dimensions accounted for 89% of the variability in the dataset. Factor 1 explained 22.84% of variance; Factor 2 explained 15.45% of variance; Factor 3 explained 24.46% of the variance; and Factor 4 explained 26.25% of variance.

Table 4 presents a summary of the MNL model output, which elucidates the travel behaviours of study participants. (The full MNL model output is provided in Appendix 3.) Only statistically significant variables are listed in Table 4. These include two *built environment attributes* (neighbourhood quality and density), five *socio-economic characteristics* (age; education, employment; income, and smartphone access), and three *transport priorities* (fitness, ease, and safekeeping). Somewhat surprisingly given the findings of prior studies (see Caulfield 2009; Zhen 2015; Delhomme and Gheorghiu 2016; Sarriera et al. 2017; Shaheen et al. 2017a,b; Alemi et al., 2018; Acheampong and Siiba 2019; Gilibert et al., 2020; Bansal et al., 2020), factors such as gender, car ownership, household size, ethnic background, and distance to CBD were not statistically significant in this study. Neither was the 'velocity' dimension. A lack of a gender gap in ridesharing may be explained by the fact that Adelaide experiences relatively little gender-based violence and insecurity in public space relative to the rest of the world, and therefore women feel comfortable ridesharing (though safety and security are important to local ridesharing users overall).

While descriptive statistics point to age and neighbourhood type as the drivers of ridesharing behaviour, the MNL model reveals that the key predictors are age and smartphone ownership. Older people (40 and over) are less likely to rideshare, or even be interested in ridesharing, than others. This is in line with the literature (Wang et al 2020). However, if they own smartphones and are casually employed, older demographics are more likely to use ridesharing services, or at least be interested in those. Casual workers may have more flexibility in arranging ridesharing trips, but also have less income to spend on private cars. As more people acquire smartphones, traditional taxi service will need to further digitize their services in order to retain their customer base. As expected, people who live in less dense neighbourhoods (with plenty of parking space) are more likely to shun ridesharing. Existing studies have also found that in ridesharing is more popular in denser neighbourhoods, owing, in part, to better ridesharing services here (Bruns and Farrokhikhiavi 2011; Hughes and MacKenzie 2016; Wang and Mu 2018; Deka and Fei 2019).

In the present study, concerns over safety and security (the 'safekeeping' dimension) appear to lead some people to avoid ridesharing. On the other hand, wealthier people - as indicated by their education and income levels and the property prices in their neighbourhood - use ridesharing more or are interested in it. While wealthier groups may be expected to have more access to private cars than poorer people, they may also be more concerned about 'ease' in relation to travel. This implies interest in active travel rather than car dependency. Moreover, the wealthy tend to be better informed about technological innovations, and have more time and money to devote to recreational activities (which may involve alcohol drinking, and therefore require a driver). In combination, these findings suggest that the choice of ridesharing is driven by the notion of socio-economic status, with cosmopolitan, educated middle-income groups embracing this novelty mode more than the lower-income groups or the "conventional suburbanites." Other studies have similarly observed that status consciousness is a major driver of transport mode choices (Ashmore et al. 2018, 2019).

Elasticity analysis

In this study, elasticity is computed to measure changes in the likelihood of choosing a travel alternative in response to a fixed unit change in an independent variable. Knowing how "elastic" or flexible people's travel choices and preferences are is quite important so that sensible policy recommendations can be made (see Hensher et. al., 2015). For independent dummy variables, the measure of elasticity is hard to interpret.[8] Therefore, we computed the pseudo-elasticity[9] of the three choices (U, I, H). For example, based on model specification and calibration, we calculated that well-educated people use ridesharing 8.3% more than other people. In the case of transport priorities, which are continuous variables, we calculated the extent of change in ridesharing behaviour or preference when the variable changed by 1% (or 10%). The aggregate elasticities (direct and cross) in the present dataset are shown in Table 5. For simplicity, U denotes ridesharing users, I denotes non-users interested in ridesharing, and H denotes uninterested non-users.

Two dimensions, 'safekeeping' and 'fitness', have the highest elasticity whereas the population density of one's residential neighbourhood has the lowest. If concerns around safety and security ('safekeeping') increase by 10%, the share of H (uninterested non-users) also increases by 9.8% whereas the shares of I (non-users interested) and U (ridesharing users) decline by 7.8% and 5.9% respectively. The 'ease' dimension is moderately elastic too. A 10% increase in the level of perceived comfort and convenience is associated with a 4.4% decrease in the share of H, while also producing small increases in the shares of I and U. Similarly, the 'fitness' dimension is somewhat elastic. A 10% increase in the perception of ridesharing as an active and healthy mode is associated with a 4.3% decrease in the share of H and a 10.2% increase in the share of I. By contrast, income is not very elastic. A 10% increase only leads to a 2.2% decrease in the share of H and a 1.3% increase in the share of U. Finally, a 10% increase in population density lowers the share of H by just 1.1%, and the resulting increases in I and U are similarly low. In combination, these elasticities suggest that, at this point, more people can be attracted to ridesharing by assuaging fears around this mode, and stressing the comfort and convenience it provides, than by attempting to increase further the levels of service in denser or wealthier neighbourhoods.

The share difference estimations for each alternative (U, I, H) are depicted in Figure 4. The three most powerful dummy variables associated with ridesharing usage are age (the 17-29 age bracket in particular), smartphone access, and, to a lesser extent, casual employment. Among those who are not currently users but are interested in ridesharing, well-educated individuals top the list with a share difference of 11.6%. This suggests that ridesharing is not an inclusive option that caters to people from all walks of life. Entire social segments, including older adults, those without smartphones, and full-time workers shun ridesharing. A key policy suggestion is to increase smartphone access (perhaps through discounts) and encourage digital literacy among older people, especially given current aging trends in Australia. As the ability to drive decreases with age, and car ownership becomes less affordable upon retirement, the elderly could make larger use of ridesharing services provided that they own smartphones and are learn how to use them. As for full-time workers, an attractive ridesharing solution may be car-pooling with multiple riders travelling to the CBD (Librino et al., 2019).

