Determining the Market Uptake of Demand Responsive Transport Enabled Public Transport Service

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Abstract: Demand responsive transport (DRT) alternatives offer improved mobility to travellers through station-to-destination or door-to-transit operations. In particular, door-to-transit DRT service acts as a feeder to major public transport hubs, making public transport more accessible and attractive to travellers. This work aims to study the mode choice behaviour of travellers between their current modes and a new service, which is a combination of DRT and public transport. The study is conducted in the Northern Beaches area of Sydney, Australia where DRT is expected to serve as a feeder to the newly introduced express bus service called B-Line. A stated preference (SP) experiment is designed where multiple-choice scenarios involving two modes, status quo (SQ) and the new service (combined DRT and public transit), are presented to the participants. The survey uses trip specific information obtained from Google API to form the attributes for the new service. The collected data are analysed using a latent class choice model (LCCM), which segments the observed sample into distinct groups where each group has its own taste and preferences towards the new service option. Results from the study reveal that one of the identified user segments shows 96 percent uptake towards the new service option, while the other user segment shows an uptake of 44 percent. Results also show that individuals making work trips are more likely to opt for the new service. Findings from this study can provide information to urban planners regarding the market uptake of DRT services. Furthermore, the findings can also help planners in implementing segment specific policies aimed at further improving uptake towards DRT along with public transport.

Keywords: demand responsive transport; mode choice; stated preference; latent class choice model

1. Introduction

Providing improved mobility by making public transport system more accessible to users has been the common objective of transport planning agencies across the world. A variety of sustainable and eco-friendly transport solutions, such as walking, bicycling, bike-share, etc., have been implemented to date, which provide seamless integration with the existing transit systems making the latter more attractive for commuting [1,2]. In other words, these feeder systems help transforming a mass transit system into a MaaS (mobility as a service) system [3]. The recent advancements in information and communication technology (ICT) have enabled the introduction of dynamic ridesharing options which aim to provide door-to-door (or door-to-transit station in a few cases) service to users [4]. One of the popular additions to these services is the demand responsive transit (DRT) option, comprising dedicated small buses, minibuses, or maxi-taxis, which aim to cater pre-booked user requests through telephone or a smartphone app [5]. The DRT service, which is also known as dial-a-ride or paratransit, initially started mainly to cater to disabled and elderly [6,7].
Bakker (1999) defines DRT as a transportation option that falls between a private vehicle and the conventional public transport, i.e., a service that offers similar level of service and mobility as private vehicles along with easy access to public transport [8]. As a result, DRT has been trialled and implemented in several rural and urban areas across the world and has evolved more as a flexible mode of transport [9–11]. The salient features of the DRT service include reduced waiting time and walking time, cheaper fares, no need to find and pay for parking, etc.

A few studies have looked at identifying the factors that could potentially impact the market uptake (demand) of DRT services in an area. For example, Daniels and Mulley (2010) identified a set of five barriers that may impact the success of DRT [12]. Kolenbet (2017) and Wang et al. (2013) found that the success of DRT services has been largely attributed to lower population density areas having poor accessibility to the public transport system [13,14]. Other factors include trip-related characteristics such as cost of service, waiting time, and walking distance [15] and socio-economic characteristics such as income, employment, education, age, and health of individuals in an area [9,16]. However, as noted by Davison et al. (2012), there are still a few examples where promising DRT schemes have failed [17]. Furthermore, a majority of studies determined the number of trips using macroscopic data such as DRT trip-specific attributes and socio-economic characteristics of the population residing in the area [10,14]. However, these studies do not analyse the trade-offs in the attributes of the current and the combined DRT and public transport modes made by individuals and explaining their underlying choice behaviour as a function of their available socio-demographic information. In other words, these studies did not take into consideration the preferences of individuals (or groups) towards the new alternatives, which could in turn determine the ridership for such services.

This study evaluates the market uptake of DRT services, which is expected to serve as the feeder to the main public transport system (bus), in the low population density and high-income area of Northern Beaches in Sydney. A stated preference (SP) survey is designed, which compares the current mode (referred to as the status quo (SQ) alternative henceforth) features against the combined DRT and main transit option (referred to as the new service henceforth). The survey re-creates the DRT + public transit alternative using the trip related information obtained through the Google Maps Directions API for the origin, destination, and departure time of the trip revealed by the participant [18]. The survey is circulated among the individuals travelling in and out of the Northern Beaches catchment area. The collected dataset is modelled using a hybrid discrete choice framework called the latent class choice model (LCCM) to classify user preferences into mutually exclusive segments based on observed individual characteristics such as socio-demographic information. The results from an LCCM are more useful in policy making to understand segment specific taste heterogeneity and market uptake towards a policy. To the best of our knowledge, this is the first study that evaluates the demand for DRT (as a feeder) and public transit combined at a disaggregate level in sparsely populated regions with poor accessibility to public transport. Furthermore, this study is the first to apply Google data in the context of evaluating DRT and public transit (the proposed alternative) service attributes. The findings from this study not only inform on the market uptake of DRT services in the Northern Beaches area to planners, but also segment-specific tastes and preferences of users towards the new alternative. The latter would help planners in framing segment specific policies aimed to further boost DRT uptake. The results from LCCM could also help in understanding the effect of socio-demographics on the mode choice behaviour of individuals.

The organisation of this paper is as follows. Section 2 reviews the previous DRT market uptake studies and identifies the gaps in research. Section 3 presents the study area characteristics and the catchment area that was selected for this study. Section 4 describes the SP design methodology used to develop the survey questionnaire. Section 5 discusses data collection and conducts an empirical analysis to get a better understanding of the data. Section 6 discusses the LCCM framework adopted for data analysis followed by the results from the model and brings out the key findings. Finally, conclusions, challenges, and future research directions are discussed in Section 7.
2. Literature Review

DRT services, which started as early as 1960s in the UK [19], have been trialled and implemented in several developed and developing economies of the world (readers are directed to the works by Enoch et al. (2004) and TfNSW (2017a) which provide an extensive review of DRT studies [9,20]). DRT operations can be classified into many sub-categories. For example, based on pickup and drop-off: Door-to-door [15] and door-to-transit [21]; routing and scheduling: Fixed [22] and flexible [23]; origin-destination pattern: Many-to-many [24] and many-to-one or vice versa [16] and one-to-one [25]. For the scope of this study, only the literature on door-to-transit services is reviewed.

