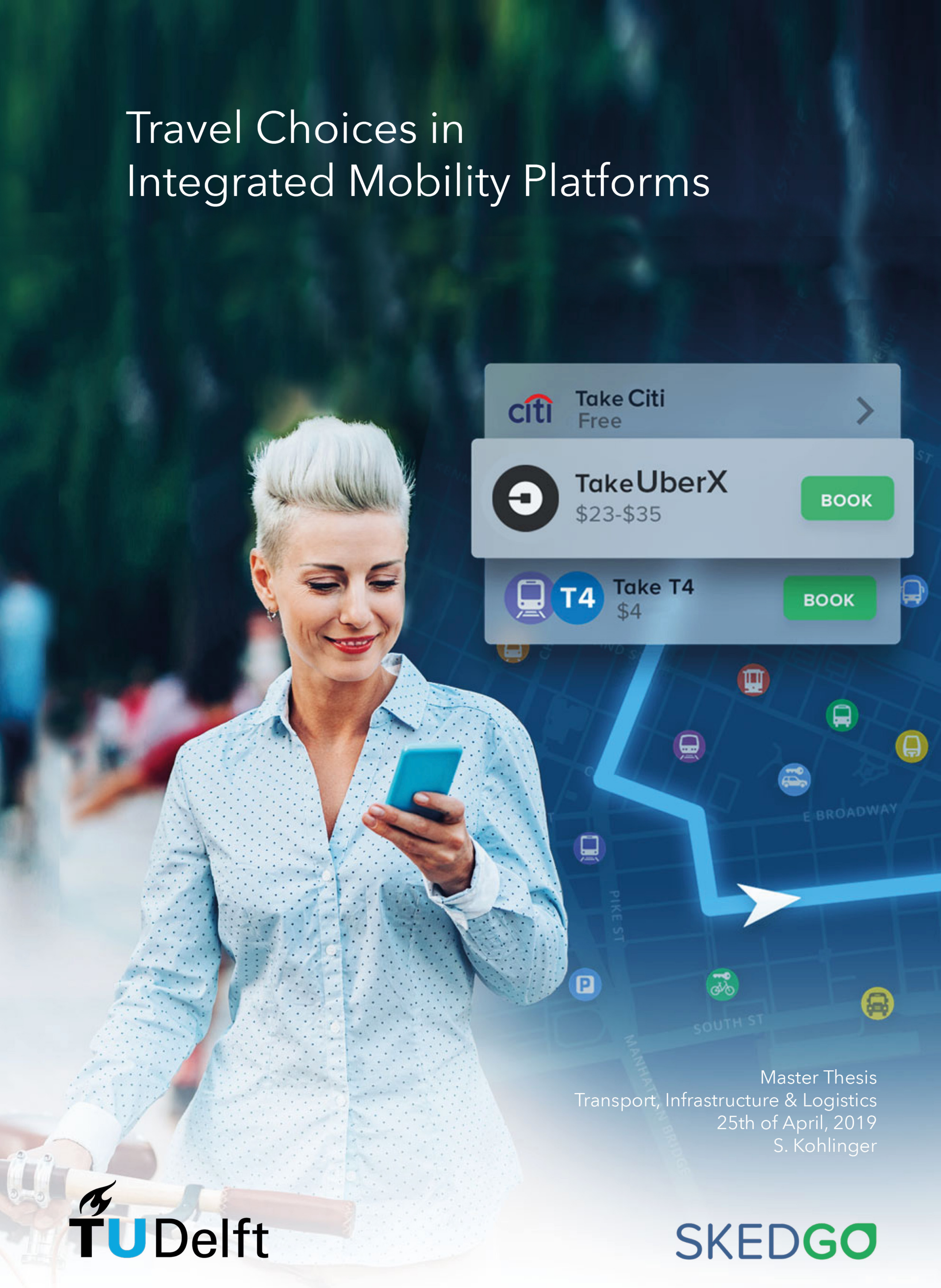
Travel Choices in Integrated Mobility Platforms



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SKEDGO

Travel Choices in Integrated Mobility Platforms

SkedGo & TU Delft

by

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Preface

Six months ago, this master thesis project kicked-off, and I began my final journey at Delft University of Technology. The report in front of you describes the research that I conducted for the MSc Transport, Infrastructure & Logistics and company SkedGo.

At the start of this research I had to get acquainted with many new research areas. Such as the concept of integrated mobility platforms and the context of smartphone applications that produce sophisticated data. I can say my analytical skills have undergone a major boost during this research. Luckily, I was also able to touch some areas that were more familiar to me. Such as the area of choice behavior, a topic I got familiar with during a course I enjoyed at the university.

One of the most exciting parts about this research was being able to conduct part of it in Sydney. Working at the office next to my supervisor Tim was very educative, having many interesting discussions about mobility and what the future could look like. Besides the work, I very much enjoyed the SkedGo Christmas social, Wednesday office lunches, the cool city of Sydney and the final goodbye gathering. For this I want to thank Tim, Adrian and all the other people in Sydney that made me feel welcome.

Next up is a big thanks to my thesis committee from Delft University; Casper, Sander and Oded. Thank you for motivating me during all our meetings, and meeting me at early hours over Skype. Even if results were sometimes not what I had hoped for, I always left your offices with a good feeling, encouraged to make the best of it.

During my thesis I met many interesting people and I am very grateful for all the interesting feedback and help that contributed to my research. A special thanks goes out to Ahmad, without whose help I couldn't have cracked the data.

Lastly, thanks to all my family and friends for the mental support and putting up with my stress tornado's. And to those of you that read past this first page, enjoy the read!

Stephanie Kohlinger
Delft, April 2019

Contents

List of Figures

List of Tables

1 Introduction

Current trends of urbanization cause a rise in the demand for transportation in urban areas (Brendel & Mandrella, 2016). This puts a growing pressure on urban passenger transport systems (Kamargianni, Li, Matyas, & Schäfer, 2016; Sochor, Stromberg, & Karlsson, 2015), resulting in increased emissions, overloaded infrastructures and congestion (Eryilmaz et al., 2014; Hildebrandt, Hanelt, Piccinini, Kolbe, & Niero-Bisch, 2015). To address these issues and keep up with the transportation demand, the need arises for new and innovative solutions towards a more efficient transport system. The main challenge for future transport system lies in finding alternatives to private car use in the form of flexibly provided mobility (Brendel & Mandrella, 2016; Hildebrandt et al., 2015).

Current development of solutions takes place in many forms, and new mobility services are constantly entering the market (Holmberg, Collado, Sarasini, & Williander, 2016). As a result, travellers today are exposed to a broad range of transport services, including new mobility services such as car-sharing and bike-sharing, and traditional services such as public transport.

It is believed that, especially in combination, various modes of transportation can complement each other and serve as an attractive substitute to private vehicles (Kamargianni et al., 2016; Smith, Sochor, & Karlsson, 2018). For example, novel transport services, such as on-demand services, can complement public transport due to their flexibility (Alonso-González, Van Oort, Cats, & Hoogendoorn, 2017).

The combined use of these modes is also known as multimodal travel. In multimodal travel, people switch their main mode of transportation for different trips in a longer period (e.g. in the course of one week), or they combine several modes of transportation in one trip, called intermodal trips (Eryilmaz et al., 2014).

For travelers, the advantage of using multiple modes and transport services together is that it can provide travelers with a flexibility in their mode choice (Schade, Krail, & Kühn, 2014). It allows users to opt for a mode that they perceive most convenient for any door-to-door trip. For example, users can for example use one mode on a home-based trip and return with another mode. It is expected that such flexibility contributes to meeting individual travelers mobility needs, and therefore decrease the need to own a car (Strömberg, Karlsson, & Sochor, 2018). Hence, multimodal travel is positioned as one of the most effective ways to tackle the negative effects on urban mobility and provide people with their mobility needs (Nuzzolo, Crisalli, Comi, & Rosati, 2014).

Integrated Mobility

The combined use of transportation modes and services is however not straightforward (Hilgert, Kagerbauer, Schuster, & Becker, 2016). Different operators often require different payment methods, subscriptions and mobile applications (Kamargianni et al., 2016). And, integrated information and planning assistance is needed to compare and combine different modes and services for trips for multimodal travel. Because of these complexities, solving mobility issues is not only limited to developing new services. More importantly, it requires a renewed organizational approach that focuses on 'integrated mobility' with improved access to different transport modes (Mulley, 2017; Strömberg et al., 2018).

This concept is also known as Mobility-as-a-Service (MaaS), it is defined as following:

'A mobility distribution model that delivers a transportation need to users through one single digital interface, by integrating and bundling different transport modes into mobility packages'. - Hietanen and Datson (2016)

A certain ambiguity exists surrounding the concept, its characteristics and in which way they can be addressed (Jittrapirom et al., 2017). But the idea behind the concept is integrated and seamless mobility, and according to Kamargianni et al. (2016) it leans on three types of integration:

1. *Payment and ticketing integration:* this applies to systems where one ticket or payment method can be used to access all available modes in a system. Examples include the OV chipcard for public transport in The Netherlands or the Opal card for public transport in Australia.
2. *ICT integration:* this is also referred to as integrated multimodal information (Grotenhuis, Wiegmans, & Rietveld, 2007). Information is provided through a centralized mobility platform that unites information of different modes and provides travel planning assistance.
3. *Mobility packages:* through packages or bundles, users can purchase a predefined volume (i.e. time or distance) of access to transport modes. These mobility packages should be altered to personal travel needs and can be paid for through subscriptions or 'pay-as-you-go' options (Ho, Hensher, Mulley, & Wong, 2017).

Out of these integration types, this research focuses on ICT integration, and more specifically, integrated mobility platforms. The functions of these platforms are provided through smartphone applications or online interfaces. Such systems are often complex as they must gather information information from multiple sources, such as public transport timetables, real-time traffic information on public and private transport systems and car-sharing availabilities (Hilgert et al., 2016; Utriainen & Pöllänen, 2018).

As the platforms improve interoperability between modes, they simplify and motivate the use of multiple transportation modes (Kamargianni, Matyas, Li, & Schäfer, 2015; Karlsson, Sochor, & Strömberg, 2016). In the past, multiple information systems had to be consulted separately to plan a multimodal trip (Pronello, Simão, & Rappazzo, 2017). With integration, users are able to compare and combine any type of mode or service, and have the possibility to rationally choose the best path for their trip (Nuzzolo et al., 2014).

Because the concepts of integration and MaaS seem promising, different types of integrated mobility platforms have emerged. But, due to the novelty of the concept, researchers are only just starting to understand (and quantify) the travel behaviour of users with respect MaaS and integrated mobility platforms. For example, it is unknown what user preferences are with respect to mobility integration (Ho, Hensher, Mulley, & Wong, 2018). Such as, what modes they prefer (Matyas & Kamargianni, 2017), what factors dominate their choices, or what they are willing to pay for different components/services in an integration. But also if users even take advantage of the platform offerings, including many different modes and multimodal trip plans.
In short, there is a need for open evaluation of existing platforms, to uncover how users behave in response to such a system.

Research into the travel behavior in response to the platforms is valuable as a profound understanding of this behavior can function as a guide towards designing efficient and user-friendly forms of integrated mobility platforms (Gan & Ye, 2018) (Kamargianni et al., 2016).

Existing Research

Up until now, only a few researches exist that provide a quantifiable insight into the travel behaviour of users in multimodal environments. And, most of this existing knowledge on the topic is gained through trials and surveys. The specific research topics also vary as part of the conducted research on the topic focuses on multimodal information systems, while another part of the existing research focuses more on the broader concept of MaaS.
Firstly, multiple existing studies investigate the mode choice behavior under multi-modal information. However, these studies do not explicitly address state-of-the-art integrated mobility platforms that include innovative modes such as car sharing. One of the most recent studies by Gan and Ye (2018) investigate mode switch decisions for platforms that integrate information on car traffic and subway park-and-ride. Since a

platform like that does not exist yet, their research is based on simulations.

Secondly, studies exist that include a broader and more innovative range of transportation modes. However, these studies focus on a complete concept of MaaS and how it should be designed. As a fully designed service does not exist yet, these studies are based mostly on surveys and trials. For example, a research by Matyas and Kamargianni (2017) provides an understanding of the decision-making process for purchasing a MaaS subscription plan. With a stated preference experiment they uncover that attributes such as flexibility and cost play an important role in the choice for a bundle. Then, Ho et al. (2018) perform another SP experiment towards MaaS offerings and the potential uptake of the concept among segments in the population. This research leads to many relevant insights, such as the willingness-to-pay (WtP) for different modes in an integrated platform (i.e. car sharing and unlimited use of public transport).

A research using revealed preference (RP) data from a trial group is performed by Strömberg et al. (2018). This research evaluates a MaaS trial called Ubigo, to assess the potential shift away from private car use that MaaS could evoke. The results show potential for MaaS to reduce private car use. However, the results are based on a trial in which people are willing to participate. For this reason it is uncertain whether these results would also apply to the general population.

As real MaaS implementations and integrated platforms were not available at the time of these researches, the necessary passive RP data for conducting these researches was also unavailable. Therefore, these researches were mostly based on stated choice experiments, as these allow exploring choice situations that are unavailable in reality(Guzzo & Mazzulla, 2004).

Stated preference vs. Revealed preference

A problem with the existing types of researches is that they cope with hypothetical bias, a case in which the results deviate from real market evidence (Hensher, 2010). Because respondents are put in hypothetical situations, their actual actions might behave inconsistently with actual behaviour. This phenomenon occurs for several reasons. Firstly, respondents do not feel the consequences of their choices and do not really have to commit to their choices. Secondly, respondents can be influenced by factors such as their perception of what the interviewer expects or wants to ask (Train, 2009). For example, a 'good subject' effect can occur, suggesting participants behave in ways they think they are supposed to behave (Chorus et al., 2007). Because of these reasons, it is often unknown what actions would enfold if a hypothetical situation actually occurred.

This hypothetical bias can be avoided using revealed preference (RP) data for research. RP data, common in transportation studies, is based on actual actions and represents actual choice outcomes. Using RP techniques therefore reflects travel behaviour in a real context. In RP research, data is usually collected through travel diaries of respondents, or more recently also through smartphone data, such as collected GPS traces or smartphone app data. But, even RP experiments are often subject to hypothetical bias because the respondents are mostly actively recruited. Respondent already willing to join experiment or trial and this can affect results. Another consequence of actively recruiting respondents for RP data is that the sample sizes are often limited (Chen, Ma, Susilo, Liu, & Wang, 2016), such as N=80 for the Ubigo trial.

To overcome such issues a solution lies in collecting 'big' and passive RP data. Big data, resulting from smartphones, enables collection of large amounts of data. Passive refers to those data not collected through active solicitation (Chen et al., 2016). Examples of such data include smartcard data, or data from travel planner applications; they are generated for purposes that are not intended, but can potentially be used for research. The upside is that this type of data leads to a very high ecological validity, and lots of data is available (Chen et al., 2016).

Challenges with these data is that the researchers are not able to control the attributes in the data. Therefore, issues as multicollinearity can appear amongst attributes in the data. Another critical challenge includes a self-selection of users that occurs, in which users select them selves into experiments. This for example occurs with smartcard data; as the use of these cards mostly attracts frequent public transport users, this particular group of users will automatically engage in the experiment. Another issue with passive RP data is that, for some data sources, not much information is known about the users as personal information is usually anonymized for privacy reasons. Such occasions can make it difficult to determine the causation of results. Lastly, if smartphone app data is used as a passive RP data source, no reference research is available that focuses on travel behaviour based on this data type. Therefore it is questionable whether this type of data is suitable for conventional travel behavior research methods.

1.1. Objective and Research Questions

Given need for research on integrated mobility platforms, preferably with a passive RP data source, this research takes on a novel approach. Passive RP data is collected from a smartphone application for integrated mobility, allowing to evaluate travel behavior in integrated mobility platforms. The data collected for this research results from an app called TripGo. In short, the app consists of a travel planner with multimodal functionalities. Therefore, the collected data consists of users' travel choices in a multimodal and integrated environment. This data allows to investigate how users actually behave in such integrated environments, with a broad variety of transportation modes available, and without being subject to hypothetical bias. Thereby, this research offers behavioural insights on integrated mobility with a high ecological validity. The main objective of this research is to create a better understanding of the choice behaviour of travellers in an integrated environment provided by a mobility platform. Simultaneously, it is experimented to apply conventional travel behaviour methods to this type of data. To accomplish the main goal and guide this research, the following series of research questions is set up:

1. **Do travellers make use the broad range of transport options provided by the mobility platform?**
2. **What factors influence travel choices for mobility services in integrated mobility platforms?**
3. **Is revealed preference choice data from smartphone applications usable for discrete choice analysis?**
4. **How can knowledge on users' travel choices improve the integrated mobility platform?**

1.2. Approach

This section elaborates on the approach and steps taken to achieving the research goal and answering the research questions. An overview of the research approach is presented in Figure 1.1. Addressing this research is done in two phases, a data phase and a choice modelling phase. The problem defined throughout this first chapter functions as a starting point for the research.

The first research phase starts with the preparation of the data. As no dedicated method is available for this step, a method is developed throughout the first research phase. During data preparation, a set of RP choice data is formulated and noise is reduced from the data as much as possible. The resulting choice data is then inspected on multiple factors (data size, consistency, formulation accuracy, sanity, noise, errors etc.). Each time an issue appears, the processing method is updated, and the data is prepared again. If first check is passed, an in depth analysis of the data is performed. This analysis also brings to light several issues, that are then again fed back into the processing method. The loops in this phase are performed many times until the choice data appears to be complete and free of errors. Each step taken during this processing is incorporated into the processing method.

In the end, the first phase results in choice data for the next phase and some data analytics that provide answers to the research questions. By deriving general statistics on the data, an answer can be provided to research question 1. These analytics also offer insight into the data and case study that is needed for answering research questions 3 and 5. The data phase of this research is reported in Chapter 3.

The second phase of this research focuses on choice models. To investigate this travel choice behavior, the method of discrete choice modelling is applied. A detailed description of this method and why it was chosen can be read in Chapter 2. The first step of this phase involves the development of choice models. These models allow to estimate the importance of different factors in travel choices. Therefore, the estimation results of these models provide an answer to research question 3. Multiple models are developed to provide an answer to this question. The choice modelling phase of this research is reported in Chapter 4.

Finally, during model application, the best choice model is applied to improve the TripGo smartphone application. The proposed application is then subjected to a number of tests on a set of test-data to validate the results. With this application an answer is provided to research question 4. This part of the research is reported in Chapter 5.

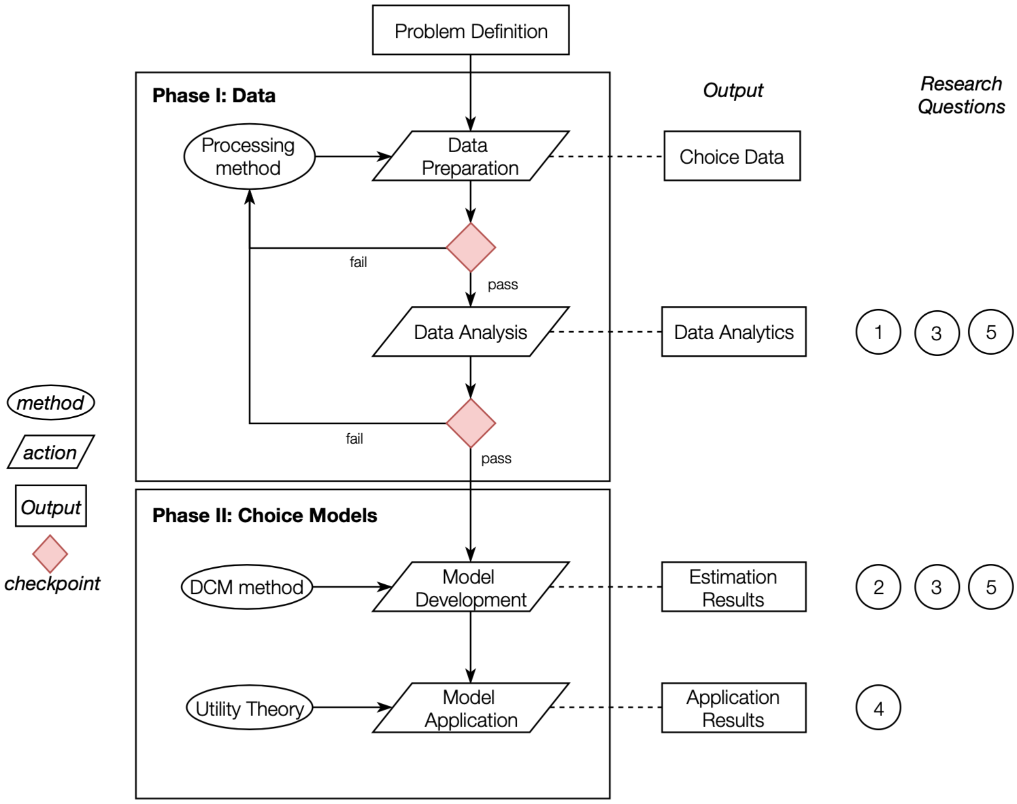

Figure 1.1: Research Approach

2
Methodology

This chapter describes the methods applied to conduct the research defined in Chapter 1. To start with, Section 2.1 explains the method used for data processing in the first phase of this research. Next, the method of Discrete Choice Modelling for the second research phase is explained in Section 2.2.

2.1. Data Processing Method

Throughout this research, a method is developed for preparing data from smartphone applications for travel behaviour studies with discrete choice models. From the applied approach (explained in Section 1.2) a method consisting of two parts is created; a first part for transforming raw smartphone app data into RP choice data, and a second part for reducing noise from the data. For constructing choice data a set of steps and rules is developed that can be applied when transforming smartphone app data into choice data. To ensure the quality of the data for travel behaviour research, the second part of this method includes an approach for eliminating noise from the data.

2.1.1. Transforming Smartphone Data into RP Choice Data

Raw data from smartphone apps are the starting point of data processing. Smartphone app data often comes in massive volumes of unstructured (or semi-structured) data strings. The steps and rules described in Table 2.1 provide a method for structuring this type of data into consistent tables. While applying this method, it is aimed for:

1. Consistent formulation of the choice data
   Consistency is important for keeping an overview in the large variety and amount of information. This is essential for deriving data analytics and formulating models.