Discussion and conclusion

This study adds to the existing literature on ridesharing by segmenting the population into three groups: ridesharing users, interested non-users, and uninterested non-users. This serves to provide more nuance to the discussion and help formulate policies that can attract the 'interested non-users' group.

To summarise, the key findings from this study are the following: population density, housing value, higher levels of education and income, casual work status, younger age, and access to smartphones are the key factors associated with higher ridesharing use, or higher interest in ridesharing, although the effects are not straightforward. Among the different age groups, younger people (17 to 24 years old) are more likely to be interested in ridesharing. Clearly, the new generation is the easiest target here. Factors such as concern over safety and security, advanced age, digital illiteracy, and suburban living may lead some people to shun ridesharing. But the effect of older age can be moderated if individuals own a smartphone or are casually employed. This suggests that ridesharing can also be increased by encouraging digital literacy among older people.

Some socio-economic factors such as car ownership, ethnic background; gender, and household size, are not associated with either ridesharing behaviours. Interestingly, other socio-economic variables such as income and house prices (a proxy for neighbourhood quality and affluence) have the positive impact on ridesharing. This suggests that the reasons to embrace this option go well beyond affordability. The "hassle-free" travel that ridesharing provides is main attractor. We conclude that the choice of ridesharing in metropolitan Adelaide is driven by the notion of socio-economic status. While the lower-income groups and the more conventional suburbanites shun ridesharing, the cosmopolitan, educated middle-income groups, who are well-versed with technology, embrace this novelty mode. However, because income and population density are not very elastic, attempting to increase further the levels of service in denser or wealthier neighbourhoods may not yield higher ridesharing rates.

The categories of 'uninterested non-users' and 'interested non-users' have obvious similarities in terms of the negative impact of age and access to smartphones. However, their behaviour is different when other factors such as transport priorities, income, education, population density, and housing prices are taken into consideration. Non-users concerned with safety and security are less interested in trying ridesharing; hence assuaging fears around ridesharing use needs to be a major policy target. Among non-users, people with access to smartphones are more interested in trying ridesharing in the future. Similarly, non-users living in high-density areas are more interested in trying ridesharing in the future. Clearly, tech savvy urbanites are the key target demographic here. The effect of population density on ridesharing could be attributed to higher demand and fewer parking spaces available for private cars in compact neighbourhoods. Also, in Adelaide Uber services are more readily available in the inner city than in the suburbs. The obvious corollary is that ridesharing and parking policies need to be coordinated.

These findings are mostly (but not always) aligned with the findings of existing studies mentioned at the outset. Discrepancies are particularly evident with regard to the residential setting of users and non-users. A number of studies have found that urban cores are more conducive to ridesharing (Bruns & Farrokhikhiavi, 2011; Shaheen et al., 2017; Mohamed et al., 2020; Alemi et al., 2018; Bansal et al., 2020; Young et al., 2020; Mitra et al., 2019; Brown, 2020). Meanwhile, other studies have found the opposite: suburbanites are more likely to use ridesharing (Wang et al., 2019; Ma et al., 2018; Vij et al., 2020; Vij et al., 2018). Another discrepancy has to do with gender. While several former studies have found that men are more likely to rideshare than women (Gilibert et al., 2020; Zhen, 2015; Sarriera et al., 2017), other studies (Shaheen et al., 2017; Alemi et al., 2018) reveal that the ridesharing industry serves primarily a female market. As no gender gaps were identified in this study, promotional campaigns should target the population at large rather than focus on particular groups, such as women, who are traditionally considered as more vulnerable.

Overall, we conclude that ridesharing behaviours and attitudes are highly context-dependent. Any efforts and policy formulation should rely on local data and analysis rather than general reviews of findings from elsewhere. Future studies should go beyond qualitative analysis of ridesharing users and non-users. The use of qualitative approaches such as semi-structured interviews is encouraged for a more in-depth undersetting of the impact of *transport priorities*, *socio-economic characteristics*, and *built environment attributes* on ridesharing.

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Notes

[1] In some English-speaking contexts, ridesharing is also referred to as ridesourcing or ridehailing (see (Cohen and Shaheen, 2018). As ridesharing is the most commonly used term in Australia, this is employed consistently in this article. The carsharing concept is somewhat different as it involves renting one's car on an hourly-basis rather than offering a ride to someone who shares a similar origin/destination (Agatz et al., 2012).

[2] Despite its many advantages, ridesharing is not universally applauded. Some critiques are academic or ideological and do not necessarily reflect the reasons why some laypersons shun ridesharing. Traditional, highly-regulated taxi industries, whose customer base has been decimated by ridesharing, have been particularly vocal in their opposition (Watanabe et al. 2016; Boutueil 2018; Li et al. 2018). From a planning perspective, one concern is that, instead of shifting drivers away from cars, ridesharing may take users away from public transport and cycling. As such it may lead to more, rather than less, congestion in cities, especially during peak hours (Simonetto et al. 2019; Mohamed et al. 2020). Moreover, smartphone platforms may enable a new type of monopolistic data extraction which is then monetised without users' permission or becomes a lucrative target for hackers (Li et al. 2018; Wang et al. 2019; Stehlin et al. 2020). User safety concerns have been raised too, as in many countries, drivers are not professionally trained or vetted by police, and vehicles do not undergo safety inspections. By employing "freelance" drivers, ridesharing is also seen as an enabler of the exploitative "gig economy" which undermines employee rights and protections (Alexander and González 2015; Sarriera et al. 2017; Li et al. 2018; Bojic et al. 2019; Wang et al. 2019; Alonso-González et al. 2020). These are serious issues which cities have only just started to tackle. (At different times, Uber has been banned from London and Melbourne.)