A series of factors have been identified that contribute to the potential success or failure of a DRT service in an area. Nutley (1988) states that most flexible transport modes (DRT) are best suited to rural areas that generally are sparsely populated and poorly connected to public transport [26]. Similarly, Adeniji (1987) and Wang and Winter (2010) found DRT to be effective in low-density urban areas and for short-distance pickups [27,28]. In a later work, Wang et al. (2013) observed lower levels of car ownership, income, education, and employment to also favour the use of DRT services [14]. Jain et al. (2017) tabulated all contributing factors, which also include shopping and social trips, gender (particularly female users), age-group, distance to the nearest transit station, and waiting time [10]. However, Anspacher et al. (2004) observed a contrasting result for the study conducted in the urban and suburban neighbourhoods of San Francisco [21]. The study found that lower-income households are 13.5 percent more likely to be ‘not at all willing’ to use DRT service than higher-income households. On the other hand, Khattak and Yim (2004) found the uptake of DRT services in the nine counties in Bay area, US to be high among high income, more educated, and high density [15]. In other words, the willingness to pay for DRT services was high, with a good portion of potential users willing to pay premium fares of $10 for a 30 min trip. The contrasting results show that different geographies have varying characteristics like household, individual, and public transport performance. Thus, there is a need to study the potential market uptake of DRT services in Northern Beaches of Sydney, which has unique set of the aforementioned characteristics.

Several studies have used macroscopic-level data for modelling the ridership of DRT in an area. For example, Wang et al. (2013) modelled the number of DRT trips across statistical divisions (referred to as lower super output area) in greater Manchester using aggregated trip specific and socio-economic characteristics of individuals in the division [14]. Jain et al. (2017) also used aggregated data at statistical area level 3 (SA3; the area division nomenclature followed by the Australian Bureau of Statistics [29]) in Melbourne to explore the overall susceptibility to use DRT service [10]. However, these studies could only observe how aggregate socio-demographics of the area can affect DRT uptake with no information available on what makes an individual choose between their current mode and DRT. Thus, there have been studies that were conducted to understand individual mode choice behaviour. Ryley et al. (2014) conducted an SP survey to compare bus/private car against the proposed DRT service in greater Manchester, UK [30]. The attributes defining the alternatives were reliability, journey time, cost, and walking time to/from destination. A random parameter logit (RPL) model was then fit to explain preference heterogeneity towards the attributes across the participants. However, it did not include the effect of socio-demographic information that could possibly explain the reason behind this taste variation. Cayford and Yim (2004) modelled the likelihood of using DRT shuttle service as a function of traveller’s socio-demographic information [31]. However, the study assumed an acceptable wait time, fare, and pickup/drop-off locations while surveying participants. In other words, the impact of elasticities towards trip specific attributes on DRT choice was not considered. Khattak and Yim (2004) conducted an SP using willingness to use DRT shuttle service (on a scale of 1 (not at all likely) to 5 (very likely)) as the dependent variable and attributes such as willingness to pay and willingness to wait along with attitudinal and socio-demographic information [15]. The authors found association (using ANOVA test) between the willingness to use the DRT and socio-economic factors such as females ($p = 0.059$), low car ownership ($p = 0.072$), etc. However, the ANOVA test cannot reveal the causation, i.e., the marginal effect of latter on the former. Anspacher et al. (2004) used ordered logit model on the revealed, stated preference, and socioeconomic data to investigate the influence of several factors...
on people’s willingness to use the shuttles [21]. However, the developed model had the following limitation: It assumed fixed parameter for trip specific variables, like distance to the nearest transit station, across the population. Individuals, in general, possess different preferences based on their socio-economic and attitudinal characteristics.

In summary, every area where DRT has been trialled offered different levels of susceptibility. Thus, there is a need to study market uptake for DRT services in selected areas for deploying on-demand transit solutions. In this paper, we focus on the Northern Beaches area of Sydney. Secondly, the data analysis techniques followed in the past studies could not account for either: 1) Taste heterogeneity towards attributes such as travel time, fare, etc.; 2) studying the combined effect of socio-demographics on taste variation; or 3) both. This study develops an LCCM that uses the observed individual characteristics, for example socio-demographic information, to classify them into mutually exclusive groups called segments. Each segment has a unique set of taste preferences (towards DRT attributes) and has a specific market representation. The advantages of an LCCM over other discrete choice frameworks such as RPL are: 1) It does not require assuming a mixing distribution to model taste heterogeneity, 2) it is a more suitable model for policy makers as it provides segment specific characteristics instead of person-specific taste heterogeneity (Hess et al., 2009), and 3) a direct effect of socio-demographics is relatively straightforward when compared with RPL where they are introduced as interaction variables. Hence, results from LCCM can provide useful information to policy makers in identifying target user segments and proposing segment specific schemes aimed at boosting DRT ridership. This paper mainly studies the choice between the SQ alternative (auto or transit) and the new service option. Considering the likelihood of using other available alternatives (except the two aforementioned alternatives) is not in the scope of this work.

3. Study Area

The state transport authority, Transport for New South Wales (TfNSW), initiated trials to test the potential of the DRT service in the Northern Beaches (NB) of Sydney, Australia. This section presents key community and socio-economic statistics of the study area, which were taken from the Australian Bureau of Statistics [32–34]. The NB area extends over 257 square kilometres and has a population of 266,344. It has an average population density of 1038 persons per square kilometre, which is lower than the statistic for the city of Sydney (1237 persons per square kilometre). Furthermore, around 70 percent of the NB area has a population density of less than 2000, which is considered low as per ABS [35]. Thus, the statistics indicate that the NB area is sparsely populated when compared to the rest of Sydney. The average household size is 2.64 persons in the area.