2. Accurate and complete representation of information
   It is the analyst's job to correctly transform the smartphone data into choice data, and include all relevant information. Achieving this requires a pragmatic approach in which the analyst accurately interprets the data in relation to the case study.

3. Minimal size of the choice data
   Capturing the information of smartphone data in consistent table can lead to large data files. A large data set is unwanted as it increases the computation times of processing and modelling software. Therefore, data must be simplified as much as possible, without reducing the accuracy of the data.

During the construction of choice sets, trade-offs must be made between these aims as they they are often interfering and can not all be optimal. For example, the most consistent and complete choice set formulations contribute to a large data set. While on the other hand, reducing the size of the data set requires a more inconsistent formulation or simplification of the available information.

Goal	**Step**	**Rules**
Understand data	**1. Understand raw data** a. Investigate small number of strings (2-5) b. Identify what information is provided in the strings c. Identify consistent and inconsistent part(s) of strings	· Consistent information is present and equally sized for each observation · Inconsistent information is absent in some observations and/or different stringsize in different observations
	2. Define what information to include in the choice data	· Choice data must at least consist of choice sets and choices
Design choice set framework		· The framework consists of a table, in which each row represents an observation · Each column represents ordered category that includes the same information for each observation
Determine size framework	**3. Determine number of alternatives in the choice data** a. Identify number of modes in the data b. Determine modes to include in choice model c. Identify number of mode combinations in the data, to uncover the number of unique alternatives d. Identify where to accommodate for double alternatives e. Create mode labels	· To exclude modes from the data, delete all observations they occur in · If total number of observations becomes too small, extract more data · If too many mode combinations exist in the data (i.e. >500), simplify: Simplify option 1: neglect order of combined modes Simplify option 2: merge double occurring modes in combinations · Identify for each alternative the maximum number of times it occurs in one observation, these are doubles · The total number of alternatives in the choice data equals the sum of unique alternatives and their doubles.
Determine size framework	**4. Determine representation of alternatives** a. Select attributes to include for each alternative b. Determine how to represent inconsistent attributes	· Each alternative represented with same number of columns · Each alternative is provided with same information · If desired attribute/component is not directly recorded in the data might be possible to compute that attribute manually · Starting point for inconsistent attributes: create a column for each existing attribute for each alternative. If the number of columns gets too large: Simplify option: identify the number of columns needed to accommodate for the alternative with maximum number of attributes required. · Represent each alternative with identified number of columns. · If attributes are now presented inconsistently per alternative, record inconsistency in alternative label
Compute choice data	**5. Create framework for choice data table** a. Create table b. Create table header	· Create columns for each element defined in step 2. For choice sets create columns for each alternative and their attributes. (#alternatives * #attributes) · For each column in the data, define category name representing what the column contains
	6. Store data from strings into framework	· Store information of strings in columns they belong, add zero's to columns that do not apply to information in the string
	7. Attribute scaling	· Scale attributes to unit such that the scales are somewhat within the same range (i.e. all attributes ranges within 10-1000)

Table 2.1: Method for constructing smartphone data into RP choice data

2.1.2. Reducing Noise from the Choice Data

With RP data, it is important to ensure the data quality and limit the amount noise that can interfere with accurate model results. This method offers an approach for identifying and resolving issues and errors in the data, in order to reduce noise. Achieving this requires a pragmatic approach, in which identified issues must be investigated to more depth in order to find a suitable solution. The designed approach is depicted in Figure 2.1.

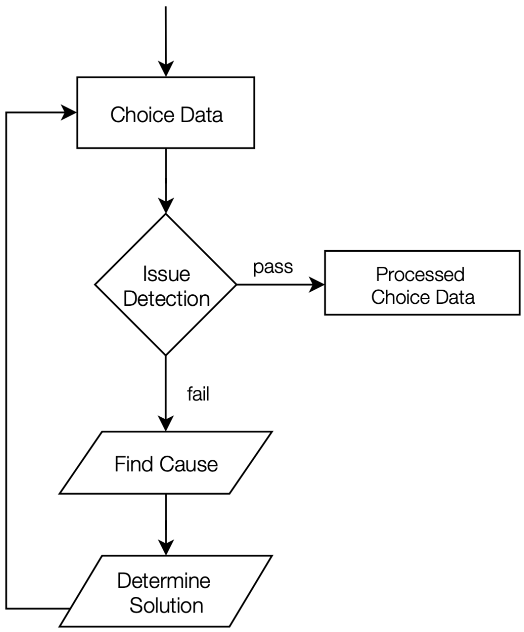

Figure 2.1: Approach to Noise Reduction

The choice data created with the method from Section 2.1.1 functions as a starting point for noise reduction. The first step in this approach is to identify issues. In the data, four types of issues can be uncovered, Table 2.2 provides the method for identifying each of these issues.

No.	Issue Type	Description	Identification Method
1.	Double records	These consist of identical observations are recorded into the data multiple times	Inspect rows for duplicates
2.	Missing information	Occurs when a value for one or more attributes of an alternative is missing	Inspect cells for empty cells
3.	Invalid attribute value	Occurs when attribute values are of unexpected sign (i.e. negative travel time)	Inspect attribute levels: · compute range [min,max] · compute boxplots
4.	Outliers	Attrribute values that are distant from other observations due to measurement errors	Inspect attribute levels

Table 2.2: Issue Identification

After identification of an issue, the next step is to investigate the cause of the issue, and to find a suitable solution. The different types of issues require different solutions, an approach to solving each issue type is given below:

- **Issue type 1: Double Record**
  A double record in the data is an invalid representation of reality. The solution therefore is to keep only the unique records.

- **Issue types 2 and 3: Missing information and invalid attribute values**
  Before deleting records with issue types 2 or 3, it must be investigated what the repercussions of deleting observations are for the data. Investigating the following points can offer insight towards a suitable solution:

  - What number of observations is affected with this issue?
  - What modes are affected with this issue?
  - Does deleting the affected observations influence mode shares in a) chosen trips and b) choice sets?

  Based on these questions it can be argued what the repercussions are for results, when a solution is applied. If it appears that eliminating observations severely influences results, it can be chosen to estimate values for the erroneous attributes (i.e. through logistic regression).

- **Issue type 4: Outliers**
  For removing outliers in this type of data, the attribute ranges are investigated and judged on the veracity of the extreme values. With this type of data, it is expected that attribute values cover a large range possibilities, and therefore conventional methods for identifying statistical outliers do not apply. The aim is to only delete those observations that appear to be outliers due to measurement errors. To achieve this, the attribute ranges must be checked and it must be judged whether the maximum values seem plausible. Observations including implausible outliers must be eliminated from the dataset.

It is important to note that in this method, eliminating issues always takes place at the level of the observation, and not at level of the alternative. This way the observations are represented as accurately as possible.

2.2. Discrete Choice Modelling

This section starts by explaining why the method of Discrete Choice Modelling is applied in this research in subsection 2.2.1. Here, it is also explained which discrete choice model is chosen to apply to this research. Next, subsection 2.2.2 explains how such models are mathematically formulated and estimated.

2.2.1. Method Selection

The data available for this research consists of RP choices in a mobility platform, and the aim of this research is to uncover the behaviour that leads to those choices. Available methods for travel behavior research include structural equation models, cluster analysis, discrete choice analysis and non-quantitative models. In this case, the available data does not include the required information for structural equation models, in which psychological factors behind travel behavior are research. And, a cluster analysis and non-quantitative methods are more suitable for other research purposes. The method of Discrete Choice Modelling is well-suited to capture the decision making process behind choices, and is therefore most appropriate to apply in this research.

In the method of Discrete Choice Modeling, it is assumed that choices are made based on certain set of factors. Discrete Choice Models (DCMs) are formulated, such that these factors are captured in so-called utility functions. By using choice data (consisting of choices for alternatives in a known choice set), it can be estimated how important each of the specified factors is for the decision-making process. Also, given the model formulation, it can be derived how well the formulation captures process that leads to the choices in the data.

With this method, researchers are enabled to (1) understand what factors play a role in choices people make, (2) derive relationships and trade-offs between certain specified factors and (3) predict future choices.

Within discrete choice modeling, several model formulations exist. Four models that are considered for this research include the multinomial logit model (MNL), the nested logit model (NL), the mixed logit model (ML) and the Latent Class Discrete Choice Model (LCDCM). In choosing one of these models, the following needs must be met:

- The model must be able to provide a realistic representation of the decision making process of users (also known as the true data generating process).
- The model must allow for straightforward economic appraisal.
- The model must be able to process a large set of RP data within a reasonable amount of time.

During this research, all of the mentioned models were tested and the most suitable model appears to be the MNL model. MNL is the most basic of the three models. It allows for easy economic appraisal, and is able to

process large data sets within a reasonable amount of time. However, because of its simplicity, it is possible that this model does not provide the most accurate representation of the true data generating process.
The other available models cause issues when they are applied to the specific data for this research:

- *Nested Logit*
  MNL can give problems when alternatives are correlated, and some groups of alternatives are more similar then others. In this study, a broad variety of modes is included in the alternatives, and many of them show similarities. Therefore, tackling the issue of correlated alternatives could be relevant in this case. An NL allows to create nesting structures in the models, and therefore ensures correlations between similar modes are captured. With this model capability, it is expected that NL provides a more realistic model. However, from testing the model, it appears that NL is in this case not able to provide a better model in terms of explaining travel behaviour.

- *Mixed Logit*
  ML is also expected to provide a more realistic model. The most important advantage of this model is that it can account for heterogeneity in the tastes of decision makers, and for panel structures in the data. A disadvantage of this model is that simulation is required for model estimation. For large data sets this leads to excessive computing times, and therefore ML is not suitable to apply in this research.

- *Latent Class Discrete Choice Model*
  A last model that seems suitable for this kind of data is LCDCM. This model allows to capture heterogeneity between different segments of respondents, while the behaviour of respondents within the segments is homogeneous. In context of an app developer this model is interesting, as it can aid in uncovering segments amongst the app users. From testing this model it appeared that these models are statistically optimal, but do not provide interpretable results. Therefore, these models are not used in this research.

Given the available models and tests, this research makes use of the Multinomial Logit model. Within this model, it is chosen to apply the theory of random utility maximization (RUM) to capture peoples decision rules. This theory implies that a decision maker always chooses the most attractive alternative from a choice set [1].

2.2.2. Multinomial Logit Model

In the MNL model, each alternative's attractiveness is represented by a utility function. It is assumed that decision makers aim at maximizing the utility they obtain from choosing an alternative, known as 'random utility maximization (RUM)(McFadden, 1974). The total utility from choosing an alternative is computed by equation 2.1, based on formulations by Ben-Akiva and Lerman (1994).

$$U_i = V_i + \varepsilon_i = ASC^{mode} + \sum_m \beta_m \cdot x_{im} + \varepsilon_i \tag{2.1}$$

with: U_i the total utility of alternative i
V_i the systematic utility of alternative i
β_m taste parameter for attribute m
x_{im} the attribute level of attribute m in alternative i
ε_i the error term of alternative i

This function consists of a systematic part V_i, consisting of the ASC (alternative specific constants) and the measured attributes, and a random component 'ε' to represent unobserved utility:

- The **alternative specific constant (ASC)** captures utility that is derived from using a mode, it is associated with factors other than the observed attributes. To estimate this constant, one of the ASCs in a model needs to be fixed to a reference level.

[1]Another theory that is taught at TUD involves random regret minimization (RRM), in this theory it is assumed decision makers choose the alternative that they would least regret. Applying this method is computationally heavy, and the subtle difference between RUM and RRM is likely not noticeable in a noisy RP data set. Therefore, it is chosen to apply RUM, with less computation time and assumable, a comparable result in terms of model fit.

- The **measured attributes** x_{im} in the utility function refer to the levels of the attributes m for alternative i. The parameters β_m is known as the taste for these measured attributes. More precisely, it represents how much utility the measured attribute adds or subtracts per unit change of the attribute.
- The **random component** ε, or error term, represents unobserved utility, or randomness in choices. In MNL, this term is independently and identically distributed (IID property) across all alternatives and observations (Train, 2009). For computational purposes, the variance of the EV type I distribution is set to $\pi^2/6\mu^2$.

Depending on the specification of the distribution of the error term, different formulations for choice probabilities can be obtained (Chorus, 2017). With the specification as described above, and a universal choice set formulation that is required for this research, the probability that a user chooses an alternative is formulated as following (Hensher, Rose, & Greene, 2005):

$$P_{ij} = \frac{A_{ij} * e^{V_{ij}}}{\sum_{i=1}^{I} A_{ij} * e^{V_{ij}}} \tag{2.2}$$

with: P_{ij} the probability of choosing alternative i in observation j

$$A_{ij} = \begin{cases} 1 & \text{if alternative i is available in observation j} \\ 0 & \text{otherwise} \end{cases}$$

V_{ij} the systematic utility of alternative i in observation j

This formulation is known as the linear-additive multiniomial logit model, or simply logit model (Chorus, 2017), with a universal choice set formulation (Hensher et al., 2005). With this formulation, the alternative with the highest perceived utility has the highest probability of being chosen.

With choice probabilities formulated for all alternatives and observed choices in the data, the taste parameters and ASCs in a model can be estimated. Estimating these parameters relies on the Maximum Likelihood-principle. This enfolds finding the parameters that make the data most likely to have occurred. The likelihood of the data consists of the product of all chosen alternatives' choice probabilities. The mathematical formulation of the likelihood is shown in equation 2.3 (Train, 2009).

$$L(\beta) = \prod_{j \epsilon J} \prod_{i \epsilon I} P_j(i \mid \beta)^{y_j(i)} \tag{2.3}$$

$L(\beta)$ likelihood of the data with estimated parameters β

β a vector containing all estimable parameters

$P_j(i \mid \beta)$ choice probability of alternative i in observation j given β

$$y_j(i) = \begin{cases} 1 & \text{if alternative i is chosen in observation j} \\ 0 & \text{otherwise} \end{cases}$$

When data sets get large, the likelihood function approaches zero. Therefore, the logarithm of the likelihood is computed, also known as the log-likelihood (LL). During estimation, it is the objective to maximize the log-likelihood function (Train, 2009):

$$\begin{aligned} LL(\beta) &= ln(\prod_{j \epsilon J} \prod_{i \epsilon I} P_j(i \mid \beta)^{y_j(i)}) \\ &= \sum_{j \epsilon J} \sum_{i \epsilon I} (y_j(i) \cdot ln(P_j(i \mid \beta))) \end{aligned} \tag{2.4}$$

Through maximizing this function, the parameters are estimated such that the the observations have the the highest probability to have occurred.

2.2.3. Modeling Approach

The aim of the modeling process is to identify the best possible model in terms of explanatory power and model fit. To find the best possible model, various model formulations are estimated with PythonBiogeme (Bierlaire, 2016). The starting point is a simple model containing only basic parameters. Step-by-step the model is expanded by adding new parameters and experimenting with new formulations. Each formulated model is then assessed on the interpretability and reliability of the estimated parameters, and on the model fit.

To evaluate the interpretability of the parameters, it is checked if the estimated values align with expectations (i.e. increasing costs should negatively influence utility). To check whether the parameters are reliable, it is checked whether the estimated parameters are statistically significant. For significant parameters at a 95% confidence interval, a t-test value of 1.96 or higher is required.

The model's goodness of fit is assessed using McFadden's rho-squared ρ^2, shown in equation 2.5. This indicator compares the likelihood parameter of a model (LL_β) to the likelihood parameter of random model with all parameters equal to zero (LL_0), also known as the null model.

$$\rho^2 = 1 - \frac{LL_\beta}{LL_0} \tag{2.5}$$

A ρ^2 close to 0 indicates the model does not much better than a random model, the closer ρ^2 gets to 1, the better the model fits the data. A comparison between the fit of two different models also relies on the likelihood estimates (LL_β). A higher LL indicates a better model. For comparing two models, it must be ensured that a model is truly better, and an improvement in LL is not due to coincidence. To test this, the likelihood ratio test can be performed if the compared models can be obtained by constraining parameters of the better fitting model. Tho perform this test, the Likelihood Ratio Statistic must be calculated (see equation 2.6). The outcome of this statistic is then compared to a threshold value to judge whether the difference in LL is statistically significant and not due to coincidence. The threshold value depends on the number of free parameters between the models, and the selected confidence interval.

$$LRS = -2(LL_A - LL_B) \tag{2.6}$$

In principal it is aimed to find a model with the best possible fit. However, the noisiness in the RP data can lead to unexpected values of parameter estimates and insignificant parameters. These issues can occur in models that may provide the best fit from a statistical point of view. However, such models lose in explanatory capabilities of the decision-making process, and are therefore not suitable to perceive as best possible model, even though it fits the data best. Therefore, identification of the best possible model is a trade-off between model fit and explanatory power of the model.

3
Data

This chapter discusses every aspect there is to the data in this research. To start with, Section 3.1 introduces the case study of TripGo, thereby explaining the context and origin of the data used for this research. Next, Section 3.2 explains how raw data is extracted, structured into choice data and how faulty observations are removed. Section 3.3 provides insights into the data through descriptive statistics on multiple topics. Section 3.5 closes the chapter with some intermediate conclusions.

3.1. Introduction Case Study

TripGo is an integrated mobility platform created by the company SkedGo. SkedGo is a Sydney-based company that provides solutions for smart trip planning and MaaS technology for businesses and governments. The TripGo smartphone app functions as SkedGo's showcase, to illustrate potential customers what possibilities consist of in terms of integrating modes of transportation. The API (application programming interface) that powers this app is the product SkedGo offers to clients. For clients, such as large companies, the API can be applied to integrate company shuttles, public transport and any other desired mode into a customized smartphone application. This way, SkedGo can assist in arranging the commute of company employees.

The TripGo smartphone application looks very similar to the business-to-business customized applications, but contrarily it has open access for anyone through a smartphone application and an online web-app. The TripGo platform integrates information on private, public and intermediate modes of transportation into one digital interface. Amongst the included information is real-time traffic information, public transport schedules (also updated with real-time information), information about the seating availability in public transport, availability and costs of parking and the whereabouts of shared vehicles. Besides providing access to all this information at once, TripGo's main function is a multimodal journey planner. This planner can assist people in multimodal trip planning, both by generating complex intermodal trip plans and by allowing users to choose between a broad range of options presented side by side.

As the application is most developed for the operating area in the metropolitan of Sydney. Therefore, this is also the focus area for this research, the area is depicted in Figure 3.1. In the Sydney area, TripGo is used to plan approximately 4.800 trips each day. In this city, an abundance of mobility services is available, and the following of these modes are integrated in TripGo:

- *Private*: car, motorcycle and bicycle
- *Public*: train, light rail, ferry, bus, tram, subway
- *Intermediate*:
  - Car rental; Swiftfleet (another platform including all participating rentals, i.e. Avis, Hertz)
  - On-demand; taxi (GoCatch, Ingogo, TaxisCombined,Mydriver), Uber, airport shuttles
  - Car-share; GoGet (station based, B2C), Car Next Door (station based, P2P)

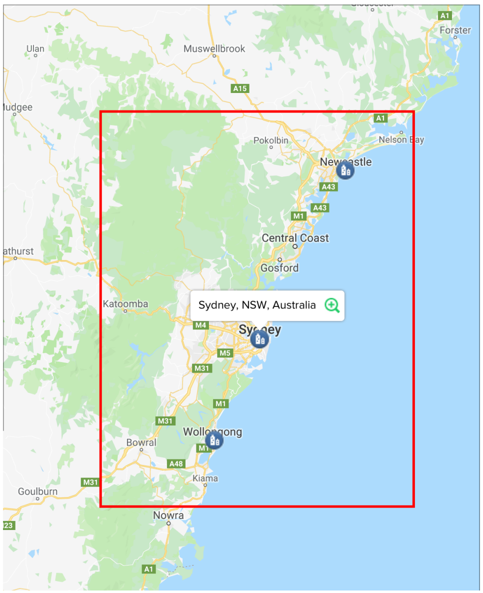

Figure 3.1: Sydney, New South Wales operating area

With these modes included, the application includes all core services that should be included in integrated mobility schemes, namely public transport, taxi, car sharing, car rental and on-demand transport (Kamargianni et al., 2016).

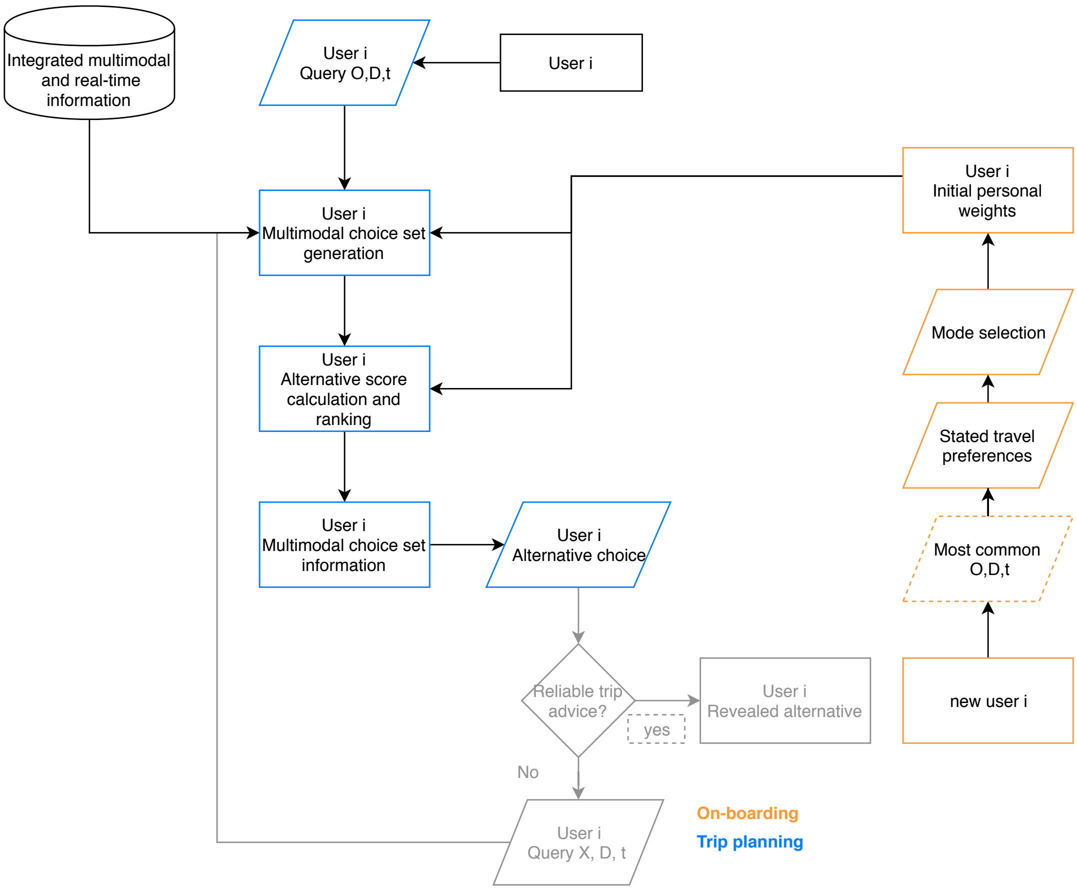

Figure 3.2: System Architecture TripGo, inspired on Nuzzolo et al. (2013)

3.1.1. System Architecture

Usage of the TripGo app can be explained according to the architecture of the system, presented in Figure 3.2. At on-boarding, users go through a three-step procedure to customize TripGo according to their preferences. First, users can state their most common origin(O), destination (D) and travel time (t) through entering their home address, work address and working times. Next, users must state their travel preferences through the slider system presented in Figure 3.3. Using the sliders, travellers can express how important the factors travel time, cost, hassle, carbon, exercise are to them. In the third step of on-boarding, users can select what modes they like to include in the travel planner (see Figure 3.4).