[3] A limitation of a survey-based approach is a lack of detailed travel data for participants (such as a weekly travel diary) or 'big data' obtained from ridesharing providers (such as Uber).

[4] By trip generation, we mean the number of trips going into and coming out of an activity centre (which implies two-way trips). Since the potential customers (trip makers) of the six selected sites are in excess of 50,000, the sampling formula devised by Godden (2004) suggests that the optimum sample size is 384. We increased the original sample size by 10% (422 responses) to account for incomplete or unreliable answers.

[5] Further details about survey administration, sampling technique, response rate and quality of survey can be found in the in the related CRC report (Allan and Soltani 2019).

[6] The categories for the dependent variable were named based on a study by Hjorteset and Böcker (2020).

[7] We also tested the effect of 'environmental concerns' on ridesharing as an independent variable but it was not found to be significant.

[8] Elasticity analysis is only feasible for metric variables; in the case of latent variables, it has little policy application or is even meaningless (see Mehdizadeh and Shariat-Mohaymany, 2020). Consider, for example, the case of the gender variable where male gender is coded as zero and female gender is coded as one. In this case the elasticity would be interpreted as the percentage change in the probability of a ridesharing behaviour or preference given a 1% change in gender, which is absurd (see Hensher et al., 2005).

[9] The average of share differences.

Figures

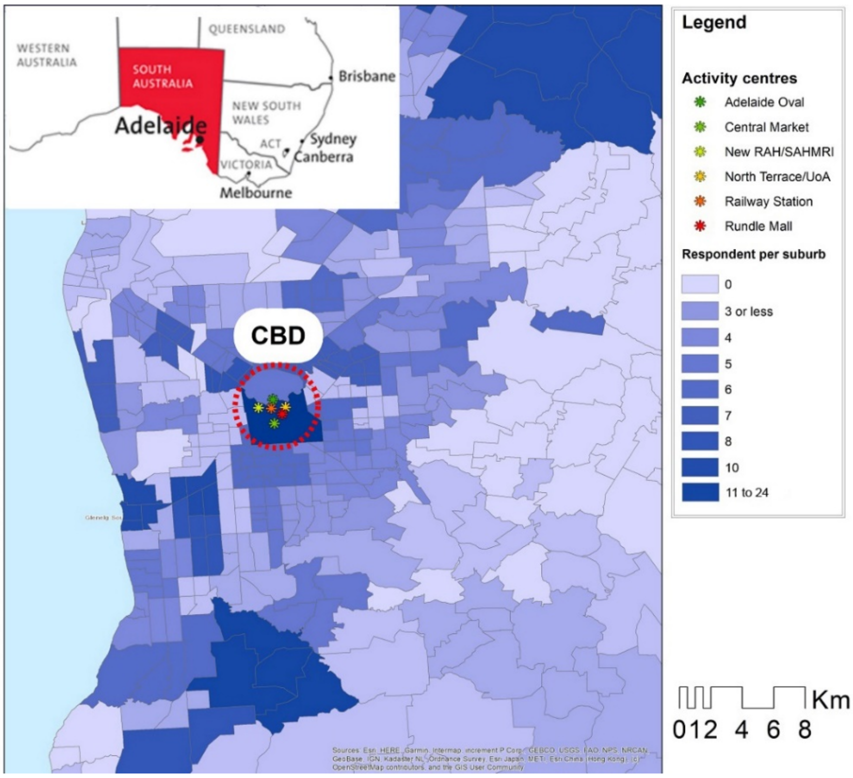

Figure 1. Home locations of sampled respondents.