Table 1 presents a comparison of the socio-economic statistics for NB and NSW. The table shows a higher percentage of females in NB when compared to NSW. The age distribution in NB shows lesser proportion of population under the age of 35 years and higher proportion for the remaining two age brackets. In particular, the percentage of residents above 55 years, which mainly comprise retired and elderly, is higher in the study area when compared to the regional statistic. The income distribution shows less low-income (below $650 pw) and more high-income (above $1750 pw) residents when compared to NSW. Furthermore, around 6 percent of residents in NB do not have access to private vehicles, which is lower than greater Sydney (11 percent). Similarly, NB has a higher proportion of households with access to at least 2 cars (53 percent) when compared to greater Sydney region (46 percent).

Figure 1 shows the catchment area (shaded in white) in the Northern Beaches (NB) of Sydney where the proposed DRT service is expected to operate. A focus group with experts and industry partners was created to identify and demarcate the catchment area. The catchment area was divided into two zones for DRT operations, namely: Zone 1, which includes Palm Beach, Whale Beach, Clareville, Avalon Beach, Newport, Bayview, and Mona Vale; and Zone 2, which covers Ingleside, Warriewood, and North Narrabeen [36]. The service operates on weekdays between 6AM and 10PM and also offers services over weekends. The one-way fare is $3.10 with concessions available to pensioners, seniors, students, and trainees.
Table 1. Socio-economic statistics of Northern Beaches, Sydney.

| Attribute       | NB Statistic (%) | NSW Statistic (%) |
|-----------------|------------------|-------------------|
| Gender          |                  |                   |
| Males           | 51.5             | 52.6              |
| Females         | 48.5             | 47.4              |
| Age (years)     |                  |                   |
| Up to 35        | 31.2             | 37.1              |
| 35–55           | 48.3             | 43.6              |
| Above 55        | 20.5             | 19.3              |
| Income ($ per week) |              |                   |
| Less than 650   | 20.6             | 24.6              |
| More than 1750  | 31.1             | 20.6              |

Figure 1. Catchment area for the demand responsive transit (DRT) service in Northern Beaches, Sydney.

The main mode of public transport in NB is bus. However, the buses ply on low frequency and the bus stops are not easily assessable to users. To partly overcome this problem, TfNSW recently introduced an express bus service, called B-Line, between Mona Vale and Sydney CBD (around 40 km down south) [37]. The new service aims to provide more reliable, frequent, and fast service to travellers. Thus, the proposed DRT service is expected to act as a feeder service to the public transit stops (including B-Line stops).

4. Design of Survey Questionnaire

A survey was developed to study traveller’s willingness to shift towards the new service in comparison with their SQ alternative (auto or transit). A focus group was conducted to identify the important attributes to define the two competing alternatives (SQ vs. new service). The focus group comprised 3 experts (all males, between 35 and 45 years old) with more than 5 years’ experience in traveller behaviour modelling and design of SP experiments. The selected attributes include: 1) In-
vehicle travel time on main mode (which accounts for at least 60 percent of the total travel time), 2) in-vehicle travel time on DRT, 3) access time, 4) egress time, 5) waiting time, 6) travel cost, 7) number of passengers, and 8) number of transfers. The attributes for the SQ alternative were revealed by the participants during the survey. The attributes for the new service were deduced using the Google Directions API. For the given trip origin, destination, and future departure time (obtained by advancing the actual departure date and time by 5 weeks; reason behind 5 weeks is explained later in this section) information shared by the user, Google API provides travel and waiting times for each mode involved (walk, bus, etc.). This obtained data were then processed to form the SQ and the new service alternatives. The assumptions made while defining the two alternatives were:

SQ alternative:
- DRT travel time, waiting time, and number of transfers is zero for auto users;
- For auto users, travel cost includes parking, toll, and fuel cost;
- Number of passengers is 30 and travel cost is the total travel fare for public transport users.

New Service:
- The B-Line service is considered as the main mode;
- DRT services will significantly cut down walking time and travel time on other transit modes since they pick users from close to their origins/destinations and serve limited passengers at a time;
- New walk time after DRT implementation will be 20 percent of the original value;
- In-vehicle travel time of DRT will be 20 percent of the remaining walk time, i.e., 16 percent of the original walk time;
- Total waiting time (for DRT and main transit) is between 5 and 7 min;
- Standard Opal (multimodal smart card used in Sydney) fares apply for the new service, i.e., 0–3 km: $2.10; 3–8 km: $3.58; 8+ km: $4.61. A $2 discount at every subsequent ride from the first transfer.

Different types of existing trip chains, such as walk–drive–walk, walk–transit–walk–transit–walk, etc., were considered each for the intrazonal and interzonal cases. Under each case, the set of assumptions (discussed above) were used to calculate the attribute values for each trip-chain. For example, for an intrazonal trip (when the origin and destination provided by the participant are within the catchment area given in Figure 1), DRT services were assumed to be available at both origins and destinations. Additionally, the following few rules were defined to avoid invalid attribute values for the new service:

- Minimum main mode travel time should be equal to accumulated travel time for modes other than B-Line minus 16 percent of the original walk time;
- Minimum DRT time should be 3 min.

Thus, the first-choice scenario was formed using the attribute values of both the SQ alternative (car or transit) and the new service discussed above. The participants were asked to select the most preferred mode for their next trip. Figure 2 shows the first-choice scenario presented to one of the auto users.

A stated preference (SP) experiment followed next to study participant’s sensitivities towards the attributes considered by presenting multiple choice scenarios to them. SP methods are increasingly being used in transportation research for forecasting the impacts of a proposed alternative or a hypothetical policy decision. The attribute values for only the new service option were adjusted across the multiple-choice scenarios. Table 2 shows the attributes levels (or multipliers) that were used to pivot the attribute values for the new service obtained from the first scenario.