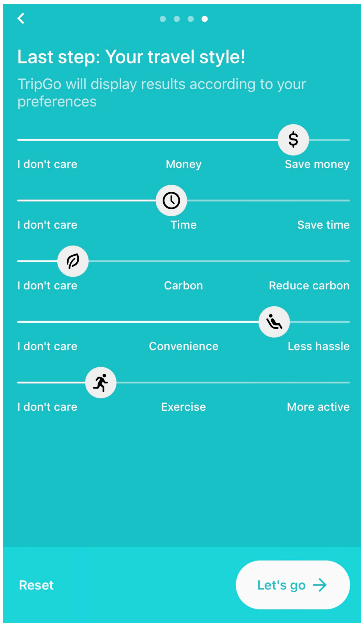

Figure 3.3: On-boarding: slider system

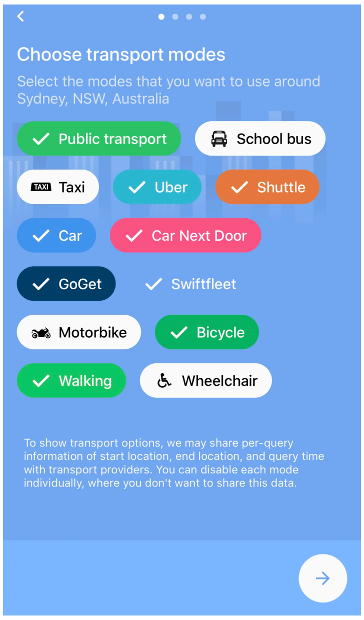

Figure 3.4: On-boarding: mode selection

After setting up the user, the app is ready for travel planning. To plan a trip, a user i must set up a query consisting of an origin, destination and an arrival or departure time. The chosen OD pair must lie within the operating area of the app (restricted to the Sydney NSW area for this research). If the query is valid, a routing algorithm generates possible trip alternatives specific for user i. At this point, the personal settings of user i feed back into the system such that the routing algorithm only takes the selected modes of user i into account. After generating trip alternatives, a function called the score determines the order in which the alternatives should appear in the user interface. Here, the travel preferences from the sliders feed back into the score function as weights for certain attributes. Finally, the ordered alternatives are presented as a choice set in the interface for the users to pick from. An example of a choice set is shown in Figure 3.5

To retrieve additional information on a trip plan, users can tap on alternatives and more details appear. The content of provided additional information varies for each mode or mode combination. But, for all alternatives it includes a detailed route (Figure 3.6) and step by step instructions (Figure 3.7) for performing the trip. In case of Uber it is also possible to book through the application (see Figure 3.8). In case of taxi's and car sharing TripGo links the user through to the platform of the mobility operator for bookings. And lastly, in case of car or bicycle TripGo can redirect users through to applications for that provide navigation.
Finally, the choice for an alternative, consisting of the last selected item, is recorded in the data as user i's 'revealed' alternative. This block is shown in grey in Figure 3.2 as this is not embedded into the system architecture of TripGo, but takes place during data processing.

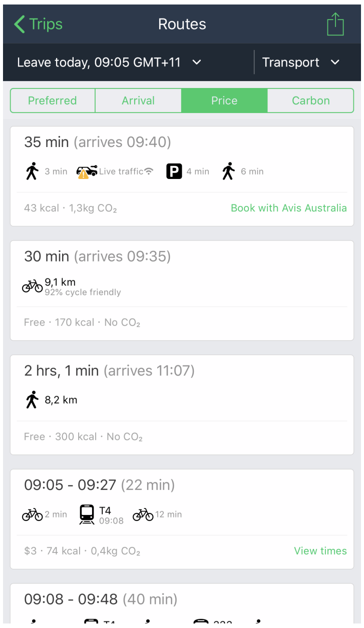

Figure 3.5: Presented alternatives

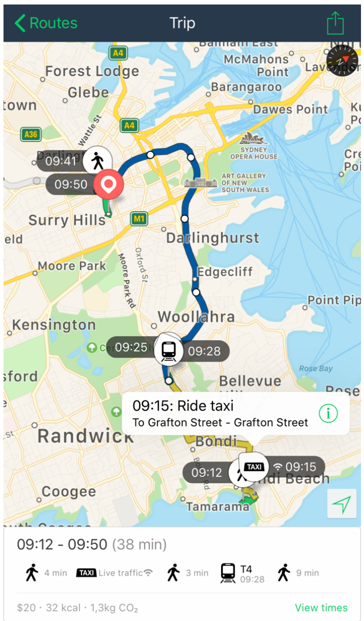

Figure 3.6: Route description

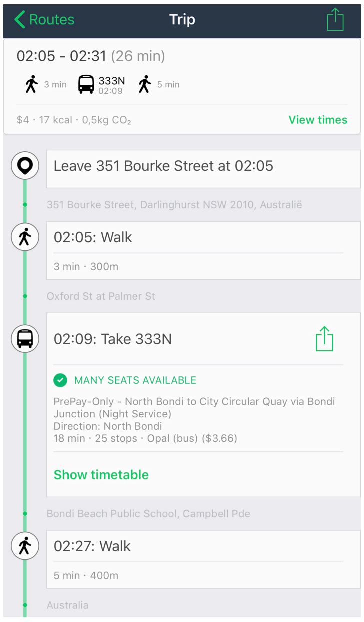

Figure 3.7: Step-by-step instructions

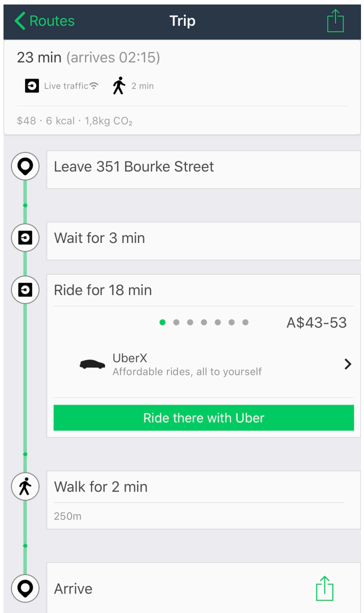

Figure 3.8: Booking function for Uber

3.1.2. TripGo Users and Self-Selection

The knowledge on the users of TripGo themselves is very limited. To keep the application attractive and easy to use, the app does not ask for any socio-demographics of users (i.e. age, education). Also it is unknown what the trip purpose is of the planned trips. Asking for such information can scare away users, and is therefore avoided.

Information that is retrieved from the users consists of their work destination and home destination (if filled out by the user), and their selected modes. However, this information is only *used* in the API for choice set generation, but it is not stored in the data, for privacy restrictions.

As for the recorded queries in the data, these are also anonymized as much as possible. The locations of origins and destinations are for example not stored in the data for privacy reasons (including these makes a user easily traceable). Furthermore, ID's of users are also untraceable, and only reveal what queries belong to the same user.

As a result of this limited user information, it is unknown exactly what the group of TripGo users consists of. Actually, the only knowledge on the user group is that it consists of people that prefer to plan their trips using this smartphone application that includes multiple modes of transportation. Based on this shared characteristic, individuals select themselves into the TripGo user group. This phenomenon is also called self-selection, it causes a bias in the sample that can not be controlled by the researcher (Lavrakas, 2013).
Given the self-selection effect for this user group, some speculations can be made about the shared characteristics of TripGo users:

- Travellers who plan their trip with a journey planner, probably make trips that are too complex to plan by heart. This holds mostly for public transport trips, in which the PT users require knowledge on schedules and departure and arrival times.
- The users involve people that are open to information on a broad range modes. If not, they would have consulted another application, such as conventional platforms for public transport or specific platforms belonging to the mobility provider of the mode they want to use.
- The user group probably does not contain frequent car users. Even though most MaaS concepts are designed to appeal to car users, SkedGo is not actively recruiting users for TripGo, or trying to draw in car users. Therefore, the app is just available as a multimodal travel planner, and such applications usually does not appeal to frequent car users.

For this research, this self-selection of users must be kept in mind while interpreting the results.

3.1.3. Discrepancy between Recorded Behaviour and Actual Behaviour

Another important issue that must be kept in mind for this research is a possible discrepancy between the behaviour inferred from the data, and actual behaviour.
Making use of the UI, the system architecture guides users through a sequence of actions; on-boarding, setting up a query, selecting a trip and potentially redirecting the user to another app. The generated data records in the app directly rely on users following this exact path that is lied out by the system. However, the app usage of users may be inconsistent with the path proposed in the application, and users' actual actions may not align with the system architecture. This has repercussions for the data, and thus this research.
Some causes for this described discrepancy in app and actual behavior include the following:

- *Mode-selection*
  During the mode-selection at on-boarding, users can choose to exclude specific modes from their trip options. The aim of this step is to for example exclude motorcycles if it is unavailable to the user. However, multiple reasons exist why users may choose not to exclude any modes at on-boarding. Such as ignorance of TripGo workings at on-boarding, curiosity towards exploring other modes or not altering preferences after on-boarding.
  Because of this, much about the availability of modes in choice sets remains unknown. If a mode is presented it is not sure whether it is actually available to the user. The other way around, if a mode is not included in a choice set, it is unknown whether it is available due to the user settings or because it is actually not available for the proposed query.
- *Decision making*
  During trip planning, the recorded choice for an alternative relies on the user tapping their finger on the alternative. The recorded choice consists of the last selected alternative in the app. However, it is possible that users' decision making does not align with their alternative selection:
  - Firstly, it is possible that users make a choice only by viewing the choice set information. In this case, they do not tap an alternative at all, and might redirect themselves to other apps for the remainder of their trip. This results in no record in the data.
  - Secondly, it is possible that the observed choice (last clicked alternative) is not the user's actual choice. TripGo is not able to track whether the selected trip is actually performed. So after a 'choice' it is still possible that the user opts out, or decides to do something else.

  Despite these issues with the definition of a choice, 'the last selected alternative' is the best possible indication of an actual choice. And therefore, this research assumes that the entries in the data include actually performed trips.

These are all aspects that are impossible to track, to see whether they occur or not. It is not recorded in the data whether a user chose to purposely exclude a mode from their choice set, or whether it was truly unavailable at the time. As these events cannot be controlled, they must be kept in mind as they do have repercussions for results.

3.2. Data Processing

To analyse the TripGo data, raw smartphone app data needs to be prepared for estimation. To achieve this, the method described in Section 2.1 is applied. This section is split up in three parts. First, Section 3.2.1 reports how raw data is extracted from the database. This is followed by an examination of the data content. Second, the data is structured into choice data that is suitable for discrete choice and descriptive analysis. Section 3.2.2 describes to detail how the method of Section 2.1 is applied, and provides arguments for each step in the process. Thirdly, Section 3.2.3 describes how noise is reduced from the data, what issues emerge and how they can be resolved.

3.2.1. Raw Data

Extracting raw data from the SkedGo database is done using PgAdmin software for online databases. Using the query presented in Figure 3.9, 100.000 observations are extracted over the period of September 2018. Most important in this query are the limits and time bounds:

- The query time (the time at which the observation is made) is set to be larger than 1/9/2018 0:00:00 GMT-0 (specified in the query as 1535760000 in epoch time[1]).
- The query time is set to be smaller than 1/10/2018 0:00:00 GMT-0.
- The limit in the query allows to extract 100.000 observations.

Extracting one month of observations allows to level out disruptions in the data that can influence behavior (i.e. disruptions in public transport or extraordinary weather). Also, 100.000 observations is sufficient for choice modeling with revealed preference data, and account for all modes. Lastly, the month of September 2018 was chosen because it is a recent month and therefore representative of the current behavior of users. Moreover, no relevant changes occurred in the API during this month.

```
select md5("userID") as userId,"tripJSON"->'queryTime' as queryTime,"tripJSON"->'queryIsLeaveAfter' as leaveAfter, "appJSON"->'choiceSet' as choiceSet
from "PlanArchiveFromSkedGo"
where regions = 'AU_NSW_Sydney'
 and "appJSON" ? 'choiceSet'
 and ("tripJSON"->>'queryTime')::bigint > 1535760000
 and ("tripJSON"->>'queryTime')::bigint < 1538352000
limit 100000;
```

Figure 3.9: SQL query for data extraction

The extracted data is saved in a CSV-file, written in JSON language. Figure 3.10 shows an example of one observation in this raw data. The observation in the example contains an anonymised user ID, and a choice set consisting of 4 alternatives. For each alternatives the following information is included:

- **Price**: the travel costs of an alternative in AUS $
- **Score**: a measure of alternative value computed by a weighted sum of the attributes
- **Hassle**: a measure of the hassle of an alternative based on unobserved variables
- **Calories**: the amount of calories burned while taking a trip, measured in kcal
- **Segments**: the structure of the trip described in different segments. Each trip leg is described by a label for the *mode* and the corresponding *duration*, or travel time. In the data, alternatives can include up to 15 segments.
- **Selected**: indicates 'true' when an alternative is selected, and 'false' otherwise.
- **Visibility**: indicates 'maximized' or 'minimized' depending on the settings of the user.
- **Arrival time**: the arrival time in epochs time
- **Departure time**: the departure time in epochs time

As can be seen, each observation is stored in strings of information. The total number of strings differs for each observation, as they each have a different number of alternatives, and each alternative contains a different number of segments. For choice modeling the data needs to be processed into a more consistent structure. This process is described in the next section.

[1] Epochs time equals the amount of seconds from Thursday, 1 January 1970 0:00:00 GMT-0

```
"0eba02380de9b8a82e787fb14137598d";
```
User ID

```
"[   {""price"": 3.53,
     ""score"": 29.7,
     ""carbon"": 1.6,
     ""hassle"": 11,
     ""calories"": 36,
     ""segments"": [
          {""mode"": ""pt_pub_train"", ""duration"": 600},
          {""mode"": ""transfer"", ""duration"": 296},
          {""mode"": ""pt_pub_train"", ""duration"": 720},
          {""mode"": ""wa_wal"", ""duration"": 37},
          {""mode"": ""transfer"", ""duration"": 323},
          {""mode"": ""pt_pub_train"", ""duration"": 300},
          {""mode"": ""transfer"", ""duration"": 639},
          {""mode"": ""pt_pub_train"", ""duration"": 300},
          {""mode"": ""wa_wal"", ""duration"": 880}],
     ""selected"": false,
     ""visibility"": ""full"",
     ""arrivalTime"": 1535759800,
     ""departureTime"": 1535755680},
```
Alternative 1

```
     {""price"": 3.53,
     ""score"": 27.7,
     ""carbon"": 1.2,
     ""hassle"": 5,
     ""calories"": 36,
     ""segments"": [
          {""mode"": ""pt_pub_train"", ""duration"": 4380},
          {""mode"": ""transfer"", ""duration"": 339},
          {""mode"": ""pt_pub_train"", ""duration"": 300},
          {""mode"": ""wa_wal"", ""duration"": 880}],
     ""selected"": true,
     ""visibility"": ""full"",
     ""arrivalTime"": 1535759800,
     ""departureTime"": 1535753880},
```
Alternative 2

```
     {""price"": 6.84,
     ""score"": 44.8,
     ""carbon"": 1.2,
     ""hassle"": 8,
     ""calories"": 48,
     ""segments"": [
          {""mode"": ""wa_wal"", ""duration"": 356},
          {""mode"": ""pt_pub_bus"", ""duration"": 3360},
          {""mode"": ""wa_wal"", ""duration"": 250},
          {""mode"": ""transfer"", ""duration"": 230},
          {""mode"": ""pt_pub_train"", ""duration"": 420},
          {""mode"": ""wa_wal"", ""duration"": 97},
          {""mode"": ""transfer"", ""duration"": 563},
          {""mode"": ""pt_pub_bus"", ""duration"": 720},
          {""mode"": ""wa_wal"", ""duration"": 915}],
     ""selected"": false,
     ""visibility"": ""full"",
     ""arrivalTime"": 1535759475,
     ""departureTime"": 1535752564},
```
Alternative 3

```
     {""price"": 0,
     ""score"": 142.1,
     ""carbon"": 0, ""hassle"": 0,
     ""calories"": 743,
     ""segments"": [
          {""mode"": ""wa_wal"", ""duration"": 18220}],
     ""selected"": false,
     ""visibility"": ""minimized"",
     ""arrivalTime"": 1535760010,
     ""departureTime"": 1535741790}]"
```
Alternative 4

Figure 3.10: One observation in JSON language

Segments and Modes
In the raw data, 24 different ‘modes’ can be found under the category ‘segments’, they can be seen in Table 3.1. The modes described in the raw data also include four trip segments that are not modes of transportation. These include ‘parking’, ‘transfer’, ‘wait’ and ‘collect’.

Segments in unprocessed data					
1	collect	9	parking	17	pt_pub_bus
2	cy_bic	10	ps_shu	18	pt_pub_ferry
3	me_car	11	ps_tax	19	pt_pub_train
4	me_car-p_OPT	12	ps_tax_MYDRIVER	20	pt_pub_tram
5	me_car-r_SwiftFleet	13	ps_tnc_UBER	21	transfer
6	me_car-s_CND	14	pt_ltd_OPT	22	wa_wal
7	me_car-s_GOG	15	pt_ltd_SCHOOLBUS	23	wa_whe
8	me_mot	16	pt_pub	24	wait

Table 3.1: Modes

The coding of these modes works as following:

- **pt_** is for transit which runs on schedules
  - pt_pub is "public transit" that is accessible to public
  - pt_ltd is for public transport with limited availability
- **ps_** is for taxi-like on-demand services
  - ps_tax is for taxis
  - ps_tnc is for uber and alike
  - ps_shu is for (airport) shuttles
- **me_** is for vehicles you drive yourself
  - me_car is for your own car
  - me_car-s is for car sharing
  - me_car-r is for car rental
  - me_car-p is for car pooling
  - me_mot is for your own motorbike
- **cy_** is for cycling
- **wa_** is for walking
  - wa_wal is for walking
  - wa_whe is for wheelchairs

Formulation of Public Transport
In Table 3.1 it can be seen that 6 of the modes describe public transport. Mode 16 is a generic way of describing public transport, whereas modes 17-20 describe specific forms of public transport. Both formulations occur in different observations in the data, this leads to an inconsistent description of alternatives and affects the interpretability of choice model. Therefore, it is chosen to exclude all observations that contain the generic formulation in the data. As such, mode 16 is not taken into account for constructing the choice sets. Section 3.2.3 further elaborates on this matter through checking the portion of data that is deleted as a result of this caution.

3.2.2. Constructing the Choice Data
For discrete choice modelling, the information in the raw data must be translated into choice data. In choice data for PythonBiogeme, information is structured in tables, such that each row represents an observation, and the columns represent ordered categories that represent the same information for each observation.
The choice data created for this research must include the following four elements:

- **User ID**: An ID that represents the device the observation belongs to. It is assumed that observations belonging to the same device also belong to the same user. This element is used to capture the panel structure of the data. This element is essential for deriving statistics on users and usage of the app.
- **Universal choice set**: A choice set containing all information on chosen and non-chosen alternatives in an observation. This information results from the trips generated in the application. In TripGo data,

each observation consists of a different choice set. Both the size of the choice set and the alternatives proposed vary per observation. Therefore a universal choice set specification (De Dios Ortúzar & Willumsen, 2011) is applied to consistently describe the choice set for each observation. To achieve this, every alternative that occurs in the data must be presented in each observation.

- **Availability**: data that indicates whether each of the alternatives is available in the observation or not. This element of the data is required when a universal choice set formulation is applied.
- **Choice**: a reference to the chosen alternative of an observation

To start with, choice sets are constructed. Creating the universal choice set is the most complicated step, as the inconsistent formulation does not allow for direct extraction from the data. The information has to be translated. The method described in Section 2.1 is applied to accomplish this transformation. Overall, the construction of these choice sets consists of two parts (steps 3 and 4 of the method in Section 2.1). First, the representation of a choice set that accommodates all alternatives is determined. This corresponds to step 3 of the method in Table 2.1. Next, the representation of individual alternatives is determined, corresponding to step 4 in Table2.1. To complete the choice data, the availability of alternatives is specified, and the choice is added to the data.

Choice set size

To start with, the size of the choice set must be determined by defining the number of alternatives in the data. Several ways exist to determine a number of alternatives in the data. For example, if each specific trip chain is defined as an alternative, more than 5.000 alternatives exist in the data. Even though this is a very complete representation alternatives, this specification results in too many alternatives. As a result, the data set becomes too large, and a very inconsistent representation of alternatives is required. Moreover, this amount of detail in the definition of an alternative is not needed for for an accurate representation of the data. Therefore, it is chosen to simplify. To identify the number of alternatives, it is chosen to take into account each mode of a trip chain, but not to account for double modes in the chain (i.e. two bus trip legs), or for the order in which the modes appear in the chain. This definition of alternatives results in 168 mode combinations, or unique alternatives that exist in the data. Most of these alternatives can occur more than once in a choice set for one observation. For example, when a user can choose between two different trains for one trip. To capture this in the data, the choice set must be expanded to accommodate for repetitive alternatives. This leads to a universal choice set consisting of 421 alternatives.