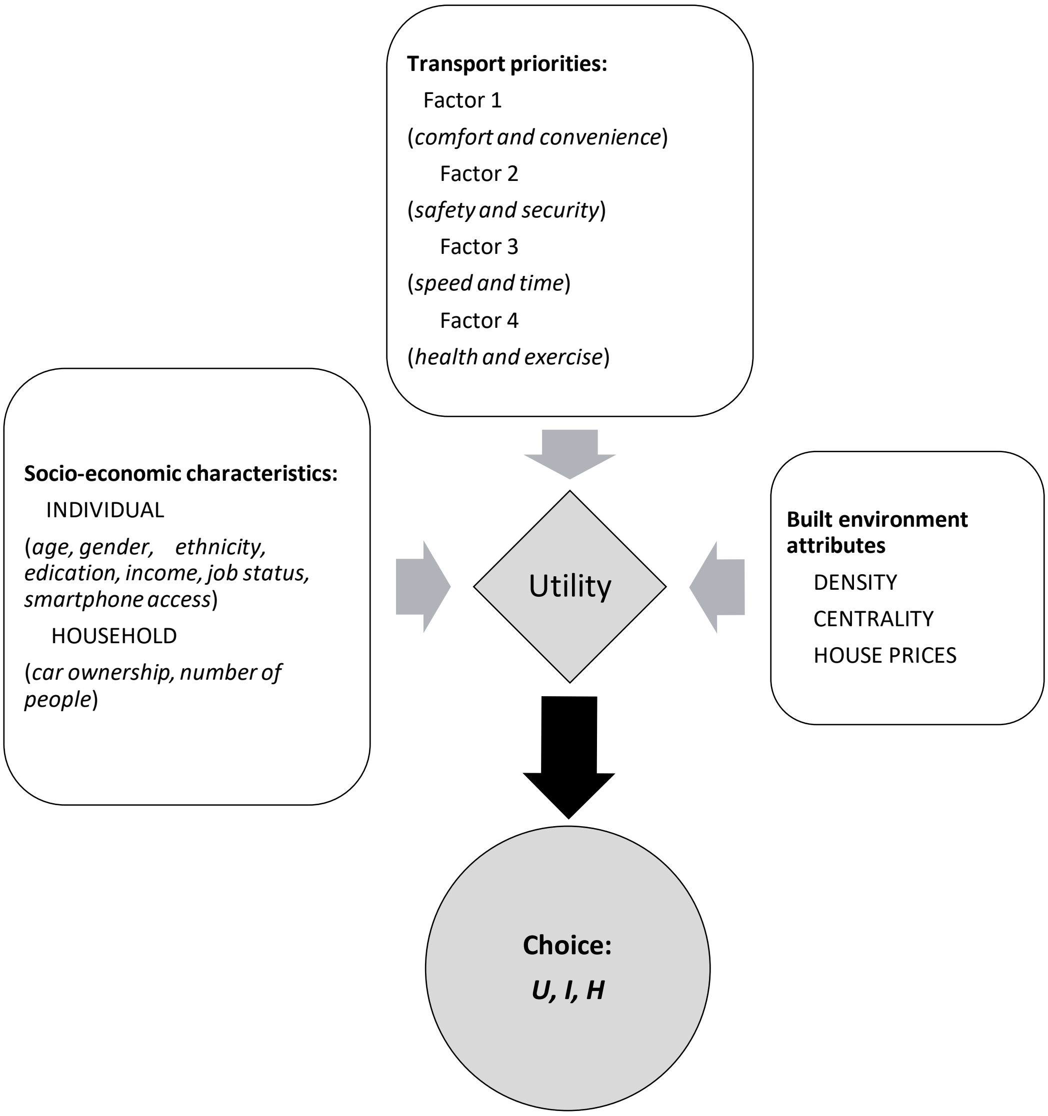

Figure 2. Conceptual framework.

Notes:

U: ridesharing users
I: non-users interested in ridesharing
H: uninterested non-users

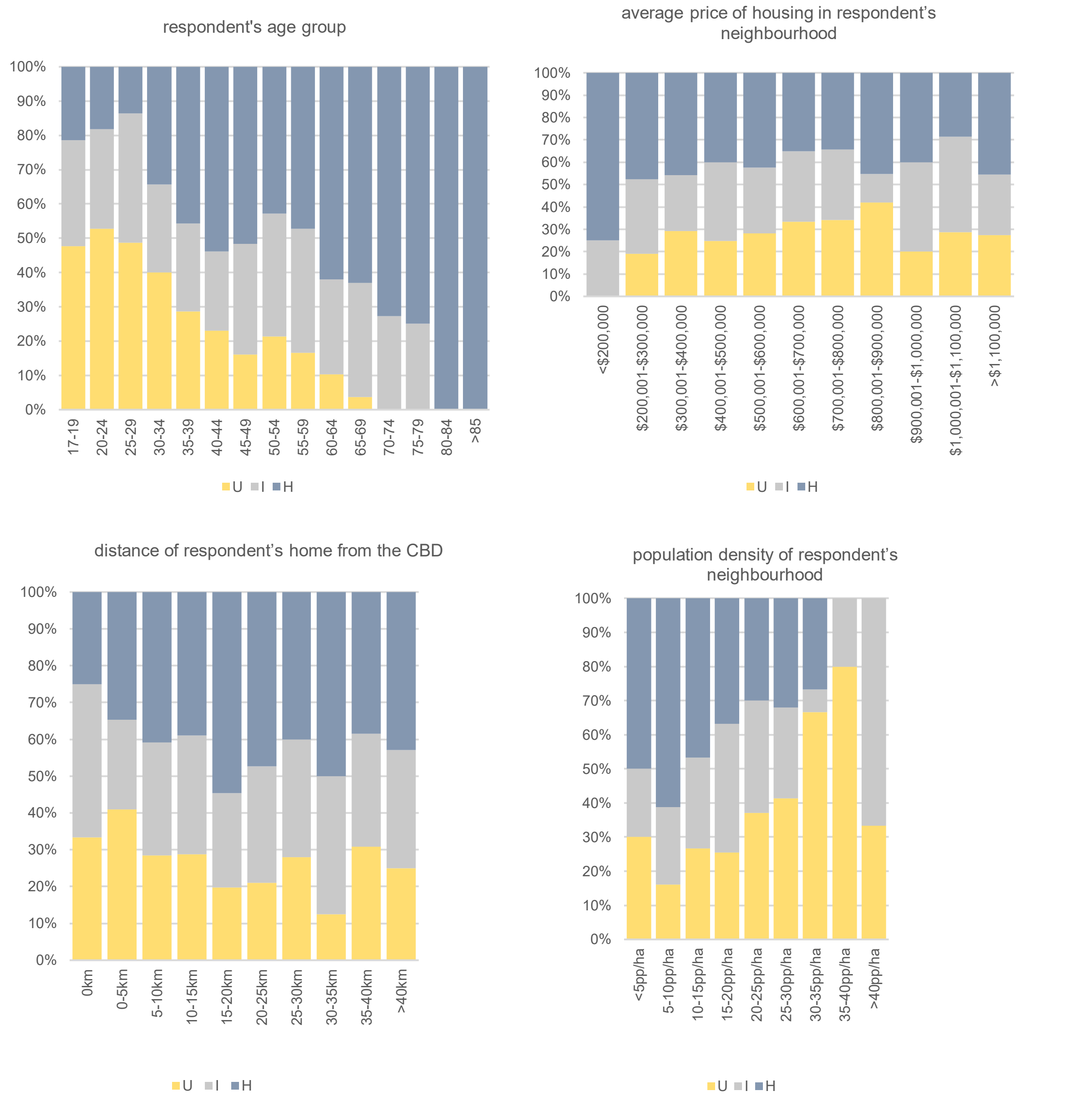

Figure 3. Relationships between key variables and ridesharing behaviour (U: ridesharing users; I: non-users interested in ridesharing; H: uninterested non-users).