There were 7 choice scenarios in all that were shown to each participant. It included the first-choice scenario (values obtained from the revealed preference and the Google API information) followed by 6 SP choice scenarios. The following rule was defined in the SP design to populate the attribute values for the new service alternative: In choice scenario 1, if the participant selects the SQ alternative and if the difference between the main mode travel times of the two modes is greater than 30 min, then form the new service option by pivoting around the SQ alternative; otherwise, pivot around the values of new service obtained from the first scenario.
The survey design discussed above was implemented in an online survey instrument developed using web-based programming (HTML, Java, Python, etc.). An online survey was selected since the survey design involved programming to get information from Google API, process it, and present SP scenarios, which made it ideal for surveying in real-time. The organisation of the online survey for this study included:

- Introduction to the survey;
- Origin, destination, date, and time of the trip;
- Revealed preference section;
- Comparison between SQ and the New Service—the 1st choice scenario;
- SP scenarios;
- Socio-demographic section;
- End of the survey.

The survey first introduced the participants to the aim, purpose and benefit of this study, eligibility criteria, organisation of the survey, data confidentiality, etc. The eligibility criteria to the survey were: 1) Participants must be above 18 years, and 2) must have travelled into, out of, or within the catchment area in the last 4 weeks. Individuals below 18 years, which generally represent school students, were not considered for this study due to the following reasons: 1) The SP experiment involved a greater cognitive load, which could be beyond the capacity of many students, and 2) it was logistically challenging to recruit students for the survey. Participants not satisfying both the criteria were dropped from the survey. It then asked the participants to provide the origin, destination addresses, and date and time of the trip. A programme was written in Python, which did the following: 1) Used Google API to identify addresses, 2) checked whether the address lies within postcodes defining the study area, checked the recency of the trip, and 3) end survey for the

Figure 2. First mode choice scenario presented to a participant.

Table 2. Attribute levels used to pivot the new service.

| Attribute                                      | Levels          |
|-----------------------------------------------|-----------------|
| In-vehicle travel time for the main mode (minutes) | 0.8, 1, 1.2     |
| In-vehicle travel time for DRT (minutes)       | 0.75, 1.0, 1.25 |
| Access time (minutes)                          | 0.75, 1.0, 1.25 |
| Egress time (minutes)                          | 0.75, 1.0, 1.25 |
| Waiting time (minutes)                         | 0.75, 1.0, 1.25 |
| Travel cost ($)                                | 0.75, 1.0, 1.25 |
| Number of passengers                           | 2, 3, 4         |
| Number of transfers                            | −1, 0, +1       |

* New Service corresponds to a multi-modal trip which combines on-demand transport with public transit.
participants not meeting the eligibility criteria. A revealed preference section followed where the participants were asked to provide information on trip-related attributes. The first-choice scenario was then generated using a programme to extract public transit travel information between the origin-destination and determine the attributes for the new service alternative. It was then followed by the 6 SP choice scenarios. Finally, the socio-demographic section asked the participants to provide information on age, gender, income, household size, number of cars, etc.

5. Data Collection

Adequate clearances were sought from the university human ethics committee prior to commencing data collection. The survey was circulated online among the people residing within the catchment area. The survey administration and data collection was managed by an agency, Qualtrics [38], which distributed the survey url (weblink: https://login.qualtrics.com/jfe/preview/SV_eVifFAFFzs12pal?Q_SurveyVersionID=current&Q_CHL=preview) among its participant pool residing in the catchment area. The survey link was shared with a total of 2017 individuals of which 193 participants completed the survey, which translates to a response rate of 9.6 percent. The average survey response duration was found to be 8 min. The effective dataset upon data cleaning comprised 176 participants (130 and 46 participants in auto and transit streams, respectively), which equates to 1232 observations (auto: 910; transit: 322).

Table 3 shows the socio-demographic characteristics of the effective dataset. A slightly higher proportion of females (52 percent) responded to the survey when compared to males (48 percent). The gender statistic also resembles its counterpart for the NB area (as shown in Table 1). The collected dataset comprises around 60 percent young population, i.e., having an age up to 40 years [39]. The effective dataset also shows a minority of participants with low incomes, i.e., 12 percent of the participants earn less than $25,000 per annum [40]. Table 3 also shows that almost 60 percent of the participants have access to at least 2 cars and only 4 percent of the participants (all of them transit users) do not own a private vehicle. The trip purpose of the participants reveals mainly the social (54 percent) followed by home/work (33 percent) trips. In summary, the collected dataset indicates that the surveyed participants are mainly young, have higher disposable incomes, have access to more than one car, and undertook the most recent trip for social activity.

Table 4 summarises the trip specific attributes revealed by the participants in each of the two streams. The average in vehicle travel time on the main mode is revealed to be around one hour to cover an average distance of 30 km (approx.) across both streams. The average trip length corresponds to a rough distance between Northern Beaches and the Sydney CBD, which is a major work-hub, indicating that many participants travel close to the Sydney CBD. The 20th percentile value shows that a majority of participants have a travel time of at least 30 min. Similarly, the 80th percentile value signifies that some participants have travel times close to 90 min. This indicates that the collected dataset comprises both shorter (less than 30 km) and longer trip characteristics. The revealed access and egress time values for auto stream is less than transit stream, which implies that the latter group has to currently walk more to get to transit stops/destination. The proposed DRT service aims to reduce this component of travel potentially making it attractive to both auto and transit users. Similarly, travel cost is higher for auto users, since it also covers toll, parking, and fuel cost (taken as $0.15 per km [41]), in comparison to transit users (who just pay travel fare). The table shows transit users have to make one transfer on average during their journey with some making even two or more. The current waiting time at the transit stop is around 11 min, which is quite high. The new B-Line service aims to reduce the wait time by maintaining bus frequencies at headways of around 7 min on average.
Table 3. Descriptive statistics of the effective dataset.