It is essential to represent all of these alternatives and their doubles, to create an integral overview of the content of the data. With the content as complete as possible, the most realistic and accurate analyses can be performed, of course leading to the most realistic and valid result possible. A disadvantage of this formulation is that a different set of extracted data can lead to a different choice set structure. This would occur if different combinations of segments are uncovered in other data.

Labels are created to distinguish each alternative, they include the following information:

- What modes of transportation are included (168 different possibilities)
- How many modes of transportation are included (between 1 and 5)

These labels are named 'Alternative 1' until 'Alternative 421'.

Alternatives representation

To keep an overview of this large and complex data, and to ease model formulation, it is required that the representation of alternatives is consistent, such that each alternative is described with the same number of columns, and the same categories.

A first step in the representation of alternatives is to decide what attributes to capture in the choice data. From the attributes in the raw data price, score, carbon, calories, arrival time, departure time and duration are important factors to include. Furthermore, an attribute is computed to represent the position of an alternative in the choice set.

To start with, for each alternative, 7 columns are dedicated to the consistently formulated attributes price, score, carbon, position, calories, arrival time and departure time. The more challenging step lies in the number of columns needed to represent the inconsistent sequence of segments and durations per mode of an alternative.

The ‘segment’ attribute in Figure 3.10 has a very inconsistent size and content, and is therefore difficult to capture without simplification. Therefore, the first step is to simplify the complex attribute of segments.
To simplify, this attribute is captured as the travel time per mode. To achieve this, the duration of similar segments in a sequence is added up (as is already done for the alternatives definition). A sequence consisting of walk (300s) – bus (200s) – walk (200s) becomes walk (500s) and bus (200s) in the choice data. This way, no double segments occur in the sequences. For a consistent formulation of each alternative, 21 attributes are needed capture the time spent on each segment of Table 3.1 (Optus modes and pt_pub excluded). However, this amount of attributes in the data leads to a too large data set for processing. Therefore, the number of columns must be reduced.

To do this, the maximum number of segments needed to represent an alternative is identified, this amounts to 7 different segments. At this point, it is chosen to represent the travel time per segment in 7 columns for each alternative. For alternatives that involve less then 7 different segments, the remaining columns are filled with 0’s. It may be noted, that with this formulation, the formulation of alternatives is not fully consistent. Because for each alternative, ‘travel time 1’ to ‘travel time 7’, correspond to different types of segments. To keep track of the travel time formulation of each alternative, the alternative label also captures what the attributes ‘TT1’-‘TT7’ enfold.

With the described structure of alternatives, 14 columns are required to represent each alternative. This structure is presented in Figure 3.11.

	Alternative 1														Alternative 2				
	Price1	Score1	Carbon1	Position1	Calories1	Arrival1	Departure1	TT1_1	TT1_2	TT1_3	TT1_4	TT1_5	TT1_6	TT1_7	price2	score2	carbon2	hassle2	...
OBS 1	31	56	1	3	57	1,5E+14	1,5E+14	120	1502	240	845	0	0	0	0	63	0	5	...
OBS 2	14	32	1	1	44	1,5E+14	1,5E+14	120	1120	240	668	0	0	0	0	24	0	3	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 3.11: Data structure for Discrete Choice Modelling

Availability
The next step towards complete choice data is to compute so called availability. The availability indicates for each observation which of the 421 alternatives were available. In the choice data, this comes down to 421 columns containing a 1 if the alternative was present or a 0 otherwise.

Choice
The choice for each observation is translated from the ‘selected’-strings. A ‘true’ is processed into a number between 1-421 to represent the chosen alternative.

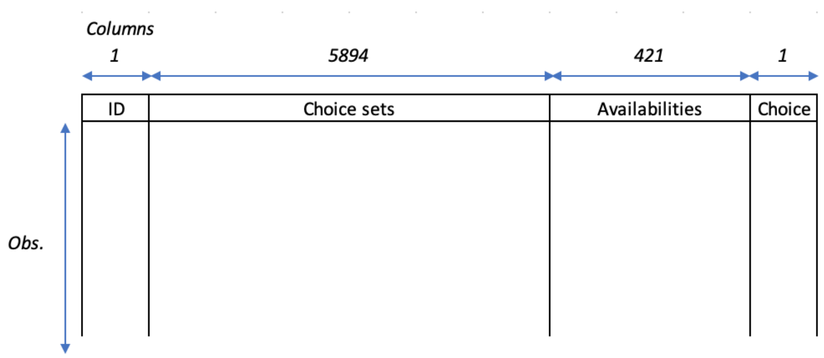

Figure 3.12: Structure of the Choice Data

Complete choice data
With the explained formulation of choice sets, 14 columns are needed for 421 alternatives, leading to a total of 5894 columns. For each observation, the information of the raw data is sorted under the dedicated columns. To complete the choice data, the choice set, availability, choices and ID’s united in one table consisting of

6317 columns. The structure of the data is depicted in Figure 3.12.

3.2.3. Noise Reduction

Originally, 100.000 observations are extracted from the SkedGo database. However, many of the records in the original data include issues that make them unsuitable for discrete choice modelling. This section elaborates on the uncovered issues, and the steps taken to solve them.

Missing information

The first issue come across in the data involves incomplete observations. These consist of records with missing attribute levels, such as prices, travel times and choices. These observations can not be inserted in a choice model, and were therefore deleted from the data. This should have no repercussions on the result, as missing information appears to occur at random, and in a limited amount of observations.

Double observations

Secondly, it is detected that some observations are recorded in the data more than once. These observations show equal query times (in seconds), ID and exactly the same choice set with alternatives and attribute levels. In reality, these are not separate observations but double records. Including these in the data leads to an overestimation of the amount of information. Therefore, it is chosen to delete the double observations and ensure only one of the records remains in the data.

Deleting the incomplete and repetitive observations from the data reduced the set from 100.000 observations to 76.248 observations. As a next step, the values of attributes are checked, and the occurring modes and mode combinations are examined based on descriptive statistics.

Pricing error

Looking at the attributes for price, it was discovered that a price of -10.000 occurs in many observations. This is of course not a valid representation of the real pricing for TripGo users, and including this in the data would lead to biased parameter estimates. Before eliminating these observations it was explored if there was a pattern that can be recognized in the occurrence of this error. Through this exploration, it was uncovered that this pricing issue solely occurs for alternatives ps_tax (taxi) and me_car-r (car rental). Deleting the observations significantly reduces the mode shares of these modes in the data. Therefore, it was chosen to perform a logistic regression using the reliable prices of these modes, to estimate the correct prices of these modes.

Inconsistent mode formulation

From studying the mode shares it appears that the specifications for public transport are not consistent. The term 'pt_pub' represents public transport in general, and terms such as 'pt_pub_train' represent specific forms of public transport. Both these formulations occur in the data as different formulations are applied in different observations. In total, 29,3% of the observations in the data describe public transport with the general formulation, these belong to users that run TripGo on Android devices. The other 70,7% of the data includes the specific formulation (train, bus, tram and ferry) or no public transport at all. Observations with the specific formulation belong to users that run TripGo on iOS devices. Including both formulations in a choice model leads to difficulty for interpreting the results. Therefore it is chosen to continue with the subset of data that only includes specific public transport formulations. This results in a data set of 53.905 observations. A repercussion for this research is that only iOS users are taken into account. However, it assumed that this does not affect results, and the data still allows to capture behaviour of the average TripGo user.

Negative prices and travel times

After further investigating the attribute levels it was discovered that that many observations include negative values for travel times and prices. Most negative values are the results of errors in the data and should be eliminated from the data to prevent bias.

The absolute values of these attributes seem plausible, which could indicate an accidental minus sign was computed in the data. However, no evidence exists that supports this speculation, and therefore it is not possible to just apply the absolute values of the erroneous attributes.

Furthermore, negative travel times for the segment 'transfer' are not a result of errors. When trip information is updated with real time information, and a delay causes a traveler to miss their transfer, the transfer time becomes negative. This indicates an in-feasible trip, and should also be eliminated from the data to prevent bias.

Most of the negatives occurred in observations that made use of the generic public transport formulation, therefore deleting the 'generic PT' observations already largely solved this problem. For the remaining negative values, no particular pattern is discovered for their occurrence. Therefore it is chosen to delete the remaining 404 observations with negatives from the data.

Positive outliers
A disadvantage of using revealed preference data is that such data often includes outliers. Discrete choice models are sensitive to outliers, as they can have a substantial effect on the (point) estimates of parameters in the model. For outliers, it is best to identify and examine them and eliminate them from the sample if appropriate (Bradley & Daly, 1997). The threshold level for outliers in travel costs is set to 550$, and for travel time it is set to 1000 minutes. Both values seem high, but can appear in realistic choice sets. For example, a two hour car drive can be compared to a 1000 minute walk, and a 500$ Uber ride during rush hour. Therefore, a 1000 minute walk in a choice set, does not invalidate the entire observation and does not need to be deleted as an outlier.

Unidentified choices
While running some preliminary models, it is uncovered that the data included observations for which the choice was specified as '0'. The 4.837 observations for which this occurred can not be used in the choice model and were therefore also excluded from the data. This leaves a final data size of 48.657 observations. Unfortunately, this solution has repercussions for the mode shares of 'me_car-r' (car rental), it almost disappears from the data with only 2 observations left.

Secluded modes
After the first provision of a data analysis, it is noted that the so-called 'Optus'-modes appear in the data. These modes (4 and 14 in 3.1 include a company shuttle and car pool alternative. However, these modes do not appear in the TripGo app, and are only available to employees of Optus. Optus is a telecom provider that arranges their employees commute with a smartphone application provided by SkedGo. Somehow, some observations of their application got mixed up in the TripGo data. Observations including these modes were therefore deleted. The universal choice set still accommodates for these alternatives, such that it is possible for SkedGo to research these modes if desired.

Scaling travel time attributes
Running first models, it also appeared that the optimization algorithmS in PythonBiogeme had trouble in finding an optimal solution. Convergence required many iterations, or convergence was not reached at all. To solve this issue, the travel times were scaled from seconds to minutes. This way the range of travel time matches the range of other attributes more closely, and therefore allows for a smoother model estimation.

3.3. Descriptive Data Analysis

This section gives an insight into the use of TripGo through an analysis of the processed data. To start with, a general descriptive analysis of the usage of TripGo is provided in Section 3.3.1. Next, more specific descriptive statistics are provided related to different elements in the choice data. These include analytics on modes, alternatives, choice sets, attributes and multi-modality.

3.3.1. Usage of TripGo

In the processed data, the observations result from 12 days over the period of 15-Sep-2018 to 26-Sep-2018[2]. During this period TripGo is used for trips with a mean trip length of 36:49 (mm:ss). The cumulative distribution of the total length of chosen trips can be seen in Figure 3.13. For most trips, the total trip length consists of a combination of the other duration segments depicted in Figure 3.13.

[2]This time period differs from the specified time period (September 2018) in the extraction query. The limit of 100.000 observations in the extraction query, results in a smaller extraction time span.

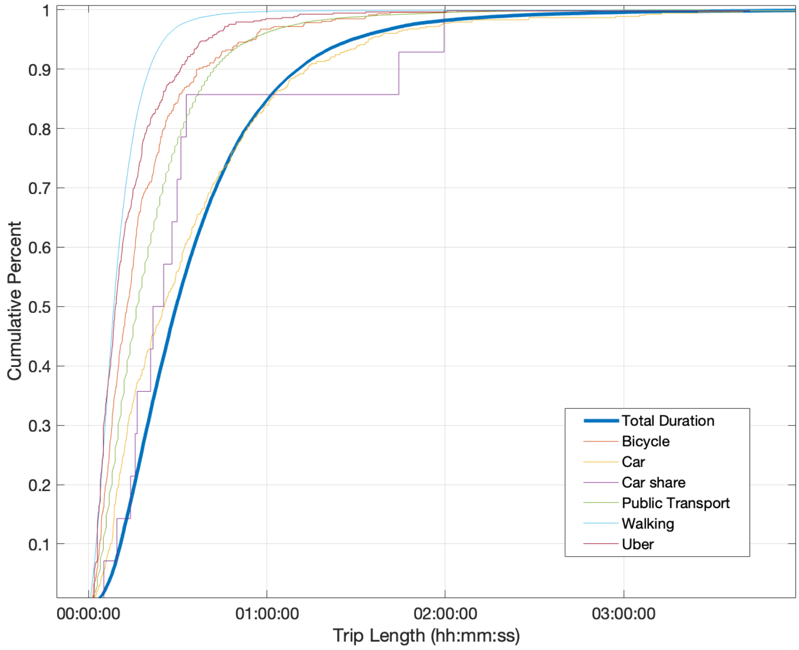

Figure 3.13: Cumulative Distribution of Trip Lengths

Figure 3.14 shows the time of the chosen trips during the of the week Monday September 17th to Sunday September 23rd, 2018. The TripGo usage of this week is indicative of the weekly travel pattern. The plot in Figure 3.14 shows a clear day and night pattern, and also shows that peak times occur during weekdays. Furthermore, it can be seen that less trips are performed on weekend days. The pattern illustrated in this figure corresponds well to average weekly travel patterns. Therefore, it can be concluded that the TripGo data captures an accurate representation of weekly travels.

Figure 3.15 further elucidates the travel pattern on a weekday. The figure indicates that peak hours occur for departure times between 7:00-9:00AM and 04:00-06:30 PM. Given this data, and the peak hours that occur in the data, the trip statistics in Tables 3.2 and 3.3 can be derived. It is assumed that trips departing during peak hours consist of commute trips.

	Number of trips
Total number of trips	29200
Weekend trips	6787 (*23,2%*)
Week trips	22413 (*76,8%*)
Commute trips	9783 (*33,5%*)
Average daily trips	4171
Average trips per weekday	4483
Average trips per weekend-day	3394

Table 3.2: Weekly TripGo Usage

The usage suggested by these numbers remains an indication of weekly and daily TripGo usage. While the data was processed, many observations were eliminated from the data, this is a reason to underestimate the weekly usage. On the other hand, it also appears that some users plan more trips than they can perform in reality. See for example Figure 3.16, it is shown that TripGo is used to plan a trip of 37-40 minutes departing at 18:15 - 19:00. The data in this case records 4 trips from 4 slightly different choice sets, but in reality it is not possible to make this trip 4 times in the given time period. For this reason it can be argued that TripGo usage is overestimated by the data.

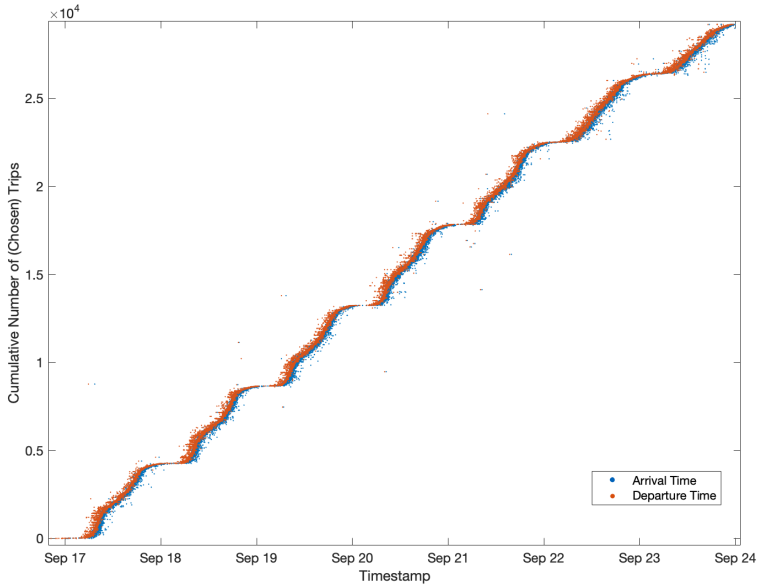

Figure 3.14: Weelky Travel Pattern

Date		**Total trips**		**Commute**			
Day	Date	#trips	%of total weekly	#morning trips	#evening trips	#commute trips	% commute/ total
Monday	17-sep.-18	4238	14,51%	1026	882	1908	45,02%
Tuesday	18-sep.-18	4395	15,05%	950	1055	2005	45,62%
Wednesday	19-sep.-18	4571	15,65%	980	977	1957	42,81%
Thursday	20-sep.-18	4573	15,66%	982	965	1947	42,58%
Friday	21-sep.-18	4636	15,88%	872	1094	1966	42,41%
Saturday	22-sep.-18	3870	13,25%				
Sunday	23-sep.-18	2917	9,99%				

Table 3.3: Usage per Day

User Frequency

The User ID's in the data are informative of what observation belongs to what ID. Table 3.4 provides statistics on these users, and the amount of observations they account for. In total, the processed data includes 7.327 different users, which account for 91,88% of the observations, the other 8,12% of observations are not equipped with a user ID.

Furthermore, a frequent user is defined to use TripGo 3 or more times per week, with this specification, 5 or more observations are required in the data to classify as a frequent user. This definition results in 2799 frequent users in the data. For the observations with missing ID's it is assumed that each of them belongs to a different user.

The graph in Figure 3.17 classifies each user according to their frequency of usage. As such, it can be seen that the majority of users makes only one observation, and 1,73 % of the users make 35 or more observations.

Because the data results from a period of 12 days, 35 observations in the data seems like many Trips to plan and perform. Therefore, this confirms the finding that users plan more trips than they actually perform, illustrated in Figure 3.16. For research purposes, it is assumed that each observation is a performed trip.

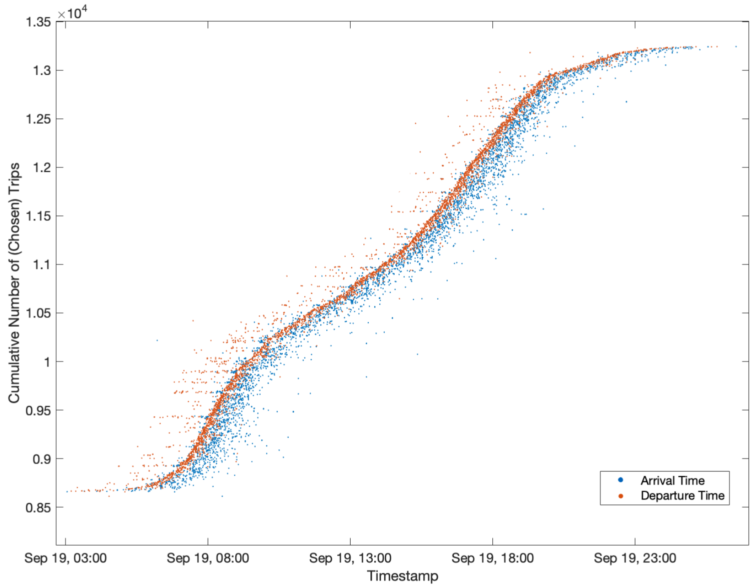

Figure 3.15: Daily Travel Pattern

	Number of users	**Percentage of users**	**Number of observations**	**Percentage of observations**
Users ID's in data	7.327		44706	91,88%
Missing ID's			3951	8,12%
Frequent users	2799	38,20%	35702	73,37%
Non-frequent user	4.528	61,80%	12955	26,63%
Check			48657	

Table 3.4: Users in the data

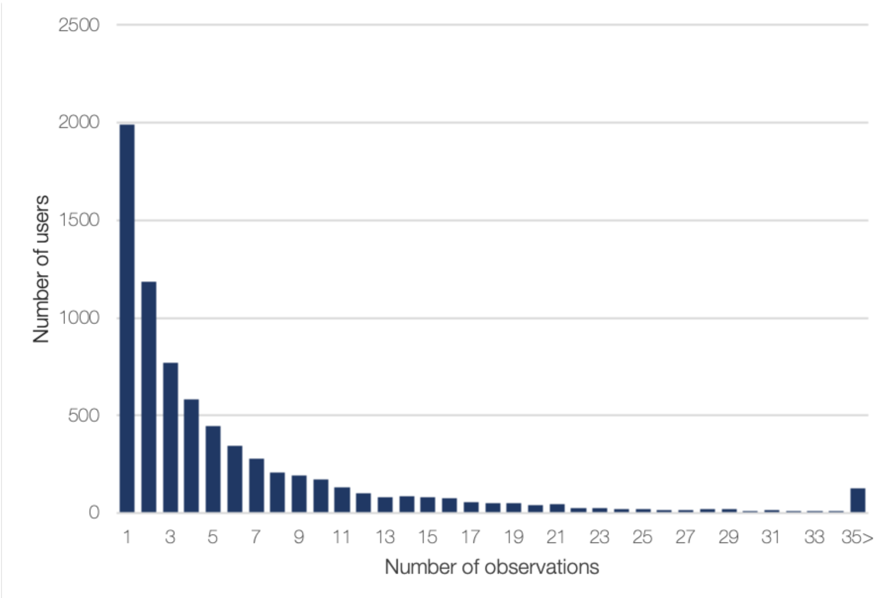

Figure 3.17: Users classified according to frequency of usage

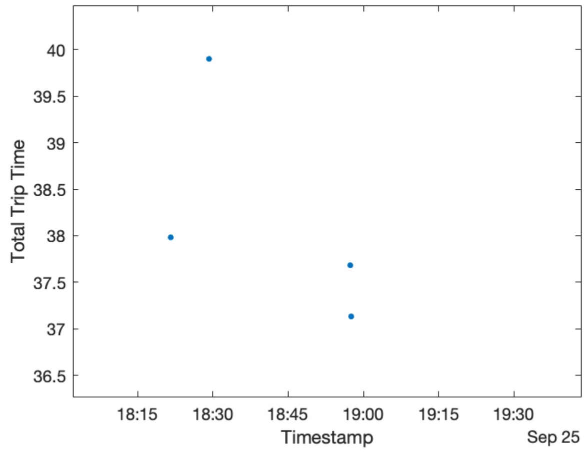

Figure 3.16: Chosen Trips of a Frequent TripGo User

3.3.2. Modes

In the processed choice data, 15 different modes of transportation occur, they are reported in Table 3.5.