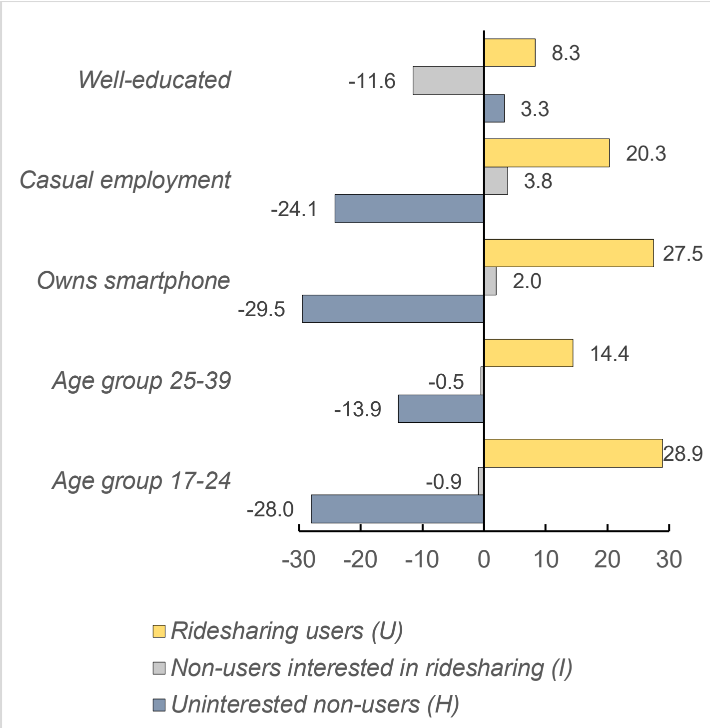

Figure 4. Share difference estimation (percentage) for U (ridesharing users); I (non-users interested in ridesharing); and H (uninterested non-users).

Tables

Table 1. Comparison of study sample to metropolitan Adelaide, South Australia state, and Australia.

Sample and population characterises		*Sample*	*Metropolitan Adelaide*	*South Australia*	*Australia*
Employment type	Professionals / management	36.2	33.8	32.9	35.2
	Labourer	8.6	9.8	11.1	10
Dwelling structure	Separate house	69.3	74.8	77.8	72.9
	Semi-detached / row house / townhouse or similar	18.1	16.9	14.8	12.7
	Flat / apartment	10.4	7.8	6.6	13.1
Ethnic diversity	Birth country of father: Australia	50.5	52.2	56.9	52.3
Age group	20-24 years	8.4	6.9	6.4	6.7
	25-29 years	7.8	6.8	6.4	7.1
	30-34 years	8.1	7.0	6.6	7.3
	75-79 years	2.7	3.0	3.2	2.8
	80-84 years	2.1	2.3	2.3	2
	85 years and over	1.1	2.6	2.7	2.1
Education	University or tertiary institution	22.3	19.3	16.2	16.1
	Highest educational attainment: Bachelor degree or above	24.5	21.2	18.5	22
	Highest educational attainment: Year 12	18.7	16.5	15.5	14.2

Table 2. Descriptive statistics of explanatory variables (n=408).

Category	*variable*	*definition*	*data type*	*min.*	*max.*	*mean*	*SD*
Transport priorities (dimensions reduced by PCA)	Factor 1	Dimension for two items: comfort and convenience	factor loading (continuous)	-3.463	1.860	.000	1.003
	Factor 2	Dimension for two items: safety and security	factor loading (continuous)	-2.551	2.156	-.000	.999
	Factor 3	Dimension for two items: speed and time	factor loading (continuous)	-3.949	1.732	.000	1.000
	Factor 4	Dimension for two items: health and exercise	factor loading (continuous)	-3.213	2.150	.000	.999
Built environment attributes	PrPrice10	Proxy variable for neighbourhood quality: average price of housing (in $10k increments)	ratio	17.940	127.880	57.979	20.676
	DisCBD	Euclidean distance of residential neighbourhood to Adelaide's CBD (km)	ratio	.00	60.00	15.517	14.898
	Density	Population density of residential neighbourhood (pp/ha)	ratio	.010	40.660	17.857	8.987
Socio-economic characteristics	Smart	1: participant has access to smartphone/digital device 0: otherwise	dummy	.0	1.0	.689	.464
	Income	Participant's individual income level (based on ABS categorisation)	ordinal	1.0	11.0	5.880	3.058
	Welledu	1: participant has graduate degree 0: otherwise	dummy	.0	1.0	.520	.500
	Casual	1: participant has a casual job 0: otherwise	dummy	.0	1.0	.100	.301
	Age1724	1: Age 17-24 0: Otherwise	dummy	.0	1.0	.238	.426
	Age2539	1: Age 25-39 0: Otherwise	dummy	.0	1.0	.262	.440
	Gender	1: male 0: female	dummy	1	2	1.22	.485
	HHSize	Number of people in household	discrete	1	5	2.63	1.209
	Australian	1: participant has Australian background 0: otherwise	dummy	0	1	.77	.418
	NCars	Number of cars available in household	discrete	0	4	1.74	1.010

Table 3. Rotated component matrix of PCA.