| Attribute      | Category         | Percentage |
|----------------|------------------|------------|
| Gender         | Male             | 48.2       |
|                | Female           | 51.8       |
| Age            | 20 years and less| 5.9        |
|                | 21 to 30 years   | 23.5       |
|                | 31 to 40 years   | 31.8       |
|                | 41 to 50 years   | 20.0       |
|                | 51 to 60 years   | 8.2        |
|                | 60 years and above| 10.6      |
| Income (AU$)   | 25 K and less    | 11.8       |
|                | 25.1 K to 50 K   | 17.6       |
|                | 50.1 K to 75 K   | 23.5       |
|                | 75.1 K to 125 K  | 34.1       |
|                | 125 K and above  | 13.0       |
| Car Ownership  | 0                | 3.6        |
|                | 1                | 38.8       |
|                | 2                | 48.2       |
|                | 3                | 8.2        |
|                | More than 3      | 1.2        |
| Trip Purpose   | Home             | 3.5        |
|                | Medical          | 2.4        |
|                | Shop             | 7.1        |
|                | Social           | 54.1       |
|                | Work             | 29.4       |
|                | Others           | 3.5        |

Table 4. Summary of trip attributes revealed by the participants.

| Attribute                  | Stream  | Mean  | Std. Dev. | 20th Percentile | 80th Percentile |
|----------------------------|---------|-------|-----------|-----------------|-----------------|
| In-vehicle travel time     | Auto    | 58.4  | 44.9      | 30              | 75              |
|                           | Transit | 61.2  | 48.2      | 28              | 96              |
| Trip Length                | Auto    | 31.7  | 21.5      | 12              | 46              |
|                           | Transit | 30.3  | 24.3      | 13              | 39              |
| Access Time                | Auto    | 3.0   | 2.4       | 1               | 5               |
|                           | Transit | 10.0  | 9         | 5               | 12              |
| Egress Time                | Auto    | 5.4   | 4.3       | 2               | 10              |
|                           | Transit | 7.7   | 4.5       | 5               | 10              |
| Travel Cost                | Auto    | 12.0  | 11.7      | 2.4             | 20              |
|                           | Transit | 7.4   | 4.6       | 4               | 11              |
| Number of Transfers        | Auto    | -     | -         | -               | -               |
|                           | Transit | 1.25  | 1.1       | 0               | 2               |
| Waiting Time               | Auto    | -     | -         | -               | -               |
|                           | Transit | 10.6  | 8.4       | 5               | 16              |

6. Data Analysis

6.1. Latent Class Choice Modelling Framework

A latent class choice model (LCCM) is a statistical tool that can reveal the underlying subgroups of individuals from the observed multivariate data based on the frequency of these variables and response patterns [42]. The model is a parsimonious technique of clustering the observed choice patterns of individuals into mutually exclusive latent segments (using information such as socio-
demographics of decision makers). Unlike the RPL model, LCCM does not require any mixing distribution to be assumed upfront (other advantages discussed earlier in Section 2). LCCMs have found numerous applications in transportation planning to study the heterogeneity in the mode choice behaviour [43,44], route choice [45–47], and modality styles of individuals [48,49].

An LCCM is comprised of two components, namely a class membership model and a discrete choice model. The class membership model expresses the unobserved latent class segments in terms of the available data, like the socio-demographic information of individuals. The choice model, on the other hand, evaluates the probability of observing the response pattern of an individual, conditioned that the individual belongs to a specific latent segment. The response pattern can be a set of choices made by an individual in an SP experiment. The integrated framework is then run multiple times by progressively increasing the number of latent classes at each run. The optimum number of latent segments is determined based on the three criteria: 1) Overall goodness of fit, 2) model parsimony, and 3) behavioural interpretation of latent segments [49].

For the purpose of analysis in this paper, the auto and transit datasets have been pooled together, which has been done due to the following reasons: 1) To develop a single model, which studies travellers willingness to shift from the SQ alternative (auto or transit) to the new DRT service, and 2) to increase the accuracy of the model by using a larger (pooled) dataset. The LCCM specification for this dataset is discussed below.

### 6.1.1. Model Specification

Consider that a collected dataset for \( N \) individuals contain two parts: Cross-sectional data on the socio-demographic information and panel data of choice patterns for every individual. We first discuss the class membership model specification. Assuming the sample comprises \( C \) latent class segments, the utility (\( U_{nc} \)) for a person \( n \) belonging to a latent class \( c \) is given by Equation (1). In this equation, \( \alpha_c \) is a vector of parameters that is exclusive to class \( c \). \( W_n \) denotes a vector of observed socio-demographic characteristics of \( n \). \( \varepsilon_{nc} \) represents the of idiosyncratic error term and is assumed to follow Gumbel distribution with a variance of \( \frac{\pi^2}{6} \). This forms the MNL kernel for the class membership model, which is given in Equation (2). In Equation (2), \( \gamma_{nc} \) is the latent class prevalence (or probability) for individual \( n \) being in class \( c \). In order to maintain model identification, one of the latent segments is set as the base category. It means that only \( C - 1 \) segments can be estimated from a class membership model, with \( \alpha_c \) vector for the base category being normalised to zero.

\[
U_{nc} = \alpha_c W_n + \varepsilon_{nc} \tag{1}
\]

\[
\gamma_{nc} = \frac{\exp(\alpha_c W_n)}{\sum_{c=1}^{C} \exp(\alpha_c W_n)} \tag{2}
\]

For the choice model, an error component logit (ECL) specification is used to capture the correlation across multiple choice scenarios for individual \( n \). Assume that an individual is presented with \( T \) choice scenarios, each of which comprises \( J \) alternatives. For this study, \( J = 2 \), which corresponds to the SQ and DRT alternatives. The utility (\( U_{njt=SQ\,c} \)) that an individual \( n \), belonging to class \( c \), derives from the SQ (auto or transit) alternative in a choice task \( t \) is given by Equation (3). In this equation, \( AS\,C_{SQ\,c} \) is the alternative specific constant for the SQ alternative in latent segment \( c \), which captures the brand effect with respect to the DRT alternative (set as the base category). \( X_{njt} \) is a vector of attributes presented in the choice task for the SQ alternative. \( \beta_c \) is a vector of generic parameters, \( Auto_n \) is a dummy variable, which is 1 if individual \( n \) has auto as the SQ and 0 for transit, \( \gamma \) is the scale parameter, which captures the difference in unobserved variance due to the presence of auto sub-sample in the pooled dataset, and \( \sigma_c \) is the estimated variance of the error component for every latent segment \( c \). The error component \( \varepsilon_{njt\,c} \) which is considered to capture the impact of multiple responses by one individual, is assumed to be normally distributed with a mean and variance of 0 and 1, respectively. \( \varepsilon_{njt} \) is again the idiosyncratic term (as \( \varepsilon_{nc} \) in Equation (1)) that follows Gumbel distribution. According to the Boston–Chicago example presented in Train (2009), \( \gamma = 1/\sqrt{k} \) where \( k \) is the ratio of unobserved variances associated with auto sub-sample to transit sub-sample,
i.e., \( k = \frac{\text{Var(Auto)}}{\text{Var(Transit)}} \) [50]. \( y \) is then multiplied to \( \text{ASC}_{SQ} \) and \( \beta \) to get the parameters for the participants having auto as the SQ alternative. The parameter \( y \) is generally estimated in the model and \( k \) can be calculated from it.