	Mode name	Explanation	Code	Type
1	Bicycle	Your own bicycle	cy_bic	private
2	Car	Your own car	me_car	private
3	Car rental	Provided by Swiftfleet	me_car-r_Swiftfleet	intermediate
4	Car share (1)	Provided by Car Next Door	me_car-s_CND	intermediate
5	Car share (2)	Provided by GoGet	me_car-s_GOG	intermediate
6	Motorcycle	Your own motorbike	me_mot	private
7	Airport Shuttle	Shuttles that run from the airport	ps_shu	intermediate
8	Taxi	Provided by GoCatch, Ingogo, Taxis Combined	ps_tax	intermediate
9	Uber	On-demand taxi service by Uber	ps_tnc_UBER	intermediate
10	Schoolbus	Schoolbus (PT with limited availability)	pt_ltd_SCHOOLBUS	public
11	Bus	Public transport	pt_pub_bus	public
12	Ferry	Public transport	pt_bus_ferry	public
13	Train	Public transport	pt_bus_train	public
14	Tram	Public transport	pt_bus_tram	public
15	Walk	Walking	wa_wal	
16	Walk (wheelchair)	'Walking' for wheelchair users	wa_whe	

Table 3.5: Modes in the Data

The availability of these modes in the data is visualised in Figure 3.18, and the exact numbers are reported in Table 3.6.

From Figure 3.18, it can be seen that the most available modes include walking and bus, followed by train and Uber. For walk, Table 3.5 shows that this mode is available in 97,99% of the observations, either on its own or as part of an alternative. Least occurring modes include tram, walk (wheelchair), airport shuttle and car rental. For tram and airport shuttle, their limited availability can be caused by their limited operating areas. The airport shuttles are only available for trips from and to the airport. Trams only have a limited coverage in Sydney and can therefore be scarce in the observations. The limited availability of the 'walk (wheelchair)' mode has to do with the users mode selection at on-boarding. At on-boarding users must choose for either walk or wheelchair. With wheelchair users being a minority, this mode is not often 'available' in the data. The limited availability of car rental is a result of data processing. As described in Section 3.2, the car rental mode brought along many errors in the data, and was therefore largely excluded.

Looking at the ratio between 'chosen' and 'available', it can be seen that walking (walk and walk-wheelchair), bus, train, ferry and schoolbus are chosen most often. This indicates that the TripGo application is mostly used to plan public transport trips. The most dominant mode in the data is walking. This can be explained by the fact that this mode is nearly always needed to perform any type of public transport trip. Even though public transport seems dominant in the platform, it can be seen that other modes are also chosen on a semi-regular basis. For example, Uber is chosen 531 times in the data, this indicates TripGo is used to plan 44 Uber rides per day.

Furthermore, because the dominance of public transport, it is remarkable that the car mode is 'available' in 39% of the observations. If a car was truly available, or owned by the users in all these observations, it is highly unlikely that their chosen alternative consists of PT for the majority of the observations. Therefore, it is indeed probable that the users' mode selection does not align with the actual availability of modes to the users.

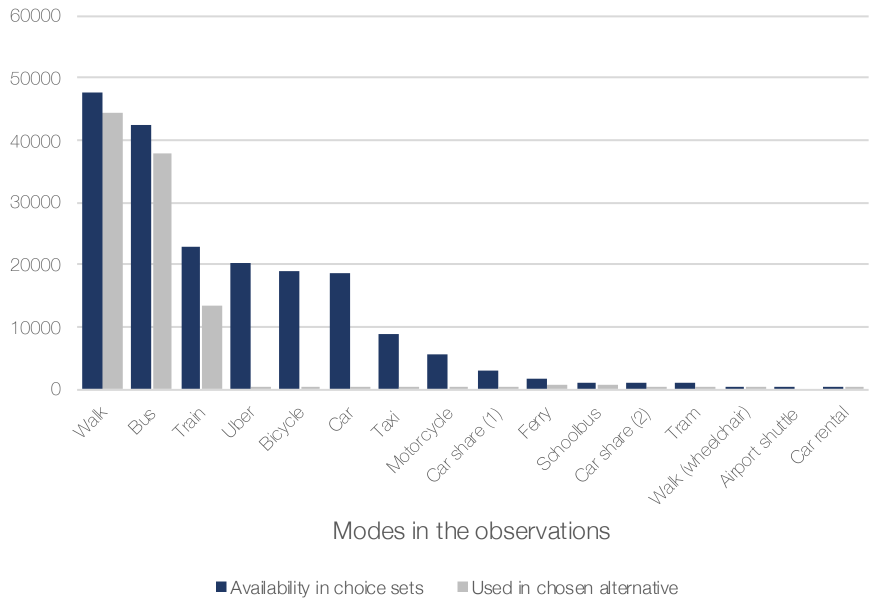

Figure 3.18: Occurrence of modes in the data

Mode name	Availability		Chosen		Ratio
	(#observations)	(% of observations)	(#chosen)	(% of choices)	(chosen/available)
Walk	47632	97,89%	44512	91,48%	0,93
Bus	42348	87,03%	37935	77,96%	0,90
Train	22748	46,44%	13562	27,87%	0,60
Uber	20165	41,44%	531	1,09%	0,03
Bicycle	19039	39,13%	458	0,94%	0,02
Car	18769	38,57%	528	1,09%	0,03
Taxi	8824	18,14%	92	0,19%	0,01
Motorcycle	5546	11,40%	102	0,21%	0,02
Car share (1)	2907	5,97%	11	0,02%	0,00
Ferry	1576	3,24%	714	1,47%	0,45
Schoolbus	1144	2,35%	684	1,41%	0,60
Car share (2)	1014	2,08%	3	0,01%	0,00
Tram	965	1,98%	345	0,71%	0,36
Walk (wheelchair)	530	1,09%	488	1,00%	0,92
Airport shuttle	20	0,04%	0	0,00%	0,00
Car rental	2	0,00%	1	0,00%	0,50

Table 3.6: Modes and occurrence in the data

3.3.3. Alternatives

In the data, 168 unique alternatives exist that each consist of a different combination of modes. All these alternatives and the modes they consist of, are specified in Table B.1 in Appendix B. Table 3.7 reveals information on the most often chosen alternatives in the data (>100 chosen). This table again confirms that public transport alternatives are chosen most by TripGo users. The share of choices for 'bus and walking' is huge, 62,2% of choices are for this alternative. The second and third largest shares go out to 'bus, train, walk' and 'train and walk' with respectively 12,5% and 10,1%. After the these alternatives, the share of choices quickly drops. Through adding up only the often chosen PT alternatives of Table 3.7, public transport trips already account for 95,22% of the trips.

In comparison, average Sydney commute trip shares consist of 5% walking, 1%cycling, 26,3% public transport and 67% motorized vehicles (Loader, 2018). This comparison confirms the self-selection amongst the TripGo user group, representing mostly public transport users. Within public transport, average Sydney mode shares consist of 45,8% train, 50,8% bus, 2,7% ferry and 0,68% tram. These mode shares are somewhat similar to the mode shares of public transport in Table 3.6. However, it can be seen that the endorsement of bus mode shares is much higher amongst TripGo users. Reason for this could be that bus trips often require more planning than train trips. Bus services include many lines and different schedules, whereas locations of train stations are often more well known, and the schedules are simpler to learn by heart.

Furthermore, it can be seen from Table 3.6 that the most chosen non-PT alternatives include car, bicycle and Uber. It is interesting insight that these modes are chosen relatively more often in combination with PT than as a unimodal alternative. This indicates that the non-PT modes in the application, are more likely to be used to complement PT trips, than to substitute for PT.

Alternative	**Availability**		**Chosen**		**Ratio**
(Mode combination in names)	(# observations)	(% of observations)	(# chosen)	(% of choices)	(% chosen/available)
bus,walk	35316	72,58%	30265	62,20%	85,70%
bus,train,walk	12099	24,87%	6067	12,47%	50,14%
train,walk	10569	21,72%	4890	10,05%	46,27%
train	1974	4,06%	1868	3,84%	94,63%
walk	28780	59,15%	926	1,90%	3,22%
bus,	879	1,81%	740	1,52%	84,19%
schoolbus,walk	909	1,87%	579	1,19%	63,70%
bus,walk (w)	417	0,86%	364	0,75%	87,29%
ferry,wal	547	1,12%	296	0,61%	54,11%
car,wal	14298	29,39%	291	0,60%	2,04%
bicycle	18475	37,97%	288	0,59%	1,56%
Uber	11669	23,98%	241	0,50%	2,07%
bus,ferry,walk	493	1,01%	200	0,41%	40,57%
Uber,train,walk	3282	6,75%	150	0,31%	4,57%
tram,walk	370	0,76%	138	0,28%	37,30%
bicycle,train	3108	6,39%	119	0,24%	3,83%
car	4723	9,71%	118	0,24%	2,50%

Table 3.7: Alternatives chosen more than 100 times

Alternative complexity

The alternatives in the data consist of 1 to 5 modes of transportation. The number of different modes included in an alternative is an indication of the degree of complexity of a or alternative. For example, using a single mode for a trip can be experienced as simpler than combining more modes in one trip.

Figure 3.19 and Table 3.8 divide the alternatives in the data over different bins, according to the number of modes that are included in the alternative. It can be observed that alternatives consisting of two modes occur most, and are also chosen relatively most. As a runner up, alternatives consisting of three modes are chosen relatively often. It is interesting to see that alternatives consisting of a single mode are chosen relatively least, while this could be perceived as a simpler way of transportation (no transfers, less effort). Usually, alternatives consisting of one mode include private modes of transportation such as car and motorcycle, but also bicycle. Therefore this finding is in line with the fact that users mostly choose for public transport alternatives, which usually consist of at least two modes (walk+PT).

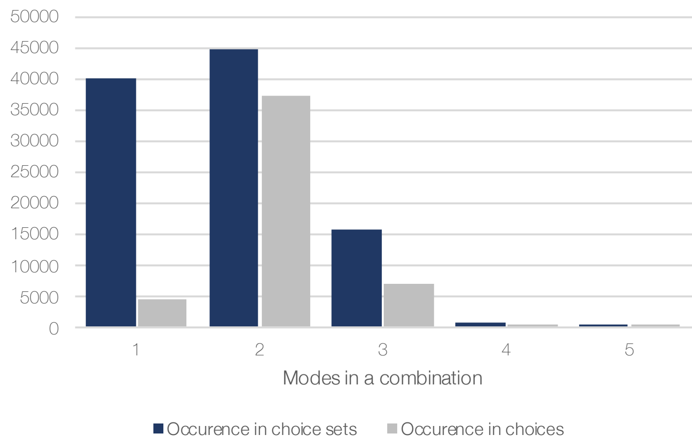

Figure 3.19: The number of modes per alternatives

Number of modes in alternative	Unique alternatives	Available in number of observations	Chosen	Chosen in entire data (%)	Ratio chosen/ available
1	15	40008	4411	9,07%	0,11
2	47	44791	37235	76,53%	0,83
3	60	15695	6930	14,24%	0,44
4	43	624	78	0,16%	0,13
5	3	16	3	0,01%	0,19
Check	168		48657	100,00%	

Table 3.8: The number of different modes in alternatives

3.3.4. Choice Sets

In this data the choice sets consist of between 1 and 19 alternatives, this can be seen in Figure 3.20. A choice set of 1 might sound peculiar, however it is possible in the API. A choice set size of 1 means, for the selected query (O,D,t) by user i, only one trip alternative is available. This can be caused because the origin (O), destination (D) and or selected time (t) lie out of the operating range of the available modes (i.e. in outskirts, or at night time). Another possible cause is that modes are not available because user i chose not to select this mode at on-boarding. Large choice sets of more than 12 alternatives can occur when many modes are available, and for some of them multiple possibilities are shown in the app (i.e. multiple bus alternatives). In this case, users have to scroll through the user interface to view the different possibilities.
In Figure 3.21 it can be seen where in the choice set the chosen alternative was positioned. From this figure, it is clear that most chosen alternatives are on the first position of the choice set, and the majority of chosen alternatives are positioned on the ‘first screen’ shown by TripGo (consisting of the first 5 alternatives).

3.3.5. Attributes

Table 3.9 shows information on the measured attributes in the data. It can be seen that the range of the attribute values is large. The maximum values of the attributes lie much higher than the means and 90st percentile values. This indicates that some ‘outliers’ are still present in the data. However, as explained in Section 3.2, this naturally occurs because of the broad range of alternatives that is proposed in choice sets. For example, it is quite normal to plan a trip that would consist of an hour car drive. If the choice set also generates a walking alternative in this case, that alternative can easily take 16 hours. The same line of reasoning holds for the price attribute, a long ride using an expensive mode can lead to high travel costs.

Besides checking these ranges, the attributes are also briefly checked for multicollinearity. This brief check does not point out any multicollinearity between the attributes cost and time, and between carbon and calories. Carbon and costs do show a pattern of increasing carbon emission with increasing costs. However, from

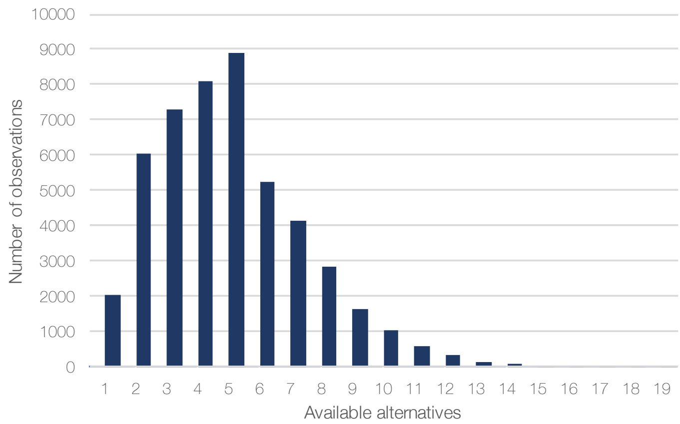

Figure 3.20: Choice set size for users

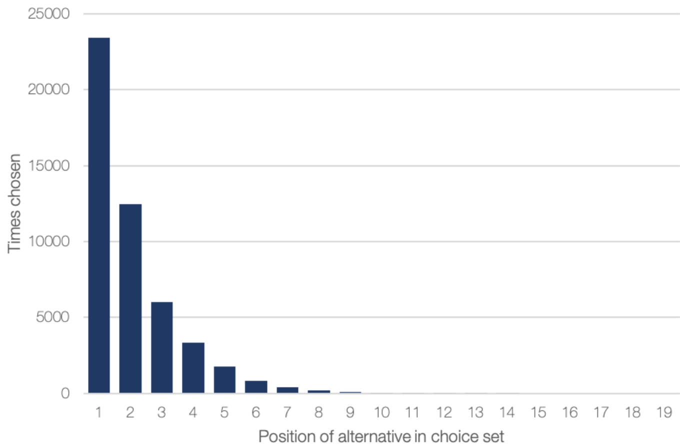

Figure 3.21: Position of chosen alternatives

this investigation only, it is unknown whether the pattern affects correlations in choice models. Details to this check are reported in Appendix C.

Attribute	**Type**	**Unit**	**Mean**	**Range**	**90th percentile**
Price	Numerical	AUS$	7,8946	0 - 521,10	20,6
Carbon	Numerical	kg CO2	0,9501	0 - 49,2	2,3
Calories	Numerical	kcal	68,2368	0 - 2.196	146,0
Travel time	Numerical	minutes	46,99	0 - 873	87,6
Position	Ordinal	-	-	[1,...,19]	-

Table 3.9: Attributes

3.3.6. Multi-modality

To get an insight into the multi-modality of choices and users in the data, the chosen alternatives are classified into different categories according to the modes they include. The classes include the following 8 compositions:

1. Public transport
2. Private
3. Intermediate
4. Public transport and private
5. Public transport, private and intermediate

6. Public transport and intermediate
7. Private intermediate
8. Walking

Out of these categories, classes 4, 5, 6 and 7 represent alternatives that include intermodal trips. Table 3.10 shows the choices in the data divided over the eight different classes. In total, only 1,16% include a intermodal alternative. However, this small number also captures the limited availability of these types of alternatives. Intermodal trips are only generated for long-distance trips, or trips between origins and destinations that are not well-connected. Therefore, the ratio between chosen and available intermodal alternatives must be consulted to get an insight on the true value of intermodal trips. From the ratio, it can be seen that the combination of public transport with private or intermediate modes is chosen relatively most after public transport. Also, the average trip duration of the chosen intermodal trips amounts to 01:10:23 (hh:mm:ss), almost twice more than the mean trip length of 36 minutes. This indicates that these alternative types are chosen for trips that are longer than average. Overall, the ratio of the unimodal and intermodal alternatives indicates that users value/have an interest in intermodal trips. Even though the alternatives are not chosen much, they are opted for more often than it is opted for unimodal alternatives private and intermediate.

No.	**Alternative type**	**Availability**		**Chosen**		**Ratio**
		(# observations)	(% of observations)	(# chosen)	(% of choices)	(% chosen/available)
1.	Public Transport (PT)	47641	97,91%	45968	94,47%	96,49%
2.	Private (P)	26965	55,42%	798	1,64%	2,96%
3.	Intermediate (I)	21624	44,44%	424	0,87%	1,96%
4.	PT + P	5915	12,16%	289	0,59%	4,89%
5.	PT + P + I	1	0,00%	1	0,00%	*100,00%*
6.	PT + I	5120	10,52%	245	0,50%	4,79%
7.	P + I	2	0,00%	0	0,00%	0,00%
8.	Walking	28813	59,22%	932	1,92%	3,23%

Table 3.10: Occurence of Unimodal and Intermodal Alternatives

From a user perspective, multi-modality is investigated through inspecting whether users choose different mode types for different trips. Table 3.11 shows that 15,30% of the users are multimodal. This part of the users has either chosen an intermodal trip, or chose different unimodal alternatives for different trips. Table 3.11 represents for the multimodal users what caused them to classify as a multimodal user.

	Number of users	**Percentage of users**	**Classification**
Total users	7327	100%	
· users that chose an intermodal trip (1)	5,98%		
· users that chose two unimodal different categories (2)	794	10,84%	
· users that did both (1) and (2)	111	1,51%	
· users that did either (1) or (2)	1121	15,30%	Multimodal travellers
· users that chose neither		84,70%	Public transport users

Table 3.11: Multi-modality of Users

3.4. Discussion

As explained in Chapter 1, integrated mobility is an important enabler for multimodal travel, which aim is to provide people with an attractive alternative to private car use. Based on this idea MaaS is often promoted as a sustainable concept, but in reality it could also lead to greater congestion with more vehicles on the road (Mulley & Kronsell, 2018). With the rise of MaaS and integrated mobility platforms, current PT users will also gain easier access to car-based services Smith et al. (2018). This could ignite a modal shift from PT to car instead of vice versa, and therefore increase the total number of car trips.
From a sustainability point of view, this identified risk is also a relevant issue with TripGo. If the app currently attracts PT users, it basically exposes PT users to alternative modes. As such, this application could only evoke

a modal shift away from PT.

At this point, results of this data analysis however show that the risk of this negative effect is limited. Even if PT users are exposed to other modes, they are unlikely to opt out of PT. This is aligns well with the findings of (Ho et al., 2017), who find that take up levels of MaaS plans are low amongst frequent PT users.

3.5. Conclusion

Amongst the TripGo users a self-selection effect occurs through which users select themselves into this research based on shared characteristics. In this case, their shared characteristic consists of the fact that they are public transport users with an interest in other modes of transportation. As public transport users are the type of travellers that like to plan their trips using smartphone applications, they self-select themselves as TripGo user. This is confirmed with the finding that 95,22% of the chosen trips consists of pure public transport alternatives.

Even though public transport is dominant amongst chosen trips, the fact that these users chose TripGo as their app suggest an interest in information on other modes of transportation. Otherwise, they could have chosen a conventional platform for public transport planning. The data illustrates a slight interest in non-PT modes; besides the high penetration of public transport for chosen trips, it can be seen that most other modes of transportation are still chosen daily in the data.

When looking at the choice for non-PT modes, it appears that bicycle, car and Uber are the most chosen non-PT modes. It is noteworthy that alternatives consisting of those modes are chosen relatively more often when the mode is combined with a public transport mode. An investigation into different trips types also shows that combinations of public transport and private or intermediate modes are chosen more often than unimodal trips of non-PT alternatives. This finding suggests that the intermodal trips offered by TripGo are in a way valued by the users. And, the non-PT modes in the application, are more likely to be used to complement PT trips, than to substitute for PT. Furthermore, it is uncovered that the intermodal trips proposed in the platform, are chosen for trips with a trip length twice larger than average.

From a user perspective it is seen that 15,30% of users makes use of TripGo's multimodal offerings even though only a small portion of the chosen trips include non-PT alternatives (or PT combinations). On a user level, users make use of multimodal offerings through either choosing intermodal trips or altering their trip types for different travels.
With the information from this chapter, it can be argued that the described that the TripGo platform can provide public transport users with an extension on their mobility options.

4 Choice Models

This chapter describes how the method of Discrete Choice Modelling is applied to the constructed choice data, to learn about users travel behaviour, and the usage of smartphone app data in these conventional methods.

In this chapter, Section 4.1 explains how the 'best possible model' for uncovering travel behaviour is specified. Next, the results of this model are presented and discussed in Section 4.2. After that, it is investigated if obtained model results can be used for economic appraisal in Section 4.3. Finally, Section 4.4 discusses the usability of smartphone app RP data for discrete choice analysis.

4.1. Model Specification

This section describes the formulation of the best possible model, in terms of model fit and ability to explain travel behaviour. For each included set of parameters it is described what the parameter aims to capture, and why it was included in the model.

To derive the best possible model, different model specifications were formulated and tested in the modelling phase of this research. Appendix D reports on the complete modelling process that leads to the formulation of the best possible model. Each relevant preceding model is discussed, and an extensive argumentation is provided for the modelling steps. The highlights of this appendix are incorporated and discussed to more detail in this chapter.

To specify the 'best possible' choice model, utility functions are created for each of the 421 alternatives in the data. These functions capture only the systematic utility of an alternative, and therefore take on the following general form:

$$V_i = ASC^{mode} + \sum_m \beta_m \cdot x_{im} + V_{\text{position},i} \tag{4.1}$$

where: V_i systematic utility of alternative i

ASC^{mode} Alternative Specific Constant for a specific mode

β_m taste parameter for attribute m

x_{im} the attribute level of attribute m in alternative i

$V_{\text{position},i}$ position related utility of alternative i

(4.2)

In total, the formulation of the best model includes 43 parameters:

- 10 Taste parameters
- 14 Alternative specific constants
- 19 Ordering dummies

This section shortly addresses each of these categories to explain which attributes were included in the formulation and what they aim to capture.