Transport priorities	*Factor or Dimension*			
	Velocity	Fitness	Safekeeping	Comfort/Convenience
Comfort	.180	.154	.153	.958
Convenience	.231	.165	.174	.876
Safety	.108	.104	.967	.146
Security	.265	.078	.910	.194
Speed	.921	.034	.026	.088
Time savings	.896	.086	.124	.136
Health	.084	.866	.246	.067
Exercise	.037	.907	-.072	.126
Environmental consideration*	.221	.353	.104	-.204
Independence*	-.175	.240	.301	.083
Travel distance*	.189	-.267	.143	-.256
Status/Image*	.245	.092	.346	-.294
Explained variance	22.84%	15.45%	24.46%	26.25%

Notes:
Extraction method: Principal Component Analysis (PCA).
Rotation method: varimax with Kaiser normalization.
Rotation converged in five iterations.
The scree plot and Kaiser criterion were used to determine the number of extracted dimensions.
An eigenvalue above 1.00 was considered as significant.
Factor loading above 0.40 was used to retain dimensions.
*The item was removed due to low factor loading (<0.4).
Transport priorities were measured on a five-point Likert scale. Respondents were asked “How do you rate the following item when choosing a ridesharing service?”

Table 4. Explanatory variables, their coefficients and significance.

choice	*coefficient*	*Variable (abbreviation)*	*Variable (full name)*	*coefficient(Beta)*	*SE*	*t-value*	*p-value*
H (uninterested non-users)	H0	Intercept		2.550***	0.793	3.214	0.001
	H1	Age1724	Aged between 17 and 24	-2.435***	0.390	-6.239	0.000
	H2	Age2539	Aged between 25 and 39	-1.438***	0.340	-4.231	0.000
	H3	Smart	Has smartphone access	-1.504***	0.342	-4.392	0.000
	H4	Factor 2	Priority for safety and security	0.494***	0.146	3.386	0.001
	H5	PrPrice10	Property price	-.098**	0.050	-1.968	0.049
	H6	Income	Individual income ($AUS)	-0.080*	0.043	-1.88	0.060
	H7	Factor 1	Priority for comfort and convenience	-0.265**	0.127	-2.088	0.037
	H8	CasualxAge	Age of individuals with casual job status	-0.203*	0.116	-1.754	0.079
	H9	Dens10†	Density of neighbourhood	-0.131*	0.073	-1.795	0.072
I (non-users interested in ridesharing)	I0	Intercept		0.325	0.541	0.601	0.548
	I1	Age1724	Aged between 17 and 24	-1.906***	0.405	-4.707	0.000
	I2	Age2539	Aged between 25 and 39	-1.095***	0.364	-3.012	0.003
	I3	SmartxAge	Age of individuals with smartphone access	-0.118**	0.049	-2.425	0.015
	I4	Factor 4	Priority for health and exercise	0.432***	0.112	3.865	0.000
	I5	Welledu	Well educated	-0.790***	0.245	-3.228	0.001

Notes:

***significant at 1%,
**significant at 5%
*significant at 10% level
†A 10% density increase

The log-likelihood value for the null model equal -448.2
The log-likelihood value for a converged model equals -355.1
The goodness of fit for the model is 0.21
The AIC value equals 1.917

Table 5. Aggregate elasticity (direct and cross) estimations.

variable	*primary alternative*	U	I	H
Income	H	+0.13	+0.18	-0.22
Dens10†	H	+0.07	+0.09	-0.11
Factor 2 (safety and security)	H	-0.59	-0.78	+0.98
Factor 1 (comfort and convenience)	H	+0.26	+0.35	-0.44
Factor 4 (health and exercise)	I	-.44	+1.02	-0.43

†A 10% density increase.

Appendices

Appendix 1: Theoretical foundation.

Transport priorities	**Socio-economic characteristics**	**Built environment attributes**	**References**
Comfort (use ridesharing more for leisure/social purposes)	Younger than average population, Highly-educated, low-income, single, childless (irregular users)	Urban areas with higher density	(Bruns and Farrokhikhiavi 2011)
NA	Middle-age, Highly-educated, High-income, married with children (frequent users)	Suburban areas	(Bruns and Farrokhikhiavi 2011)
NA	Young, Female-dominated, non-single, own car	NA	(Caulfield 2009)
Comfort (substitute to public transport/private; parking and policy restriction inside city)	Young to Middle-age, Male-dominated, Employed, have access to car	NA	(Gilibert et al. 2020)
Comfort (regard private vehicles as less comfortable or useful; use ridesharing more for leisure/social, work/school trips)	Middle-age, Female-dominated, Have children, attitude (have environmental concerns, positive attitude toward public transit)	Living location was found ineffective	(Delhomme and Gheorghiu 2016)
Comfort (use ridesharing more for leisure/social, work/school trips)	Middle age, Financial benefits, attitude (acknowledge the environmental threats, but value private vehicle as more comfortable, safe, and low maintenance travel option)	NA	(Gheorghiu and Delhomme 2018)
Comfort (higher-income people use ridesharing more for leisure/social trips; lower income people use ridesharing for work/study trips)	Younger than average population, Female-dominated, Educated, Income is divers but more of Low-income, Financial benefits	Urban areas with higher density	(Shaheen et al. 2017b)
Comfort (substitute to public transport), Safety, Speed (faster)	Young, No difference in users gender, Educated, Employed, Financial benefits, Smartphone users, majority owned private vehicle	Urban areas with higher density	(Mohamed et al. 2020)
Comfort, Speed (faster)	Younger than average population, Female-dominated, Higher-income, Own a private vehicle	Urban areas with higher density (reside inside city boundaries)	(Young et al. 2020)
Comfort (for shopping, recreational, and travel mode transfer purposes); Health-related factors (physical impairments)	Younger elderlies, Female-dominated, Highly-educated, High-income (wealthy), White ethnicity, more familiar with new technologies and smartphones	Urban areas with higher density	(Mitra et al. 2019)
NA	Young, Low-income, financial reasons, African Americans and Hispanic ethnicity	Urban areas with higher density (low-income neighbourhoods)	(Brown 2020)