Similarly, Equation (4) gives the utility specification \( (U_{nj-DRT})_c \) for the DRT alternative. Equation (5) gives the ECL kernel for evaluating the probability of choosing the SQ alternative in a single choice task. A similar equation can be written to determine the probability for DRT.

\[
U_{n(j=SQ)t|c} = (\text{ASC}_{SQ|c} + \beta c X_{njt} - (1 + \gamma c Auto_n) + \sigma c \xi_{nj|c} + \epsilon_{njt})
\]

Equation (3)

\[
U_{n(j=DRT)t|c} = \beta c X_{njt} + \sigma c \xi_{nj|c} + \epsilon_{njt}
\]

Equation (4)

\[
P_{nj=SQ|c} = \int \frac{\exp((\text{ASC}_{SQ|c} + \beta c X_{njt} - (1 + \gamma c Auto_n) + \sigma c \xi_{nj|c} \exp(\beta c X_{njt} + \sigma c \xi_{nj|c} \exp(\xi_{nj|c} \exp f(\xi_{nj|c} \exp d|))}
\]

Equation (5)

Let \( Y_n \) be the vector of observed response pattern across \( T \) choice scenarios for individual \( n \). Then, the probability of observing \( Y_n \) conditional on latent class \( c \) is given by Equation (6). In this equation, \( y_{njt} \) represents an indicator, which is equal to 1 if individual \( n \) selects alternative \( j \) in scenario \( t \) and 0 otherwise. Equation (7) gives the total probability of observing \( Y_n \) across \( C \) latent segments, which is calculated as the expected value of latent class prevalence and its corresponding conditional choice probability. Equation (7) is repeated over all individuals \( N \) to give the likelihood function. Equation (8) gives the likelihood function for the LCCM, which is solved until convergence using the maximum simulated likelihood method [50].

\[
P(Y_n|c) = \prod_{t=1}^{T} \prod_{j=1}^{J} (P_{njt|c})^{y_{njt}}
\]

Equation (6)

\[
P(Y_n) = \sum_{c=1}^{C} Y_{nc} \prod_{t=1}^{T} \prod_{j=1}^{J} (P_{njt|c})^{y_{njt}}
\]

Equation (7)

\[
L(\alpha, \beta, \gamma, \sigma) = \prod_{n=1}^{N} \prod_{c=1}^{C} Y_{nc} \prod_{t=1}^{T} \prod_{j=1}^{J} (P_{njt|c})^{y_{njt|c}}
\]

Equation (8)

6.2. Results and Discussion

Several model specifications were initially developed and compared against the proposed LCCM framework using the pooled dataset. Table 5 shows a comparison of the goodness-of-fit statistics for the alternative model specifications. The models 1 to 7 used in Table 5 are described as follows:

Model 1: MNL estimating \( \text{ASC}_{SQ} \) and \( \beta \)
Model 2: MNL estimating \( \text{ASC}_{SQ}, \beta \) and \( \gamma \) where \( \gamma \) is only multiplied with \( \text{ASC}_{SQ} \) * Auto
Model 3: MNL estimating \( \text{ASC}_{SQ}, \beta \) and \( \gamma \) where \( (1 + \gamma \text{Auto}) \) is multiplied with \( (\text{ASC}_{SQ} + \beta \text{X}_{njt}) \)
Model 4: Extending Model 1 by considering lognormal distribution for in-vehicle travel time
Model 5: Extending Model 2 by considering lognormal distribution for in-vehicle travel time
Model 6: Extending Model 3 by considering lognormal distribution for in-vehicle travel time
Model 7: The proposed LCCM discussed in Section 6.1.1
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Table 5. Goodness of fit for different model specifications tested.

| Statistic | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|-----------|---------|---------|---------|---------|---------|---------|---------|
| LL (zero) | -853.95 | -853.95 | -853.95 | -853.95 | -853.95 | -853.95 | -853.95 |
| LL (final)| -795.57 | -773.22 | -788.28 | -700.1  | -681.86 | -611.45 | -528.07 |
| # Parameters | 5       | 6       | 6       | 6       | 7       | 7       | 16      |
| Adj. $p^2$  | 0.0625  | 0.0875  | 0.0698  | 0.1731  | 0.1933  | 0.2757  | 0.3628  |
| AIC        | 1601.14 | 1558.44 | 1588.56 | 1412.20 | 1377.73 | 1236.9  | 1088.14 |
| BIC        | 1626.72 | 1589.14 | 1619.26 | 1442.90 | 1413.55 | 1272.71 | 1170.0  |