4.1.1. Taste Parameters

Parameter		**Unit**	**Related to mode(s)**
β_{TC}	travel cost	util/AUS$	
$\beta_{calories}$	calories	util/kcal	
β_{carbon}	carbon emissions	util/ kg CO_2	
$\beta_{combine}$	included mode(s)	util/mode	
β_{TT}	travel time	util/min	
$\beta_{Ttransfer}$	transfer time	util/min	tram, train, ferry, tram, schoolbus
$\beta_{Tcollect}$	collecting vehicle time	util/min	shared car
$\beta_{Tparking}$	parking time	util/min	shared car, car, motorcycle
β_{Twait}	waiting time	util/min	taxi, Uber
β_{Twalk}	walking time	util/min	walk

Table 4.1: Taste parameters

Table 4.1 presents the taste parameters included in the best model. For each taste the name and unit of the parameter are included. And, if applicable the specific modes they are related to are reported in the table too. From the modeling process in Appendix D.1, it is concluded that inclusion of each of these taste parameters in the model leads to significant improvement in model fit.

The first parameter, β_{TC}, captures the taste for travel cost amongst users. Next, $\beta_{calories}$ captures the taste for 'activeness', with the amount of calories that is required to perform a trip as corresponding attribute level. β_{carbon} captures the taste for 'sustainability' as it relates to carbon emission of an alternative.

$\beta_{combine}$ captures the complexity of an alternative through accounting for the number of different modes in an alternative. In this specification, walking is excluded from the mode count, as counting walking as a mode leads to bias in the parameter. This issue can be illustrated with the following example: for public transport, TripGo allows planning door-to-door trips, but also stop-to-stop trips. Both types of trip plans require an access and egress mode to reach the final destination. Therefore, the trips can be seen as equally complex. However, in the data the door-to-door trip contains at least two modes (the access/egress mode and the public transport mode), while the stop-to-stop trip only includes the public transport mode. This problem is overcome through excluding walking from the mode count to capture the complexity of a trip. The limitation of this parameter is that it does not allow capturing when the same mode is used more than once (i.e. bus, bus) as durations on similar modes were added up during the data processing [1]. The consequence for the model is as following: according to the data, a transfer with two trains receives a combine value of 1, while a transfer from train to bus receives a 2. This is a difference in 'complexity', while the alternatives may actually be equally complex. This issue however only occurs within public transport trips of multiple PT modes. And, in these alternatives the complexity of a transfer is also captured by $\beta_{transfer}$, and therefore no bias is expected in the results.

The next 6 attributes in Table 4.1 represent tastes for multiple values of time. The parameter for travel time, β_{TT}, captures the in-vehicle time of a trip. The five other time parameters are specified to capture taste for time spent on collecting vehicles, transfers, parking, waiting and walking. These parameters only appear in the utility functions of alternatives in which the related modes occur.

[1] It was considered to substitute the formulation with 'different modes' by 'the number of segments' in a trip. However, after a brief study of the data, it appeared that counting 'segments' represents the trip complexity less accurately. The number of segments in the data is very inconsistent and therefore not representative of trip complexity. For example, an alternative consisting of Uber and train is often described with 2 segments (one for Uber, one for train). But for public transport trips, a trip consisting of two trains can sometimes be described with 5 segments; train, walk, wait, transfer, train. In these cases, an more or less equally complex trip is described with a very different number of segments. Therefore, the number of different modes included seems the most accurate way to capture alternative complexity.

4.1.2. Alternative Specific Constants

ASC	Mode(s) represented
ASC_bicycle	bicycle
ASC_car	car
ASC_bus	bus
ASC_car-s	car sharing, car rental
ASC_ferry	ferry
ASC_motor	motorcycle
ASC_schoolbus	schoolbus
ASC_shuttle	airport shuttle
ASC_taxi	taxi
ASC_train	train
ASC_tram	tram
ASC_uber	Uber
ASC_walk	walk, wheelchair
ASC_walkbus	walk + bus, wheelchair + bus

Table 4.2: Alternative Specific Constants

The ASCs in Table 4.2 are specified to represent preferences for modes in the data. Because some of the modes in the data (Table 3.5) are nearly identical, they are merged into one representative ASC in the model. This includes the ASC for car sharing, capturing the two car sharing services and car rental [2]. Furthermore, the ASC for walking captures both walking and wheelchair.

The last parameter in Table 4.2 represents a combined ASC for walking and bus. Preliminary models with only an ASC for walking estimate ASC_walk to be insignificant. Because the number of observations that include walking is more than enough for proper estimation, this insignificant value indicates a model misspecification. Therefore, the relation between walking and public transport was further explored. The insignificance may arise because public transport is often chosen in the data. But public transport but mostly requires walking, leading to many choices including walking as a mode, even though walking might not be the preferred mode. Therefore the model has difficulties with assigning a reliable value to this parameter. To address this issue, different constants were tested for capturing the additional utility of the combination of walking and different PT modes. Eventually, ASC_walkbus is included in the model as it is the only identifiable constant that contributes to a better model fit. With this parameter included, utility functions for alternatives that include walk and bus as modes include the following ASC's: $ASC_{walk} + ASC_{bus} + ASC_{walkbus}$.

Finally, the values of ASCs are estimated relatively to one another. Therefore, one of the ASCs in the model must be fixed to a selected reference level. In this research it is chosen to set the ASC for bus to 0 as a reference level.

4.1.3. Ordering dummies

Dummies, also known as attribute specific constants, are specified for each position in the choice set to represent the effects of alternative order in decisions. Research on survey design and on user interface design both indicate that the order in which information is presented matters. In surveys, the order of alternatives can strongly influence results (Schwarz & Hippler, 2011). This effect is known as 'order bias' when the choice for a particular alternative is affected by its position in the response array (Coney, 1977). Additionally, from researching the design of user interfaces it is known that much of the information presented on a display is not incorporated into a user's decision-making process (Schaffer et al., 2018). A study by Fessenden (2018) shows that users spend most of their attention on the first screenfull of information. In the TripGo interface that consists of the first 5 alternatives of the choice set.

To capture only the travel behaviour of TripGo users, and not their behavior in the user interface, it is important that the effects of ordering are distinguished from parameters related to travel behaviour in the model.

[2] Car rental shows many similarities to 2-way car sharing, and because the number of observations for this mode is very limited, it is chosen to accommodate this mode in the constant for car sharing.

To do this, dummies are specified to capture utility related to the position of an alternative. Dummies are constants that allow to capture utility that is related to nominal or ordinal variables. The position of an alternative in the choice set can range from 1 to 19, and therefore 19 dummies are specified to represent each position. To model this, following utility specification is incorporated in each utility function in the model:

$$V_{\text{position},ij} = \sum_{p=1...P} D_p \cdot P_{ijp} \qquad \vee \quad p \quad \epsilon \quad [1,...,19] \tag{4.3}$$

$V_{\text{position},ij}$ position related utility of alternative i in observation j

D_p Ordering dummy for position p

$$P_{ijp} = \begin{cases} 1 & \text{if alternative i is on position p in observation j} \\ 0 & \text{otherwise} \end{cases}$$

The dummy for position 1 of the choice set is fixed to 0 as a reference level. All other dummies are estimated relatively to this first position. During the modelling process, the dummy for position 19 was also set to 0, as not enough observations with a choice set size of 19 are available to provide a significant estimate for D_{19}. Finally, from Appendix D.4 it is concluded that accounting for the effect of order, with 18 position dummies in the model leads to a significant improvement in model fit (LRS = 2195).

Data Segment for Frequent Users

The best possible model consists of the parameters described in the past subsections. It is notable that this model does not account for the amount of observations a user makes in the data, also known as the user frequency. To explore whether user frequency has an effect on choice behaviour, the best possible model is tested on different data segments for frequent and non-frequent users in Appendix D.5. From the estimation results for both data segments, no difference in behaviour or model fit amongst the two groups can be infered. Therefore, the estimation of the best possible model is performed on the complete data sample, without segmenting for frequent and non-frequent users.

4.2. Estimation Results

Estimation of the model parameters takes place on a subset of the data. This subset consists of a random sample of 80% of the observations in the processed data. The other 20% is saved as hold-out data for model testing and validation.

The derived estimation results of the the model specified in Section 4.1 are reported in Table 4.3 and 4.4. The estimation report shows a Rho-square compared to the null model of 0,486. This indicates that this model is able to explain about 50% of the decision making process that leads to the choices recorded in the data. Considering the noisiness of the data, and the complex decision making process that is aimed to be captured this is a very acceptable model fit.

Number of estimated parameters:	40
Sample size:	38.927
Init log likelihood:	-56.365
Final log likelihood:	-28.956
Likelihood ratio test for the null model:	54.818
Rho-square for the null model:	0,486

Table 4.3: Estimation report

Name	Value	Robust t-test
ASC_bicycle	-3,66	*-32,81*
ASC_car	-3,72	*-23,52*
ASC_bus	0	
ASC_car-s	-3,09	*-5,95*
ASC_ferry	1,87	*15,90*
ASC_motor	-4,25	*-25,38*
ASC_schoolbus	0,962	*9,31*
ASC_shuttle	-8,52	*-12,24*
ASC_taxi	-3,21	*-18,05*
ASC_train	0,901	*14,78*
ASC_tram	1,16	*9,83*
ASC_uber	-2,45	*-19,14*
ASC_walk	-0,145	*-1,99*
ASC_walkbus	1,04	*18,37*
BETA_TT	-0,0303	*-18,18*
BETA_TTransfer	-0,0547	*-15,49*
BETA_TTwalk	-0,084	*-29,4*
BETA_Tcollect	-0,297	***-1,04***
BETA_Tparking	0,215	*4,46*
BETA_Twait	-0,0637	*-3,35*
BETA_calories	-0,0017	*-2,89*
BETA_carbon	-0,144	*-2,72*
BETA_combine	-1,36	*-20,47*
BETA_TC	-0,0234	*-4,85*
D_p1	0	
D_p2	-0,466	*-26,13*
D_p3	-0,837	*-35,34*
D_p4	-1	*-33,89*
D_p5	-0,986	*-26,11*
D_p6	-0,918	*-17,87*
D_p7	-0,939	*-13,39*
D_p8	-0,942	*-9,92*
D_p9	-1,19	*-8,59*
D_p10	-1,1	*-5,44*
D_p11	-1,46	*-4,55*
D_p12	-1,23	*-3,18*
D_p13	-1,97	*-2,91*
D_p14	-0,941	***-1,49***
D_p15	-5,76	*-10,41*
D_p16	-4,59	*-10,29*
D_p17	-1,75	*-2,01*
D_p18	-1,14	*-2,00*
D_p19	0	

Table 4.4: Parameter Estimates

Significance of parameter estimates
The robust t-tests of the parameter estimates in Table 4.4 are consulted to check the precision of the estimated values. It can be seen that only two parameters in this model appear to be statistically insignificant, as their t-tests do not meet the threshold value of 1.96 for a 99% significance level. The associated insignificant parameters include the collecting time parameter $\beta_{Tcollect}$ and the dummy for position 14 D_p14.
For $\beta_{Tcollect}$ it is expected that this is due to insufficient attribute variance, from checking the data it is seen that the attribute value for collecting time is set to 2 minutes in 94% of the cases.
For D_p14 it appears that enough observations are available that include an alternative on position 14. Also, no severe correlations exist between D_p14 and other parameters. Therefore it remains unknown why this parameter is insignificant.

Sensibility of parameter estimates
Looking at the estimated values of the parameters, it appears that all of the parameters are of the expected

sign, except for $\beta_{Tparking}$. This parameter is positive, indicating that an increase in parking time has a positive effect on utility. Intuitively, this is an incorrect representation of actual travel behavior. Yet, a plausible explanation exists for this unexpected sign. The issue enfolds of a ‘flaw’ in the model that can be explained by the fact that this model does not only capture travel behaviour. The model also, and more specifically, captures the travel behaviour in response to an information system.
In the TripGo app, some car trips are administered with information on parking times and location, whereas other car trips do not include any information on parking. As most car trips do require parking, it is likely that users choose a car trip with parking information over one without it. Therefore, it is a plausible explanation that users value this type of information, leading to a positive parameter estimate for $\beta_{Tparking}$.

4.2.1. Results Interpretation

This section discusses the model estimation results, and relates the retrieved values to the travel behaviour of TripGo users. To create an integral overview, it is first discussed what the results consist of for ASCs, taste parameters and ordering dummies. Then, at the end of this section the obtained insights are combined to provide an understanding in the choice behavior of the users.

Alternative Specific Constants

A visual overview of the estimated values of the ASCs is shown in Figure 4.1. Most outstanding in the ASC estimates is the large difference in ASC values of public transport modes and non-PT modes. This insight aligns well with the insights from the descriptive statistics in Section 3.3, where the public transport modes are also dominant. Yet, out of these values it cannot directly be derived what modes are most preferred amongst decision makers. The ASCs are only indicative of actual preferences, because some of the modes in the data are described with more detail than others. For example for public transport, one of the negative aspects of the mode, transfers, is captured with a specific parameter for transfer time. This negative aspect is therefore excluded the preference parameter, resulting in more positive ASCs for public transport. As an other example, the constant for ferry is by far the largest, but it can not be concluded that this is the most preferred mode in the data. Especially ferries are often combined with other modes and include transfers. Therefore the ASC value overestimates how much this mode is actually preferred. Because such subtleties play a role in the ASCs for different modes, the ASCs do not capture an average preference relative to all other modes. To make conclusions about travel behaviour, an integral insight on all parameter estimated is required.

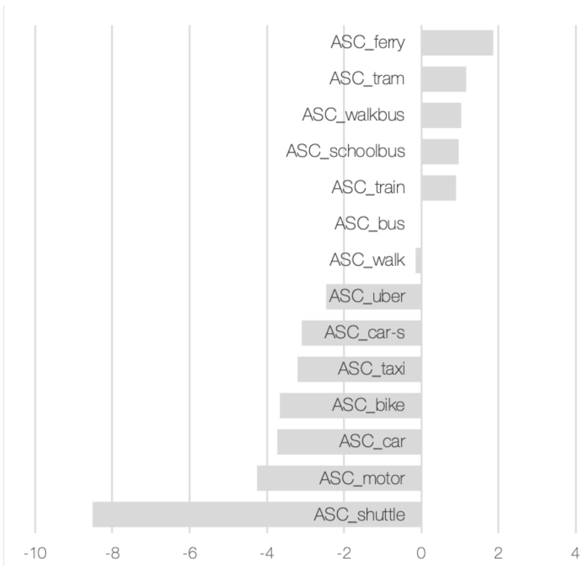

Figure 4.1: Estimated ASC values

Relative Importance of Taste Parameters

To uncover which betas are most important in decision making, the parameter estimates for the betas in the model cannot directly be compared to one another. Each beta is formulated in a different unit, and is associated with a different range of possible attribute levels. Therefore, the relative importance of the estimated parameters is computed to assess what taste parameter has the largest potential impact on utility. Normally, the relative importance is obtained by multiplying a taste parameter with the associated attribute range in the data. This way, it can be investigated what attribute has the largest influence in terms of utility. However, in this noisy RP data, the total attribute range includes extreme attribute values. Therefore, using the total attribute range in the computation gives a biased overview of the relative importance. To obtain a realistic insight in the importance of the taste parameters it is chosen to use the 75th percentile of the attribute range to compute the relative importance.

The values for the relative importance of taste parameters are reported and visualised in Table 4.5 and in Figure 4.2. According to Figure 4.2, walking time and number of modes combined in an alternative have the largest influence on utility. The more walking time is incorporated in a trip alternative, the lower the associated choice probability. The same reasoning holds for the number of modes; the more different modes included in the alternative, the lower the choice probability. Besides these two taste parameters, the in-vehicle travel time also stands out with its potential impact on utility.

As only differences in utility matter in the choice for an alternatives, it is to be noted that walking time and included modes are much more likely to make a difference in the choice for an alternative than travel time. Walking time and number of modes can vary much more amongst alternatives for the same trip, whereas in-vehicle travel time does not differ as severely between alternatives within the same choice set.

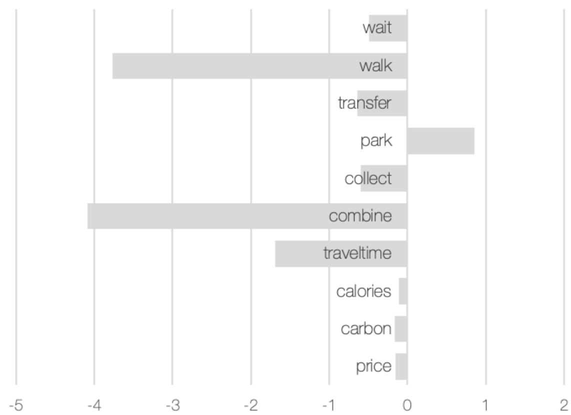

Figure 4.2: Relative importance of taste parameters

Attribute	75th percentile	Parameter estimate	Relative Importance
Calories	64	-0,0017	-0,109
Carbon	1,1	-0,144	-0,158
Collecting time	2	-0,297	-0,594
Combine	3	-1,360	-4,080
In-vehicle time	55,78	-0,030	-1,690
Parking time	4	0,215	0,860
Transfer time	11,78	-0,055	-0,645
Travel cost	6,69	-0,023	-0,156
Waiting time	8	-0,062	-0,496
Walking time	26,01	-0,145	-3,771

Table 4.5: Relative importance of parameter estimates

Out of the other parameters, it is remarkable that the importance of travel cost is low. It was suspected that the cost of an alternative are an important factor in the decision making process. It could be the case that travel cost indeed do not matter much to the users in TripGo. For most alternatives, the cost differences are small, especially among different PT options. For example, to perform a trip in which a bus costs 3$ and a train costs 4$ and walking is for free, costs are probably not a critical factor in the decision.

Furthermore, it is also suspected that the parameter estimate for travel costs is slightly biased. A reason for this is that the travel costs in the data do not accurately represent actual travel costs. For public transportation, the TripGo application shows pay-as-you-go costs, but these costs are only valid for people that buy a new ticket for every trip. Travellers in possession of an Opal card benefit from discounts and rewards for making multiple journeys a week, travelling out of peak hours, transferring between PT modes and performing sequences of trips on a day. On top of these benefits, users can have public transport subscriptions that reduce costs even more. Given this information, the actual travel costs of public transport are lower than those reported in the data. Because of this, the data may suggest that users opt for a more costly alternative, and do not care that it costs more. While in reality it costs them less. As a result, the model is likely to slightly underestimate the value of the cost parameter.

Next, carbon emission and calories also have a small, close to 0, influence on utility. For carbon, it was expected that people do not take the amount of carbon emission into account in their travel choices.
For calories, a larger impact on utility was expected on utility as people might have a strong taste for being active or not in their travels. Looking into this parameter, it appears that the estimate is somewhat correlated with the parameter for walking time (correlation = -0,637). Correlation between parameters indicates that the model has difficulties in assigning values to either one of the attributes, it represents a 'joint uncertainty'. Meaning, a joint move of the estimators can result in a similar likelihood of the data. This is also the case for walking and calories, and therefore the measure of activeness that was intended to be measured by the calories parameter is incorporated in in the walking time parameter. This statement is also confirmed throughout the modelling steps in Appendix D.3. In the models without a specific parameter for walking time, the parameter for calories is much more important. When the walking time parameter is incorporated in the choice model, the importance of the calories parameter decreases.

Ordering effects
The estimated values of the model's position dummies are plotted in the graph in Figure 4.3. It can be seen that the position of an alternative indeed affects its choice probability. Over the first 3 alternatives, the utility of the position rapidly drops from 0 to -1. After that, the curve proceeds with dummy values close to -1 over the positions 6-10. This approximately enfolds of the second screen full of information in TripGo. For the last positions of alternatives, p11-p19, the dummy estimates follow a more inconsistent pattern.

Overall, this curve is in line with the expectation that attention to alternatives decreases as alternatives are positioned farther below in the choiceset. However, it was expected to observe a drop in utility after position 5, as this is where the first screenfull of information ends. Given this boundary, not all users may scroll down any further in the interface.
An explanation for the more flat course of the curve could be the effect of recency. This means alternatives positioned at the bottom of the choice set also have a higher endorsement (Schwarz & Hippler, 2011). Because the choice set size varies in this experiment, the effect of recency benefits another position for every different size of choice set. This could suppress the expected drop in utility after D_p5.

The noisy course of the curve after position 14 could occur for several reasons or combinations thereof. Firstly, only a limited number of observations contain choice sets of 15 or more alternatives, this can cause some bias the estimates of the dummies. In addition, the noise can also be explained by the effect of recency. Towards the end of the curve, recency may benefit a position for some choice set sizes, and detriment the position for other choice set sizes. Furthermore, recency can also explain the rise at the end of the curve. The alternatives on the last positions always benefit from recency, as the last possible positions are per definition always at the bottom of the choice set.

Furthermore, correlations between the estimates of position dummies and other parameter estimates are checked. As a starting point, it was suspected that these parameters could correlate, as the current ordering mechanism in TripGo also makes use of multiple measured attributes. Nevertheless, no correlations were found between position dummies and the travel related parameters. Therefore, it can be concluded that the model is capable to disentangle the effect of ordering from the users' travel behaviour.