Transport priorities	**Socio-economic characteristics**	**Built environment attributes**	**References**
Comfort (substitute to public transport)	Younger than average population, Own fewer vehicles, non-single,	NA	(Rayle et al. 2014)
Comfort (previous public transport users), Speed (time -saving)	Young, Single, childless, Low-income, Financial benefits, Immigrants, Hispanic and African Americans ethnicity , did not own a vehicle	NA	(Cohen and Shaheen 2018)
Comfort (previous public transport users, use ridesharing more for leisure/social purposes)	Young, Male-dominated, , Highly-educated, High-income	NA	(Zhen 2015)
Comfort, (substitute to public transport; use ridesharing more for leisure), Speed (time-saving)	Young, Male-dominated, Childless , Educated, Low to middle income, White ethnicity, Financial benefits, Do not own private vehicle but have access to vehicle	Urban areas with higher density	(Sarriera et al. 2017)
Comfort (long-distance business trips made by non-motorized modes)	Young, Female-dominated, Highly-educated, High-income, Non-Hispanic ethnicity , Technology-oriented lifestyle, Smartphone users, Having less access to private vehicle	Urban areas with higher density	(Alemi et al. 2018)
Comfort (previous public transport users; long-distance business trips made by non-motorized modes)	Younger than average population, highly-educated, childless, Technology-oriented lifestyle, Smartphone users;	NA	(Alemi et al. 2019)
Comfort (use ridesharing more for leisure/social trips) and safety (avoid driving drunk)	Young, Highly-educated, High-income, Technology-oriented lifestyle	Urban areas with higher density	(Bansal et al. 2020)
NA	Young, Male-dominated, Middle-income	Suburban areas	(Iqbal 2020)
Comfort	Young, Male-dominated, Highly-educated, High-income, Financial benefits	Suburban areas (busier cities)	(Wang et al. 2019; Ma et al. 2018)
Comfort and Speed (easiness of usage/no need for transfer /less waiting time)	Young to middle-age, Middle/lower income, Education was insignificant, Financial benefits	NA	(Kumar and Joewono 2018)
Comfort (may be disabled and regular public transport users)	Young, Male-dominated, Highly-educated, Employed, Low-income, having children , Financial reasons, Lifestyle	Metro, regional and remote areas	(Vij et al. 2018, 2020)
Comfort (use ridesharing more for leisure/social trips) Speed (high maintenance/cleanliness/sign up methods/reliability and availability/ mobile app quality)	Young, Male-dominated, Highly-educated, Middle/low-income	NA	(Sotani et al. 2018)

Appendix 2: Logit models.

A logit model assumes rational behaviour among individuals. In this case, the assumption was that a trip-maker will choose a particular travel mode among a set of available alternatives in the hope of maximising his/her utility. The utility function (*U*) for each mode has two parts (McFadden, 1973). The first is the measurable or observed utility of the alternative *k*, which depends on both the specific attributes of the alternative *and* the characteristics of the individual trip-maker (*i*). The second part is a random component that represents the effects of unmeasurable (or unobserved) attributes and characteristics on the utility.

Hence, in an MNL model the utility (*U*) of selecting alternative *k* can be described as:

$$U_k(X_k|\beta_k) = \beta_k^T X_k + \varepsilon_k$$

where:

β_k includes the coefficients to be estimated

ε_k is the unmeasured random error for selecting alternative *k*

The likelihood of selecting mode *k* out of a set of alternatives for an individual *i* is:

$$p_{ik} = \frac{\exp(\beta_K^T X_{ik})}{\sum_{p=1}^{K} \exp(\beta_K^T X_{ik})}.$$

Once β has been calculated, the MNL logit model can be associated with the likelihood function *L* as below:

$$L(\beta) = \prod_{i=1}^{N} \prod_{k=1}^{K} \left[\frac{\exp(\beta_K^T X_{ik})}{\sum_{p=1}^{K} \exp(\beta_K^T X_{ik})} \right]$$

A Maximum Likelihood Estimation (MLE) can then identify the most appropriate coefficients for maximising the utility:

$$\hat{\beta} = argmax_{\beta} L(\beta)$$

The choice likelihoods for each alternative is calculated by plugging $\hat{\beta}$ into the MLE equation. The calibration of MNL models is based on the entire dataset, through examining the log-likelihood at convergence, then comparing the subsequent adjusted pseudo R-squared, and the Akaike Information Criterion (AIC) for determining the best-fitted form of the model (Train 2003).