Models 1–3 apply an MNL that assumes invariant parameters across the population. Models 4–6 model taste-variation through in-vehicle travel time by assuming a log-normal distribution. Finally, model 7 is the LCCM. The idea behind developing these seven models is to compare the model performance of LCCM against the other two, which further supports the selection of LCCM for this study. The models are developed and estimated using the Pythonbiome software package [51]. Model 1 shows the MNL results on the pooled dataset, which assumes equal unobserved variance (i.e., fixing $\gamma = 1$) for auto and transit sub-samples. The model gives poor model fit statistics (e.g., adjusted rho squared, AIC and BIC values). Models 2 and 3, which estimate the scale parameter ($\gamma$) show: 1) a significant effect size for $\gamma$, and 2) improved model fit statistics when compared to model 1. This indicates that the auto sub-sample (comprising 130 participants or 910 observations) has a statistically different unobserved variance when compared to the transit sub-sample (46 participants or 322 observations), which eventually shows up in different effect sizes for $\Delta SIG$ and $\beta$ across the two sub-samples [50]. Similar observation is made when comparing models 4–6 where the goodness of fit improves when $\gamma$ is estimated. Furthermore, models 4–6 perform better than models 1–3 indicating that randomising the parameter (using 1000 standard Halton draws) for in-vehicle travel time further improves the model fit. Model 7, which also estimates class specific $\gamma$ along with $\Delta SIG$ and $\beta$, has the highest adjusted rho-squared and the least AIC and BIC values indicating the best model fit among the other models reported in Table 5. Hence, the results from the LCCM (Model 7) are reported and discussed in this section.

For the class membership model, socio-demographics are included as dichotomised variables, which represent: 1) Females (1: females; 0: males), 2) low-income individuals (1: Income less than $25K; 0: Otherwise) [40], 3) work trips (1: Trip purpose is work; 0: Otherwise), and 4) short-distance trips (1: Trip distance is less than 30 km; 0: Otherwise). The value 30 km is selected as it represents the average trip length revealed by the participants (refer to Table 4). The choice model comprises trip-related attributes (in-vehicle travel time, travel cost, access time, etc.) along with the error component term ($\sigma$), which is simulated using 1000 standard Halton draws during the maximum likelihood estimation (Equation 8).

Table 6 presents the parameter estimates for the two-segment LCCM using the pooled dataset. Several other LCCMs are also tested by trying different combinations of variables (socio-demographics and trip attributes) and the model has been chosen based on the following criteria: 1) Higher goodness of fit statistics (shown in Table 6), and 2) meaningful parameter interpretation of the trip specific attributes. Furthermore, additional LCCMs are developed by increasing the number of latent segments to three. However, the chosen model is preferred over three-segment LCCMs as it has: 1) A lower BIC value (2-LCCM: 1170.0 vs. 3-LCCM: 1193.5), and 2) model parsimony (2-LCCM: 16 parameters against 3-LCCM: 25 parameters).

Table 6 shows that the participants belonging to class 2 have a negative (and highly significant) effect towards in-vehicle travel time (−2.59), travel cost (−3.79), and access time (−5.19) attributes. In other words, participants belonging to this segment experience increased disutility (hence, lesser probability of selecting the two alternatives) with every unit increase in the trip-related attributes. While the parameter for egress time bears a negative sign (−0.166), which again corresponds to disutility, it is found to be statistically insignificant. On the other hand, the participants in class 1 have insignificant parameters for in-vehicle travel time, travel cost, and access time, indicating that they are indifferent towards them, and are sensitive towards egress time, which can be seen through a
negative and significant parameter value (−0.27). Thus, Table 6 shows contrasting tastes differences towards trip-related attributes between the two identified segments. The ASC parameter for class 1 is negative (−0.557) and significant indicating that the participants in this segment have a lower brand effect towards the SQ alternative (auto or transit) when compared to the new service. On the other hand, the ASC parameter for class 2 (2.8) is statistically insignificant, which means that the participants in this segment do not have any affinity towards either mode.

Table 6. Parameter estimates of the two-segment latent class choice model (LCCM).

| Parameters             | Class 1 | Class 2 |
|------------------------|---------|---------|
| Class Membership Model |         |         |
| Work trip              | 1.06*** | 0       |
| Constant               | −1.15** | 0       |
| Discrete Choice Model  |         |         |
| In-vehicle Travel Time | 0.00479 | −2.59*** |
| Travel Cost            | 0.0116  | −3.79*** |
| Access Time            | 0.265   | −5.19*** |
| Egress Time            | −0.27   | −0.166  |
| ASC$\text{SQ}$ (DRT as base) | −0.557*** | 2.80 |
| Scale ($\gamma$)       | 0.203   | 0.414*** |
| Sigma ($\sigma$)       | 0.00116 | −6.46*** |
| Uptake for the New Service (%) $^*$ | 96 | 44 |

Goodness of Fit

- Log-likelihood (zero) = −853.95
- Log-likelihood (converged) = −528.07
- No. of parameters = 16
- Adjusted rho-squared = 0.3628
- AIC = 1088.14
- BIC = 1170.0