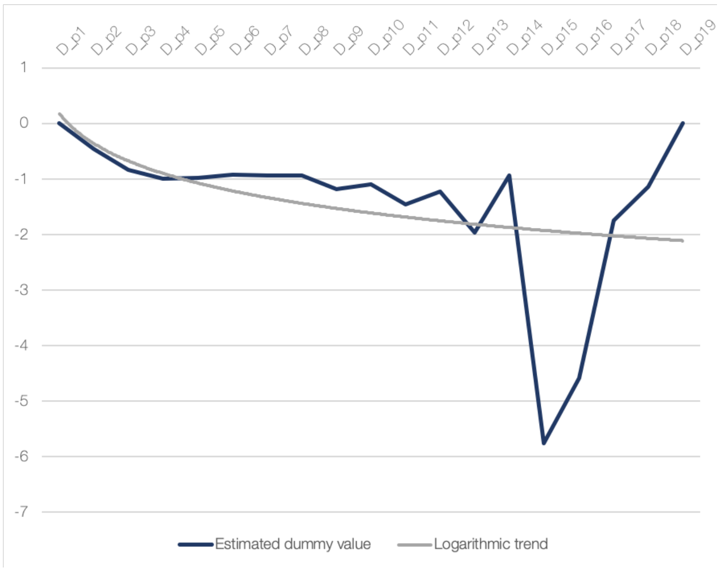

Figure 4.3: Dummy estimates

Choice Behaviour

Users' choices for alternatives are largely determined by the alternative specific constants in the model. It is notable that the differences in ASC values between PT and non-PT are relatively large compared to the potential impact of the taste parameters. Therefore, especially in the choice between PT and non-PT trips or intermodal trips, the variable attributes values are unlikely to make a difference. The estimated constants of the choice model strongly benefit public transport modes, with values much higher than for other constants (Figure 4.1).

As stated, differences in walking time and the number of modes in an alternative, provoke the largest impact on utility. They therefore also have the most potential to influence the choice between PT and non-PT. For trips between less well-connected OD pairs, public transport is often accompanied with larger walking times and multiple modes required to perform the trip. In such cases the utility of all PT alternatives deteriorates while other modes are less affected by these factors. This results in a higher choice probability of the non-PT alternatives that are less or not affected by these factors. Also combinations between PT and non-PT modes may be considered in this case, as a trade-off may occur between the number of modes and transfers needed for a PT trip, and including a low-ASC mode to avoid those transfers.

However, in the majority of choice situations, public transport dominates the mode choice. In particular, for trips between accessible locations, the variability of the measured attributes over different alternatives is too small to influence the choice between PT and non-PT. For the different modes of public transportation, the values of the related ASCs are close. Therefore the choice between different public transport alternatives is largely determined by the values of the measured attributes. Trips with minimal modes in the alternative, and minimal walking, in-vehicle and transfer times appear most attractive.

4.2.2. Discussion

The choice behavior inferred from the model results is related to the effect of user group self-selection. From the data analysis it is uncovered that the group of TripGo users consists largely of public transport users. This presumably occurs because the TripGo app mostly appeals to PT users, and therefore mostly draws this user type into the user group. The findings for choice behavior, inclusive of preferences for public transport, are in line with the revealed self-selection effect.

The constants that capture the preference for public transport represent unobserved factors related to the transportation modes. These unobserved factors can include many different considerations that cause users to tilt towards PT. First of all, habit execution may play a role, in which users repeatedly choose the same modes because they are familiar and comfortable with their choice. But other factors may also play a role, such as barriers or obstructions for using the other modes in the app. Here it can be thought resistance from memberships required to use Uber or car sharing. Or the newness of car sharing that provokes people to stick to their known conventional modes of transportation (Hensher & Ho, 2016).

Even though these preferences exist amongst the TripGo users, it is also seen that non-PT alternatives, or combined alternatives do make an appearance amongst the chosen alternatives. This is seen in the data analysis, and the choice model results allow to sketch the situation for which this is most likely to occur. Namely, when PT is at a disadvantage, for example for OD pairs that are not well-connected. This can occur either when the trip is planned from and/or to an inaccessible location, or when the trip is planned outside of the operating hours of public transport services.

It is likely that this is also the added value of TripGo for users. As mostly PT users use the app, but the app integrates many modes of transportation, it might be questionable why they use this app if they benefit from the extensive possibilities to the fullest. TripGo can complement PT with other modes, and can fulfill mobility needs and provide good alternatives when PT does not suffice.

Furthermore, the order of alternatives significantly affects choice probabilities. It could therefore be argued that this factor can overcome preferences between mode. This opens up the possibility for manipulation of the users. This is captivating but, however, placing a 'low ASC alternative' first in the choice set, and a 'high ASC alternative' last probably does not increase the choice probability of the low ASC alternative, as people are likely to opt out in such a case. When low ASC alternatives are placed first, the experience of using TripGo deteriorates.

4.3. Economic Appraisal

With the estimated parameters, it is possible to infer trade-offs between any pair of attributes. The most common known trade-off is the one between cost and time, also known as the Value-of-Time (VoT). The VoT is a monetary valuation of time that indicates the willingness to pay for a reduction in travel time. It is computed with the following equation:

$$\text{Value-of-Time} = \frac{\beta_{TT}}{\beta_{TC}} = \frac{\delta V/\delta TT}{\delta V/\delta TC} = \frac{\delta TC}{\delta TT}$$

In travel behaviour research these values are often used to measure the benefits of newly implemented transport policies or investments in infrastructure. For SkedGo, it is interesting to obtain this value for a validation of their API. The current API makes use of the VoT for several purposes, such as their score computation to determine the order of alternatives. Other trade-offs can be used to validate routing algorithms, for example to make sure that optimal trips are generated for the users in the data.

4.3.1. The Value-of-Time

From the best possible model, the retrieved VoT amounts to 77,69 AUS $/ hour[3]. This value is unexpectedly high judging from comparison to peers. Government guidelines in the state of New South Wales state a value of travel time of $16.26 per hour applicable to private car occupants, on-board train time, on-board bus time, ferry travel, cycling time and walking time (NSW Government, 2016). For business trips a VoT of $52.76 per hour can be applied to all business travels. The VoT resulting from this research lies far out of this range, and is therefore unreliable.

A possible explanation for this could be that that the parameters for travel cost and travel time are picking up on other factors that play a role in decision making. Therefore, the correlations between the parameters of the best possible model are checked and reported in Table E.1 of the appendix. From this table it can be seen that indeed, the travel costs of an alternative is correlating with the parameter for travel time (correlation=-0.726). This is a logical correlation, as the more CO_2-heavy modes are also associated with higher costs (think

[3]To retrieve the value of time in AUS $ per hour, the travel time parameter [util/minute] must be multiplied by 60 minutes

of cars or taxis compared to public transport or walking). This finding also aligns with insights from the multicollinearity check that was performed in Section 3.3.

Through fixing the carbon parameter to zero, the effect of the cost parameter on utility increases. This is a legitimate result, as in that case the cost parameter also captures some of the effects that were previously represented through the carbon attribute. As a result the VoT of this model takes on a more reliable value, 53,17$/hour, with only a minor decrease in model fit. This corresponds well to the VoT for business trips specified in government guidelines. However, the VoT is still too high, as it can not be assumed that all TripGo trips are for business purposes. If commute trips equal business trips, approximately 40% of the trips in the data involve a business (see Section 3.3). Therefore, if the VoT should respond to that of average public transport users, it should still be lower. The full estimation results of this model can be found in Appendix E.1. Because the derived VoT is still not within the expected range, Section 4.3.2 investigates what causes the VoT to take on such a high value.

Other Trade-Offs
Given the still unreliable value of the VoT, it may seem complicated to infer dependable trade-offs from the model results. Nonetheless, economic appraisal is a result of travel behaviour. As the model is well capable of describing that behaviour, it should be possible to derive dependable trade offs between parameters that are less correlated. Therefore some other trade-offs between parameters are computed, to explore if extra insight could be obtained into the travel behaviour of TripGo users:

- The ratio between in-vehicles time and waiting time equals a classical 1:2 distribution. Meaning a 2 minute reduction of in-vehicle time is traded off with 1 minute of waiting time.
- The ratio of in-vehicle time and walking time equals about 1:3, this is also a very dependable distribution. More specifically, users trade-off between a 1,7 minute walk and a 5 minute reduction of in-vehicle travel time (this computation also includes the extra calories required for walking)
- The ratio of in-vehicle travel time to transfer time is less reliable, about 1:2.

These types of trade-offs can also offer an insight into behaviour of the TripGo users. Furthermore, this information can be used in TripGo to generate more optimal routes that suit users' preferences.

4.3.2. Investigation of the VoT

Other model formulations are explored to investigate whether it is possible to derive a reliable VoT from this data source, and to pinpoint what causes the VoT of the best possible model to be outside the expected range.

Basic model
To start with, a basic model is formulated in which only the travel time and cost play a role. In this model a reference value can be obtained for the VoT, if the model purely relies on time and costs.
The utility functions of that model are as following for all alternatives:

$$V_{ij} = \beta_{TT} * TT_{ij} + \beta_{TC} * TC_{ij}$$

The estimation results of this model are reported in Table 4.6.

Parameter Name	Value	Robust t-test
BETA_TT	-0,0377	*-72,97*
BETA_TC	-0,111	*-71,06*
Null log likelihood:	-56.366	
Final log likelihood:	-47.965	
Rho-square:	0,149	
VoT (AUS$ / hour)	20,38	
Relative importance		
BETA_TC	2,29	
BETA_TT	3,30	

Table 4.6: Basic Model Results

It can be seen that the model fit ($\rho^2 = 0,149$) is much poorer compared to the fit of the best possible model. The VoT resulting from this model, $20,38/hour, is however very reliable. This retrieved VoT value functions as a trust builder for economic appraisal. It illustrates the capability of choice models for extracting a reliable monetary trade-off from this data source. With a model that represents the simplest of travel choice data sets, a reliable VoT can be derived. This shows that the data of this research is reliable for economic evaluation purposes, but that different modelling approach is required.
For the continuation of this investigation in this section, it is investigated what causes the high VoT of the best possible model and if a model exists with a good model fit, and a reliable VoT. During these remaining steps, the basic model VoT functions as a reference value.

Full model
To investigate whether the high VoT of the best possible model results from a specific mode in the data, a full model is consulted. This full model includes travel time parameters for each mode in the data. The estimation results of this model are reported in Appendix E.2.

In short, the model fit of the full model ($\rho^2 = 0,488$) slightly improves compared to the best possible model. However, the full model contains many issues such as statistically insignificant parameters, unexpected parameter signs and identification issues. Therefore it loses in explanatory power and was previously not perceived as 'best possible model'.

With travel time parameters specified for each mode, the Willingness-to-Pay (WtP) for an hour reduction in travel time per mode can be computed. This is notion equivalent to the VoT, but in this case calculated per mode. The resulting WtPs values of this full model are reported in Table 4.7. A reference level from literature is added in this table to asses whether the full model retrieves sensible WtPs. From the results it is seen that none of the WtP values are within an acceptable range of the reference value, and therefore they are seen as unreliable values.

From checking the correlations associated with the parameter estimates, it appears that significant correlations occur for the ASCs of parameters and the corresponding travel time parameters. Therefore, the parameters used for WtP computation do not capture the a pure minute of travel time, but are also proxies for other factors, and distort the WtP computation. Because of these correlations it can not be concluded whether the high VoT of the best possible model is a result from a specific mode in the data.

Mode	WtP	Reference value	Source
bus	$115,84/hr	$8.36/hr	Douglas and Jones (2018)
car	$72,83/hr	$15.58/hr	NSW Government (2016)
car share	$45,43/hr	*$6.40/hr*[4]	Ho et al. (2017)
ferry	-$6,00/hr	$14.19/hr	Douglas and Jones (2018)
motor	$142,89/hr		
schoolbus	$52,37/hr		
shuttle	$1.824,28/hr		
taxi	-$44,39/hr		
train	$76,99/hr	$12.33/hr	Douglas and Jones (2018)
tram	-$5,41/hr	$20.69/hr	Douglas and Jones (2018)
Uber	$167,51/hr		
bicycle	$364,16/hr		
collect	$690,17/hr		
parking	-$735,26/hr		
transfer	$184,51/hr		
walk	$388,44/hr		
wait	$179,31/hr		

Table 4.7: Willingness-to-Pay for a reduction in travel time

Intermediate Models

Known at this point is that the basic model gives a reliable VoT. From consulting the modeling steps reported in Appendix D.1, it can be seen that the VoT takes on an unreliable value as soon as ASCs are specified in the model. Appendix E.3 provides a side by side comparison of the basic model and a basic model with ASCs. It can be seen that the model with ASCs provides a much better model fit, but a less meaningful VoT. This indicates that the VoT becomes less reliable with the specification of ASCs. From checking the correlations of the basic model with ASCs, it appears that the cost parameter and time parameter are slightly correlated (<0.5) with the constants for the modes. This is a possible reason for the biased VoTs. Therefore, an attempt is done at simplifying the ASCs, such that less correlations occur between the parameters. As a next step it is explored if intermediate models exist, with less ASCs or simpler ASC structures, that could provide a model with a reliable VoT and a good model fit.

In Section E.4 of the appendix, the formulation and estimation results of the intermediate models are reported. In these models, a simplified ASC structure is applied to the basic models without ordering dummies, and to the best possible model. For the first mentioned models, the VoT improves with the simplified ASC structure. However, the model fit decreases compared to the ASC structure per mode, and the VoT is still not within a reliable range. For the best possible model, it can be seen that a simplified ASC structure deteriorates the VoT value after the carbon parameter has already been fixed to 0. Therefore, these intermediate models offer no solution to the issue.

4.3.3. Discussion

Table 4.8 provides an overview of all the estimated models for economic appraisal. From this overview it can be concluded that the basic model offers the most reliable VoT, and the best possible model with fixed carbon provides the best trade-off between model fit and a reliable VoT.

In the basic model, a reliable VoT is obtained because this model provides the most pure trade off between travel time and travel costs. This model solely captures the effects on utility of an additional unit of travel time and travel cost. When additional parameters are specified in the model, parameters start correlating. They start to catch up on subtleties in the data, and get confounded with other parameters. This is inherent in the use of RP data, with its noisy nature and in which effects as multicollinearity are inevitable. Difficulties arise in disentangling factors from one another, and therefore the parameters do not purely measure the effect they aimed to capture. They also become proxies for other things, such as other specified parameters, or the non-linear effects of costs and time. These developments distort the ratio between the travel time and travel cost parameter, leading to a less meaningful VoT in models with more parameters.

			Model Formulation											
Model Name	ρ^2	VoT ($/h)	ASCs	travel time	costs	carbon	calories	combine	walking time	collect	transfer time	parking	wait	position
Basic Model	0,149	20,38	none	x	x									
MNLattributes-1	0,430	132,57	per mode	x	x	x	x	x						
MNLintermediate1	0,425	106,86	simplified	x	x									
MNLintermediate2	0,455	87,17	simplified	x	x	x	x	x						
MNLintermediate3	0,460	71,32	simplified	x	x	x	x	x		x	x	x	x	
Best Possible														
· *original*	0,486	77,69	per mode	x	x	x	x	x	x	x	x	x	x	x
· *without carbon*	0,486	53,17	per mode	x	x		x	x	x	x	x	x	x	x
· *intermediate*	0,481	57,13	simplified	x	x	x	x	x	x	x	x	x	x	x

Table 4.8: Choice Models and VoT

4.4. Usability of Smartphone app RP Data for Discrete Choice Analysis

Prior to the concluding remarks in the next section, this section discusses the results of applying the method of discrete choice modelling to smartphone data in general. As mentioned in Chapter 1, using this kind of smartphone app data for travel behaviour research has not been done yet. Therefore, it is unknown what for what research purposes this type of data is suitable.

From Section 2.2, it can be concluded that choice models can be informative of decision making process in smartphone applications. With the best possible model having a proper fit, behavioural factors can be identified that explain travel choices. To uncover the underlying mechanisms that lead to these factors, a deep understanding of the data is required. Many of the explanations provided for the model results are based on an intuition that is created with the thorough data analysis. Inherent in this data source is that no knowledge is available on the user group. All knowledge on the case context has to be inferred from the data and use of the application. Therefore, it is essential to perform a thorough data analysis and understand how the contents of the data relate to the use of the app. Doing this allows users to substantiate findings in the model results with well-reasoned arguments and retrieve accurate explanations of behavior.

From Section 4.3, it is seen that a different modelling approach is required for economic appraisal. When the aim is to capture travel behavior, as much information as possible is taken into account in the model. However, for economic appraisal this approach is not most suitable, as with RP data the model parameters start correlating. These correlations hamper the derivation of 'pure' trade offs between pairs of parameters, as other subtleties get caught up in the trade-off.

To be able to use the RP data for economic appraisal, different model formulations should be explored with the aim to find a good model fit and a reliable VoT. An option here is to explore correlations of parameters involved in the trade-off computation. It can then be attempted to alter the model formulation such that these correlations are minimized, as such, the VoT value should improve. Furthermore, a basic model can be formulated to explore whether it is possible to obtain a reliable VoT value from the data source.

In this case, a reliable VoT value can be derived from a basic model that only captures travel time and travel cost. The retrieved VoT can be used as a reference value for finding a model that has both a reliable VoT and a good model fit. In this case, no such model exists. The model that performs best in terms of model fit and reliable VoT is an altered version of the best possible model. The carbon parameter that correlates with the costs parameter is fixed to zero, this minimizes the correlations of parameters for the VoT computation, and therefore improves the obtainable VoT value.

4.5. Conclusion

To identify travel behaviour, a 'best possible model' is formulated and estimated. This model has a proper model fit, and significant and interpretable parameters. Therefore this model is well-able to describe travel behaviour.

According to the model results, the mode choice is somewhat (pre-)determined by unobserved factors related to the transportation modes. For a mode choice between PT and non-PT alternatives, the choices are dominated by mode preferences. The measured attributes are only likely to make a difference in for trips that are outside the operating area or hours of public transport. In this case, all public transport alternatives in a choice set can suffer from large walking times and many transfers between modes. This will decrease the choice probability of public transport, and therefore increase the choice probability for non-PT alternatives, or combinations with PT modes. But, in the majority of cases the mode choice leads to a public transport alternative. Between PT alternatives, the choice is also subject to other factors; walking time and number of modes combined in an alternative have the largest influence on utility.

For economic appraisal, the best possible model does not directly lead to a dependable monetary trade-off for the VoT. This occurs because the model parameters correlate due to the noisy character of RP data. Therefore, the inferred VoT do not represent a pure trade-off between money and time. In this case, a simple model, representing only travel time and travel cost leads to a reliable value for the VoT. This value can be used as a reference value for exploring other models, and investigate whether an intermediate model exists that can provide a good model fit and a reliable VoT. In this case, the model that provides a combination of the best fit and a reliable VoT consists of an adjusted best possible model. To adjust the model, the carbon parameter is fixed to 0, such that it does not correlate with the travel cost parameter. This model improves the VoT, but still does not provide a value that can be trusted for economic appraisal.

5

Model Application & Validation

This final research step suggests an application of the best possible choice model for TripGo. This model application aims to improve the smartphone application, such that it better aligns with the uncovered user preferences. First, the proposed concept for the model application is described in Section 5.1. Next, a model validation is performed in Section 5.2. The validation provides a proof of concept and evidence for the suggested improvements.

5.1. Model Application

As stated in literature and confirmed in this research, the presentation order of information affects users' decision making process. Through improving the ranking of alternatives in the choice set, TripGo can assist its users in making quality travel choices. Based on Random Utility Theory, the UI can suggest the best alternatives first, according to the users' own preferences. This way, more convenient alternatives end up higher in the choice set, leading to a higher probability of being chosen. This in turn improves the user experience with TripGo, as users consult and execute better trip plans.

The remainder of this section consists of two parts. Firstly, Section 5.1.1 explains the function that is currently used to rank alternatives in TripGo choice sets. Next, a new way is proposed for ordering the alternatives into the TripGo choice sets. The mathematical formulation of this proposition is described in Section 5.1.2.

5.1.1. Current ranking function

Ranking of the alternatives in the interface is currently based on the so called scoring function. This function captures SkedGo's own definition of utility. It consists of several measured attributes, some of which are multiplied by weights. Besides capturing measurable attributes, this function also tries to capture some immeasurable attributes such as 'productiveness' on modes, and the 'hassle' of a trip. The function for computing the score of an alternative is as follows:

$$\begin{aligned} Score &= \text{time\_weight} \cdot \text{time\_factor} \\ &+ \text{price\_weight} \cdot \text{price\_factor} \\ &+ \text{carbon\_weight} \cdot \text{carbon\_factor} \\ &+ \text{hassle\_weight} \cdot \text{hassle\_factor} \\ &+ \text{exercise\_weight} \cdot \text{exercise\_factor} \\ &+ \text{time\_penalty} \end{aligned} \tag{5.1}$$

with:

price_factor	The price of the trip, converted to US$
carbon_factor	The total CO_2 emissions converted to US$ using the cost for offsetting those carbon emissions
exercise_factor	The total calories, converted to a dollar values by using a formula that equates 1km of walking = 3 US$
time_factor	= VoT * (0.2 * total duration + 0.8 * unproductive_time) The unproductive time is determined by unproductive weights that are set for each mode: i.e. unproductive time bus = 0.6 * duration_bus
time_penalty	((arrival_time - estimated_arrivaltime) + (departure_time - query_time)) * unproductive_time_weight
hassle_factor	a factor consisting of different elements: - Distance covered walking, cycling or in wheelchair along paths deemed "unfriendly", e.g., no cycling path for cycling, or having to push a bicycle along a road where you aren't allowed to cycle - Number of transfer for public transport - Hassle penalty for having very short transfer times - Mode-specific hassle, e.g., for hailing a taxi or TNC, or for taking a bicycle on public transport, for using a private vehicle (car, bicycle, motorbike) - Distance between where you park a private vehicle (car, bicycle, motorbike) and the destination

The weights in this function result from the user's input in the sliders depicted in Figure 3.3. The input from the sliders is measured relatively to each other, and the range of weights ranges between 0.1 to 2.
Overall, the score and each of the elements it consists of can be seen as a penalty; the higher the score, the more inconvenient the alternative. The structure of the function and the weights included are formulated based on intuition. For example the unproductive time, it aims to capture the productiveness of a mode. Each mode is associated with its own 'unproductive value'. For instance with travelling on a bus, TripGo claims to be 75% unproductive. While driving a car travellers are labeled as 100% unproductive. According to the described function, the score is computed for each alternative and recorded in the data. The alternatives in choice sets are supposed to be positioned in ascending order of the score. However, from checking the data it appears that appears that the function is not applied consistently. In 16,5% of the choice sets, the alternative with the lowest score is not on the first position, and only 67,6% of the choice sets follow the exact ascending order of the score.