Finally, elasticity is measured to predict changes and policy implications. The logit model is generally evaluated based on its capability to regenerate the aggregate choice distribution for each alternative. This is called the ‘market share’ of alternative *k* and is defined as:

$$P_k(X_k|\hat{\beta}_k) = \sum_{i}^{N} \hat{p}_{ik}/N$$

The elasticity (E) of feature *p* for mode *k* is defined as follows:

$$\mathrm{E_k}(X_{k,p}) = \frac{[P_k(X_{k-p}, X_{k,p}.(1+\Delta)|\hat{\beta}_k) - P_k(X_k|\hat{\beta}_k)]/P_k(X_k|\hat{\beta}_k)}{|\Delta|}, k \in \{1, \ldots, K\}$$

Appendix 3: MNL output.

```
--> NLOGIT
   ;lhs=choice
   ;choices=HATE(H),INTEREST(I),USERS(U)
   ;effects:AGE1724(*)/AGE2039(*)/SMART(*)/SAFETY(*)/PRPRICE(*)/INCOME(*)/COMF(*)/CASUAL(*)/HEALTH(*)/WELLEDU
(*)/DENS10(*)/AGE(*)
   ;pwt
   ;model:

U(HATE)=H0+H1*AGE1724+H2*AGE2039+H4*SMART+H5*SAFETY+H6*PRICE10+H7*INCOME+H8*COMF+H9*CASUAL*AG
E+H10*DENS10/
   U(INTEREST)=I0+I1*AGE1724+I2*AGE2039+I4*SMART*AGE+I5*HEALTH+I6*WELLEDU$
Normal exit:   6 iterations. Status=0. F=    355.1732

-----------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable              Choice
Log likelihood function       -355.1732
Estimation based on N =    408, K =  16
AIC =     1.9175  Bayes IC =     2.0748
AICf.s. =     1.9209  HQIC =     1.9798
Model estimated: May 31, 2006, 14:42:46
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only   -442.7397  .1526 .1357
Chi-squared[14]         =    135.13309
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=   408, skipped    0 obs
--------+--------------------------------------------------
Variable| Coefficient    Standard Error  b/St.Er. P[|Z|>z]
--------+--------------------------------------------------
      H0|    2.54974***       .79324       3.214   .0013
      H1|   -2.43464***       .39023      -6.239   .0000
      H2|   -1.43852***       .34003      -4.231   .0000
      H4|   -1.50367***       .34235      -4.392   .0000
      H5|     .49384***       .14584       3.386   .0007
      H6|    -.09824**        .04993      -1.968   .0491
      H7|    -.08020*         .04266      -1.880   .0601
      H8|    -.26491**        .12688      -2.088   .0368
      H9|    -.20351*         .11602      -1.754   .0794
     H10|    -.13084*         .07306      -1.795   .0720
      I0|     .32491          .54105        .601   .5482
      I1|   -1.90632***       .40496      -4.707   .0000
      I2|   -1.09532***       .36368      -3.012   .0026
      I4|    -.11814**        .04871      -2.425   .0153
      I5|     .43230***       .11186       3.865   .0001
```

```
     I6|   -.78993***      .24473      -3.228   .0012
--------+--------------------------------------------------
Note: ***, **, * = Significance at 1%, 5%, 10% level.
-----------------------------------------------------------

+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is AGE1724  in choice HATE              |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                          Mean    St.Dev   |
| *     Choice=HATE            -.2076     .5884   |
|       Choice=INTEREST          .1061     .2226   |
|       Choice=USERS            .1859     .2605   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is AGE1724  in choice INTEREST          |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                          Mean    St.Dev   |
|       Choice=HATE             .0603     .1823   |
| *     Choice=INTEREST         -.2975     .5430   |
|       Choice=USERS            .2217     .2972   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is AGE2039  in choice HATE              |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                          Mean    St.Dev   |
| *     Choice=HATE            -.1713     .3660   |
|       Choice=INTEREST          .1039     .2017   |
|       Choice=USERS            .1364     .2156   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is AGE2039  in choice INTEREST          |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                          Mean    St.Dev   |
|       Choice=HATE             .0574     .1282   |
| *     Choice=INTEREST         -.1896     .3237   |
|       Choice=USERS            .1142     .1675   |
+---------------------------------------------------+
+---------------------------------------------------+
```

```
| Elasticity            averaged over observations.|
| Attribute is SMART     in choice HATE             |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                              Mean    St.Dev   |
| *     Choice=HATE             -.4620     .4800   |
|      Choice=INTEREST          .3067     .2837   |
|      Choice=USERS             .3406     .2463   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is SAFETY   in choice HATE             |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                              Mean    St.Dev   |
| *     Choice=HATE              .9812     .4677   |
|      Choice=INTEREST         -.7779     .4849   |
|      Choice=USERS            -.5926     .4101   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is INCOME   in choice HATE             |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                              Mean    St.Dev   |
| *     Choice=HATE             -.2245     .1644   |
|      Choice=INTEREST          .1787     .1323   |
|      Choice=USERS             .1349     .1170   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is COMF     in choice HATE             |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                              Mean    St.Dev   |
| *     Choice=HATE             -.4426     .2509   |
|      Choice=INTEREST          .3552     .2134   |
|      Choice=USERS             .2630     .1714   |
+---------------------------------------------------+
+---------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is HEALTH   in choice INTEREST          |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                              Mean    St.Dev   |
|      Choice=HATE             -.4271     .2764   |
```

```
| *     Choice=INTEREST          1.0185     .2664   |
|       Choice=USERS            -.4449     .2822   |
+--------------------------------------------------+
+--------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is WELLEDU  in choice INTEREST          |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                             Mean    St.Dev   |
|       Choice=HATE              .0910     .1027   |
| *     Choice=INTEREST          -.2390     .2823   |
|       Choice=USERS             .1176     .1145   |
+--------------------------------------------------+
+--------------------------------------------------+
| Elasticity            averaged over observations.|
| Attribute is DENS10   in choice HATE              |
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
|                             Mean    St.Dev   |
| *     Choice=HATE             -.1097     .1048   |
|       Choice=INTEREST          .0873     .0759   |
|       Choice=USERS             .0659     .0621   |
+--------------------------------------------------+
```