*** significant at 95%; $^*$ average value evaluated over 50 simulations of error components.

The scale parameter for segment 2 is highly significant (0.414). As discussed earlier in Section 6.1.1, $k = 1/0.414^2 = 5.83 = \text{Var(Auto)}/\text{Var(Transit)}$. This indicates a greater unobserved variance in the auto sub-sample when compared to the transit sub-sample. Additionally, this scale parameter leads to two sets of parameters, one each for auto and transit as the SQ alternative. For example, the parameter for in-vehicle travel time for transit and auto is −2.59 and 0.414*(−2.59) = −1.07, respectively. Similarly, the parameters for cost (transit: −3.79; auto: −1.57) and access time (transit: −5.19; auto: −2.15) can be obtained. It can be observed that the participants having auto as the SQ alternative have lower effect sizes when compared to the participants with transit SQ alternative. This finding can be explained as follows: Car travel is generally more flexible when compared to transit. For example, the time to access car park is usually much lower when compared to bus stops and train stations. Additionally, 1) travel is typically not quite onerous in a car in contrast to transit (which often experiences standing and over-crowded conditions), and 2) car users generally have more disposable income and are thus not very sensitive towards price. Due to these reasons, car users are usually not greatly perturbed with a unit increase in the attributes. The scale parameter for segment 1 (0.203) is found to be insignificant, which indicates that there is no statistical difference between the unobserved variances. Similarly, the error variance parameter ($\sigma = −6.46$) is significant for segment 2, which indicates the presence of the unobserved correlation across multiple-choice scenarios in the SP experiment. However, this parameter turns out to be insignificant in segment 1. Table 6 also shows the average market uptake for the new service in class 1 and 2 as 96 and 44 percent, respectively. In other words, the participants belonging to class 1 are more likely to use the new service over cars when compared to class 2.
The results from the class membership model show that individuals commuting to/from work are more likely to belong to class 1 in comparison to class 2 (fixed as the base category). Thus, it can be said that the people who make work-related trips are more likely to be in class 1, which represents the user segment characterised by a high uptake (96 percent) for the new service. This finding can be explained as follows: As discussed earlier in Section 5, around half of the participants have a trip length of at least 30 km, which is the distance to the areas around Sydney CBD. An express bus service, called the B-line service, operates at frequent intervals connecting Northern Beaches to the Sydney CBD. The proposed DRT service aims to supplement the B-Line service by providing easy and direct access to the latter while maintaining similar level of comfort and convenience as offered by private car. Thus, the new service provides a conducive mode allowing commuters to do other activities such as reading, responding to emails, etc., while on DRT or B-line bus. This leads to reduced (or no) disutility towards in-vehicle travel time, cost, and access time (since DRT facilitates close to home pickup), which justifies the insignificant parameters for these three attributes. As the DRT service is not currently available around the Sydney CBD, reaching the destination (workplace) from the bus stop is rather challenging which could explain the negative and significant parameter for egress time. On the other hand, class 2 is more likely to be composed of people who travel for non-work purpose (social, shopping, etc.) and are less inclined to use the new service. This observation can be interpreted as follows: Table 3 shows that more than 60 percent of the trips are made due to non-work purposes, and 70 percent of the non-work trips are made using cars. The household travel survey report of Sydney also brings out a similar finding where cars account for around 65 percent of the social/recreational trips with transit contributing only 6 percent [52]. In other words, as cars offer greater flexibility, these are the preferred mode of travel for the participants belonging to segment 2 with only 44 percent uptake for the new service.

The value of travel time savings (VTTS) for the individuals under this segment is calculated as AU$13.7/hr, which is similar to the one (AU$15.5/hr) found by Saxena et al. (2018) [47]. The obtained VTTS value implies that the participants in this segment are willing to pay additional AU$13.7 to reduce the travel time by an hour. This indicates travel disutility for individuals in general, which makes sense and is consistent with previous literature. A similar value, AU$17.3/hr, is also obtained from Model 3 (where in-vehicle travel time, cost, and scale are significant), the results of which are presented in the Appendix A. Using the income distribution shown earlier in Table 3, the weighted average salary is calculated around AU$75 K (assuming the median of income range). Assuming work duration of 35 h/week and 52 working weeks, in general, the hourly wage rate of the participants comes to be AU$41 on average. This value is much larger than the obtained VTTS indicating meaningful interpretation of the results.

7. Conclusions, Limitations and Future Works

Previous research efforts have found demand responsive transit (DRT) to be an effective feeder service to the existing public transport system. It provides an improved mobility service to travellers, thus making public transport a more attractive travel option in comparison to private vehicles. This work conducts an SP survey to determine the market uptake of the new service option against the status quo alternative (auto or transit) in the lower population density area of Northern Beaches in Sydney. Results from the LCCM indicate the presence of two user segments, one of which shows a higher willingness to shift towards the new service.

The findings from this study provide the following information to planners. First, the LCCM identifies user-segmentation and the corresponding uptake for the new service within each identified segment. This proportion has not been reported previously in the literature in the context of DRT market penetration. Such metric can be useful in quantifying the market uptake and acceptability of the new service (i.e., DRT service) in a selected area. Second, the model also identifies the characteristics of each identified segments, which can facilitate framing policies aimed at improving the DRT uptake. For example, segment 2 users are found to prefer private car for social/recreational trips. Thus, planners and operators can come up with schemes (identifying suitable schemes is beyond the scope of this paper), which can potentially lead to a shift towards new service in this segment.
The above findings should be discussed in the light of the assumptions and the constraints considered, which become the limitations of this study. First, the SP survey mainly considers the likelihood of selecting the new service in comparison to the existing mode. It does not take into consideration the possibility of moving to a third alternative (apart from the SQ and the new service). Second, the individual sample sizes for auto and transit datasets (130 and 46 participants) are relatively small (due to low response rate in a low density area of Northern Beaches, Sydney), particularly for the transit stream, which could explain some of the parameters not turning up statistically significant and/or of expected sign.

Future research will focus in the following directions: 1) A more comprehensive survey dataset from the study area will be collected to obtain meaningful information, and 2) the prospect of introducing DRT services in other regions of Sydney, including the well-connected areas, will be studied. Work is currently underway on both the directions.

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**Appendix A**

**Table A1.** Parameter estimates from Model 3 discussed in the paper.

| Parameter                  | Model 3          |
|----------------------------|------------------|
| ASC (DRT as base)          | 0.195 *          |
| In-vehicle travel time     | -0.205 ***       |
| Location parameter        | --               |
| Scale parameter            | --               |
| Access Time                | -0.278 ***       |
| Egress Time                | -0.108           |
| Cost                       | -0.237 ***       |
| Scale (γ)                  | 0.444 ***        |

**Goodness of Fit**

| Parameter                  | Value   |
|----------------------------|---------|
| Log-likelihood (zero)      | -853.95 |
| Log-likelihood (converged) | -788.28 |
| No. of parameters          | 6       |
| Adjusted rho-squared      | 0.0698  |
| AIC                        | 1588.56 |
| BIC                        | 1619.26 |

“*” significant at 95% “**” significant at 90% “***” significant at 85%.

Table A1 shows negative parameters for the trip specific attributes indicating that the participants, in general, are sensitive towards them, which is consistent with the results from the LCCM and behavioural sense. The scale parameter is significant indicating that the unobserved variance in the auto sub-sample is larger than transit sub-sample. The VTTS according to this model is calculated as AU$17.3/hr. This VTTS value is similar to the value obtained from the LCCM (AU$13.7/hr) and the previous literature.
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