5.1.2. Proposed ranking function

With the application of the specified discrete choice model, the current ranking function of alternatives is replaced with Random Utility Theory (Ben-Akiva & Lerman, 1994). The ranking of alternatives then occurs in order of descending utility. To compute the utility of alternatives, the utility functions of the best possible choice model are used, with the estimated parameters as weights. The parameters capturing the ordering effects are excluded from the model that is applied, as it is aimed to rank based only on travel preferences.

In TripGo, it is possible that the routing algorithm generates alternatives other than the 421 found in the extracted data. To accommodate for all theoretically possible alternatives, a general utility function must be formulated for implementation. It looks as following:

$$V_i = \overline{\beta}_m \cdot \overline{x}_{im} + \overline{ASC_i^{mode}} \cdot \overline{L} \tag{5.2}$$

$$\overline{\beta}_m = \text{Vector containing all parameter estimates } \beta$$
$$\overline{x}_{im} = \text{Vector containing the corresponding measured attributes}$$
$$\overline{ASC}_i^{mode} = \text{Vector containing the estimated values of the ASCs}$$
$$\overline{L} = \begin{cases} 1 \text{ if mode L is present in alternative i} \\ 0 \text{ otherwise} \end{cases} \quad \text{vector containing the mode label}$$

Filled out, the function looks as following:

$$V = \begin{bmatrix} \beta_{\text{price}} \\ \beta_{\text{carbon}} \\ \beta_{calories} \\ \beta_{combine} \\ \beta_{Tcollect} \\ \beta_{TT} \\ \beta_{Tparking} \\ \beta_{TTwalk} \\ \beta_{Ttransfer} \\ \beta_{Twait} \end{bmatrix}^T \cdot \begin{bmatrix} x_{\text{price}} \\ x_{\text{carbon}} \\ x_{\text{calories}} \\ x_{\text{combine}} \\ x_{\text{collect time}} \\ x_{\text{in-vehicle time}} \\ x_{\text{parking time}} \\ x_{\text{walking time}} \\ x_{\text{transfer}} \\ x_{\text{waiting time}} \end{bmatrix} + \begin{bmatrix} ASC_{\text{car\_s}} \\ ASC_{\text{schoolbus}} \\ ASC_{\text{walk}} \\ ASC_{\text{bus}} \\ ASC_{\text{walkbus}} \\ ASC_{\text{train}} \\ ASC_{\text{ferry}} \\ ASC_{\text{tram}} \\ ASC_{\text{bicycle}} \\ ASC_{\text{car}} \\ ASC_{\text{taxi}} \\ ASC_{\text{motor}} \\ ASC_{\text{shuttle}} \\ ASC_{\text{uber}} \end{bmatrix}^T \cdot \begin{bmatrix} L_{\text{car\_s}} \\ L_{\text{schoolbus}} \\ L_{\text{walk}} \\ L_{\text{bus}} \\ L_{\text{walkbus}} \\ L_{\text{train}} \\ L_{\text{ferry}} \\ L_{\text{tram}} \\ L_{\text{bicycle}} \\ L_{\text{car}} \\ L_{\text{taxi}} \\ L_{\text{motor}} \\ L_{\text{shuttle}} \\ L_{\text{uber}} \end{bmatrix}$$

This function captures all travel related factors that appear in the specified choice model. In this specification, the parameter estimates are included in vectors $\overline{\beta}$ and $\overline{ASC}$, the measured attributes are captured in $\overline{x}$ and $\overline{L}$.

5.2. Validation

To determine whether the model output is acceptable, a model validation must be performed. During validation the model's performance is tested on a set of hold-out data. The hold-out data enfolds a data sample that was not used for model estimation. As such, it can be used to test a model's performance in 'reality'.

Validation of the model application faces a complexity; the choices in the data have been made with an order bias, but the applied model does not capture this effect. As the model application only captures travel behavior, and excludes the factors that capture order, the performance of the applied model can be underestimated. This bias also overestimates the performance of the score as a ranking function. To get a proper indication of the performance of the model application compared to the current ranking function, four validation tests are performed on the hold-out data:

1. **Hitrates**: to assess the predictive capabilities of the score and the utility model.
2. **Out-of-sample LogLikelihood**: to test the performance of scoring and utility to describe behaviour.
3. **Order changes**: to to get an indication of how much the orders change with the model application.
4. **LogSum**: to asses the total utility of the choice set as a result of the order changes

5.2.1. Test 1: Hitrates

Hitrates are a measure of the predictive capabilities of a model. To compute the hitrate, observed choices in the validation data are compared to predicted choices of a model for each observation. The percentage of correct predictions is called the hitrate.

A predicted choice is specified as the alternative with the highest probability of being chosen in a choice set. For the applied utility model this includes the alternative with the highest utility. For the score this includes the alternative with the lowest score. Table 5.1 shows the hitrates of the two models on the test data.

Model	Hitrate
Applied Utility Model	0.7041
Score Model	0.5361

Table 5.1: Model Predictive Capabilities

It can be seen that the utility model performs better than the score, with hitrates of respectively 0.70 and 0.54. Even though the order bias favours the score in the case of hitrates, the predicitve capabilities of utility still outperform those of the scoring function.

5.2.2. Test 2: Out of sample-LogLikelihood

The out of sample-LogLikelihood allows to test the model fit on hold-out data. It is checked what the likelihood is of seeing the hold-out data, given the model. This way, the plausibility of the model can be assessed in terms of describing the underlying process that generates the data.

For both notions, score and utility, the out of sample-LogLikelihood is derived through computing the models' LogLikelihood on the validation data. For each observation, the choice probability of the chosen alternative under the given model is computed. Taking the logarithm of this probability, and summing over all observations results in the total LL of the validation data under the prevailing model. In function form it looks as following:

$$LL(\hat{\beta}) = \sum_{j \epsilon J} \sum_{i \epsilon I} (y_j(i) \cdot ln(P_j(i \mid \hat{\beta}))) \tag{5.3}$$

$LL(\hat{\beta})$ the LogLikelihood of the data given estimated model parameters $\hat{\beta}$

$\hat{\beta}$ Estimated parameters of the tested model

$P_j(i \mid \hat{\beta})$ choice probability of alternative i in observation j given $\hat{\beta}$

$$y_j(i) = \begin{cases} 1 & \text{if alternative i is chosen in observation j} \\ 0 & \text{otherwise} \end{cases}$$

With this test statistic, it can be assessed which of the models, score or utility, is most plausible, resulting in the highest probability of the validation data to have occurred. For the estimated model, this test also allows to investigate whether the model is overfits the training data. Overfitting occurs when the model corresponds too closely to the particular set of estimation data, and as a result fails to fit out-of-sample data.

Utility Model

To compute the out of sample-LogLikelihood of the utility model, the estimated parameters of the best model of Chapter 4 are inserted into the proposed ranking function of Section 5.1.2. Table 5.2 shows this model results in a rho-square of 0,45 for the hold-out data. This model fit is similar to the fit on the training data (ρ^2=0,486). Therefore, no overfitting of the data occurs with the applied model. The slight deterioration in ρ^2 for the utility model on the hold-out data can be explained by the fact that the applied model does not take into account the ordering parameters, whereas the choices in the validation data do contain an order bias. This is also illustrated by the out of sample-LogLikelihood of the complete best possible model (ρ^2= 0,482).

Score model

To assess the performance of the current ranking mechanism, a multinomial logit model is formulated based on the score. For this model, a general utility function is specified, capturing the the score for each alternative:

$$V_{ij} = -\text{score}_{ij} * \beta_{score}$$

As mentioned, the score of an alternative is the company's measure of disutility. Therefore, the negative of the score is inserted into the utility function. Furthermore in this model, a parameter β_{score} is specified to scale the score to a more suitable range for utility. This factor allows to translate the score into a range that aligns better with the notions of utility and likelihood. To obtain an optimal scaling factor, the value of the score parameter is estimated on the training data. This way, an as fair as possible comparison can be provided with the utility-based model.

The computed out of sample-LL's show that the scaled score model results in a ρ^2 of 0.084. This indicates that the score describes less than 10% of the decision making process that leads to the choices in the data. This model performs much better at the hitrate test, than in the LL test. From the hitrates it appears that the model is quite good at assigning the lowest score to the best perceived alternative. With that alternative also positioned at the top of the choice set, order bias favours this notion. For the log-likelihood computation on the other hand, it is important that the scores, or utilities, of alternatives also have proper ratios between themselves. As such, the best alternative receives the highest probability of being chosen, and other alternatives should receive a much lower probability of being chosen. If with the score, the computed values are very close to each other, the score function might be able to identify the chosen alternative with accuracy. But the choice probabilities for each scored alternative in a choice set are in that case quite similar. Therefore, the model does not perform much better than a random choice between alternatives. Thus, it can be concluded that the score is not able to capture the process that leads to the choices in the data.

Overall, it can be concluded that the utility model outperforms the score model in terms of out of sample-LL.

Applied Model *(without order)*		**Scaled Score Model**	
Null LogLikelihood	-14026,5	Null LogLikelihood	-14026,5
LogLikelihood	-7695.850	LogLikelihood	-12,589.344
Rho-square	0,4513	Rho-square	0,08419
		BETA_score	0,0230

Best Possible Model *(with order)*		**Raw Score Model**	
LogLikelihood	-7359,940	LogLikelihood	-51878,644
Rho-square	0,4513	Rho-square	–
		BETA_score	1

Table 5.2: Out of Sample-LogLikelihoods

5.2.3. Test 3: Order changes

To gain insight into the amount of change this model application would bring about in the order of alternatives, the current order of choice sets is compared to the new order of choice sets.
Firstly, it is seen that applying utility as ranking function leads to an order change in 86,5% of the observations. The position of the chosen alternative changes in 44,3 % of the cases. Figure 5.1 shows the position of the chosen alternatives with the current ranking and with ranking based on utility. It can be seen that the especially among the first 6 places alternatives seem to move up the choice set, from position 7 and on the positions seem similar. This may not seem like a drastic change in order, however, as uncovered from the choice model results, those first places is where the differences in utility due to position are largest.

5.2.4. Test 4: LogSum

The LogSum can be used to compute the expected utility of a choice set. It is computed with the following equation:

$$LS = ln(\sum_{j=1..J} \exp(V_j))$$

Computing the utility of a choice set in TripGo can be done with the best possible model, this notion takes into account both the utility resulting from travel behavior, and from the position in the choice set.

For this test, the expected utility of the test data is compared to the expected utility of an improved version of the test data. In the improved version of the data, alternatives in choice sets are ordered according to descending utility.

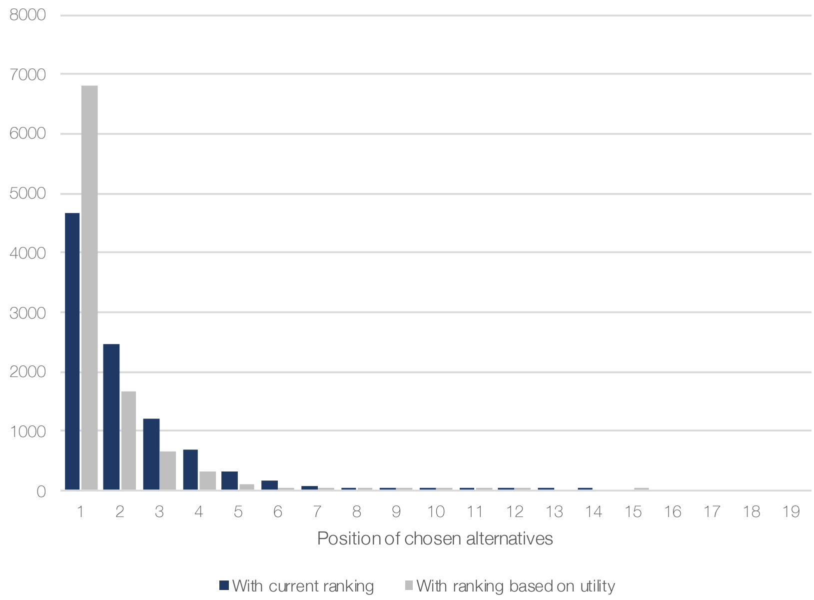

Figure 5.1: Position of chosen alternatives

From the LogSum it is seen that the average expected utility for the original test data amounts to -5,4 for the first five alternatives. When the alternatives are then ordered according to descending utility, more valuable alternatives end up higher in the choice set. As the position matters in the utility of an alternative, the expected utility of the choice set increases. At average, the expected utility of the first five alternatives of the choice set increases to -4,9 at average.

This shows that indeed, the new ordering mechanism improves the usefulness of the app by showing the users a more valuable choice set, despite of what they choose.

5.3. Conclusion

The best possible choice model can be applied to improve the order in which alternatives occur in the TripGo interface. To do so, a utility function is formulated that computes the utility of an alternative based on mode preferences and measurable attributes. The estimated parameters of the best possible model are used as weights in this utility function.

To test the performance of the applied model with the current ordering function of 'score', several tests are performed. The applied model performs best on all tests. The score function performs well in the hitrate test. But the out of sample LL test illustrates that the score function is not capable of capturing behaviour that leads to choices. It is therefore suspected that the hitrate test overestimates the capacity of the score function due to order bias.
Furthermore, the LogSum test shows that the order of alternatives improves with the applied model, and leads to higher valued choice sets in TripGo.

6

Conclusion & Recommendations

This chapter provides an answer to each of the research questions formulated in Chapter 1. After answering each of these questions in Section 6.1 , recommendations are provided in Section 6.2

6.1. Answering the Research Questions

1. Do travellers make use of the broad range of transport options provided by the mobility platform?

To answer this research question it must first be understood who the travellers in this mobility platform are, and what the mentioned broad range of transportation options consists of. For the TripGo users a self-selection effect occurs, in which public transport users select themselves into the user group. This is a cogent development as public transport users are the type of travellers that like to plan their trips using smartphone applications. The broad range of transportation options in TripGo consists the many different modes integrated into the platform, but also the possibility for planning complex trips consisting of multiple of modes.

Given the self-selection that creates this user group, it is found that that 95,22% of the chosen trips consists of pure public transport alternatives. It can therefore be said that the broad range of transportation modes is not made use of to the fullest extent. However, a certain interest exists in the information on other modes. This is sensible because travellers could have chosen a conventional app for public transportation without multimodal offerings. The data shows that modes other than PT are still chosen on a daily basis, even though they make up for a small portion of the total amount trips.

With respect to the intermodal trips offered by TripGo, it is seen that combinations of public transport and private or intermediate modes are chosen more often than unimodal trips of non-PT alternatives. This finding suggests that the intermodal trips offered by TripGo are in a way valued by the users. And, the non-PT modes in the application, are more likely to be used to complement PT trips, than to substitute for PT. These sort of combinations especially occur for trips with a longer triplength.

From a user point of view, it is seen that a somewhat larger part makes use of TripGo's multimodal offerings. 15,30% of users makes has either chosen intermodal trip(s), or altered their mode of transportation for different travel.

With the information, it can be argued that the described that the TripGo platform is mainly used for public transport, but it can provide public transport users with an extension on their mobility options.

2. What factors influence travel choices for mobility services in integrated mobility platform?

Choices for trips in the integrated mobility platform are largely determined by preferences for transportation modes. These preferences benefit public transportation modes over other modes. Especially, in the choice between PT and non-PT alternatives or combinations, other factors are unlikely to make a difference.

Besides the preferences, walking time, number of modes in an alternative and in-vehicle time have the largest impacts on choices. Therefore, they also have the most potential to influence the choice between PT and non-PT. For trips between less well-connected OD pairs, these factors can put PT alternatives at a disadvantage compared to other modes. And therefore, it is in such situations that non-PT modes have the highest probabilities of being chosen.

But for the majority of choice situations, public transport dominates the mode choice. For the different modes of public transportation, the preferences per mode are almost equal. Therefore the choice between different public transport alternatives is largely determined by the values of the measured attributes. Trips with minimal modes in the alternative and minimal walking, in-vehicle and transfer times appear most attractive.

Lastly, a small part of the choices in the data is also explained by the order in which alternatives are presented in the data. In general, users are most likely to opt for the first alternative they are presented with. The probability of choosing an alternative decreases as an alternative moves further down in the interface.

3. Is revealed preference choice data from smartphone applications usable for discrete choice analysis?

Discrete choice analysis is suitable for several purposes. These include the explanation of travel behaviour, economic appraisal and predicting future choices. To answer this research questions, it is therefore commented on the usability of the data for these three purposes.

Firstly, it can be concluded that choice models are suitable for deriving travel choice behavior from smartphone app RP data. The formulated choice model has a very acceptable fit, and includes significant and interpretable parameters, and thus allows to explain travel behaviour. As the knowledge on users is limited it is difficult to determine causation of the model results. This is inherent in this type of data. Therefore, to be able to accurately interpret choice model results, a deep understanding of the data is required resulting from a thorough data analysis.

Economic appraisal with this type of data as an input for choice models is less straightforward. It is seen that a different modelling approach is required for economic appraisal. When the aim is to capture travel behavior, as much information as possible is taken into account in the model. However, for economic appraisal this approach is not most suitable, as with RP data the model parameters start correlating. These correlations hamper the derivation of 'pure' trade offs between pairs of parameters, as other subtleties get caught up in the trade-off. In this case, a solution lies within the formulation of a basic model. This model shows it is possible to retrieve a reliable monetary trade-off from the data.

Lastly, it can be concluded from this research that choice models based on RP data are suitable for predicting future choices. It is seen that a choice model application is able to predict with a hitrate of 70%.
To conclude, discrete choice modeling is an appropriate method for analysing smartphone app RP data. Specifically for understanding travel behaviour and predicting future choices the method is well-suited. For travel behavior, analysts are however limited in their knowledge on users. Therefore the discrete choice analysis is recommended to be complemented by a general data analysis. For economic appraisal, a more investigative and pragmatic approach should be applied to infer reliable values.

4. How can knowledge on users' travel choices be applied to improve the integrated mobility platform?

The aim of integrated mobility platforms in general is to provide people with an attractive alternative to private car use. However, if TripGo currently attracts PT users, it basically exposes PT users to alternative modes. As such, this application could only evoke a modal shift away from PT. At this point results of this study however show that the risk of this negative effect is limited. Even if PT users are exposed to other modes, they are unlikely to opt out of PT. This is an interesting finding as public transport users will eventually also be exposed to MaaS offerings. For this application to evoke a modal shift away from car, ways should be explored to get users of private vehicles to engage with the app.

Furthermore, for this platform specifically, the obtained knowledge on travel behaviour consists of the preferences and tastes of TripGo users. Through an application of the best possible choice model, TripGo can be improved, such that it better aligns with the uncovered user preferences. Through improving the ranking of alternatives in the choice set, TripGo can assist its users in making quality travel choices. Based on Random Utility Theory, more convenient alternatives end up higher in the choice set, leading to a higher probability of being chosen. This in turn improves the user experience with TripGo, as users consult and execute better trip plans. Moreover, despite the choices made by users, they are provided with more valuable choice sets.

6.2. Recommendations

This section provides three recommendations for further research. The recommendations offer interesting opportunities for SkedGo, as well as for further research.

6.2.1. Recommendation 1: Personalizing Parameter Estimates

At this point, the best possible choice model describes behaviour of the average TripGo user. However, from travel behavior studies, it is known that people can be very heterogeneous in their preferences and tastes. And, providing personal advice is an important aim for traveler information systems to be attractive. Therefore it is recommended to, after implementing the random utility ranking function, design a feedback loop in the TripGo application that updates a users personal weights with the choices they make. This way the TripGo application is adjusted to preferences on the level of the user, instead of on aggregate level. Another benefit of such a feedback loop is that the weights will alwayt remain up to date, even if behavior changes over time.

To update the parameter values, the estimates of this research can be applied as a starting point. Next, several methods exist that could be used for updating the parameters:

1. A first possible method is designed by Nuzzolo et al. (2013). With this method, discrete choice models are estimated after a choice is added for a user. This method is especially designed to update the personal preferences in travel planners. However, it should be explored if this method is not associated with long computation times.
2. Another method lies within Baseyan parameter updating (Arentze & Molin, 2013). This method is also especially designed to learn users' personal travel preferences based on the choices they make. This method promises an effective adaption of preferences with short computation times. Campigotto, Rudloff, Leodolter, and Bauer (2017) also apply the Bayesian algorithm, but use estimated parameters from a short personal stated preference research as a starting value. This could also be interesting as this would provide personal weights from the moment of on-boarding.
3. Furthermore, it could be explored if the Machine Learning technique of recommender systems could update the estimated parameters. However, this is mostly interesting from a research point of view. Such methods have not been applied yet for parameter updating purposes, and therefore it is unknown whether it would be feasible and effective.

6.2.2. Recommendation 2: Draw in Car Users

At the moment it is seen that the TripGo app mainly draws in public transport users. For the platform to evoke a modal shift away from private vehicle use, a way must be found to get car users to engage with the app. Therefore it should be explored how to make the service more attractive to frequent car users. An approach to doing this is to perform a qualitative research to the need of car users, and try to adjust the interface to those needs. If booking and payment functions seem to be a boundary for using TripGo, it could be explored if those functionalities could be provided in the app, possibly in cooperation with other parties.

6.2.3. Recommendation 3: Proof of the TripGo API as a Product

The TripGo smartphone application is of course a showcase, the product offered by SkedGo is however the API that powers the application. An example of a complete product offered by SkedGo is the customized application OptusGo. Through this app, employees of Optus can choose from a range of transportation options for their commute. It would be of high value if proof can be provided that this application can evoke a modal shift away from car for the employees of such companies. With the customized application, it is possible to measure this because it is possible to force all employees into the application, allowing also to capture car users. This way, it can be measured what the impact of the app is, and it can be explored if policies can be applied to pull people away from their cars (i.e. payed parking). With such proof TripGo can become leading in the area of MaaS platforms, and evidently contribute to solving current mobility issues.

A
Scientific Paper

Travel Choices in Integrated Mobility Platforms

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Abstract

This research investigates the travel behavior of users of an integrated mobility platform. Passive revealed preference data is collected from a smartphone application for integrated mobility. This data, consisting of the choices in a multimodal journey planner, allows to evaluate travel behavior in integrated environments with a high ecological validity. As such data has not been used yet for conventional travel behavior researches, this research also experiments with the application of conventional methods to this type of data. It is found that for the specific integrated platform, mostly public transport users engage with the platform. Public transport is dominant within the planned trips of users, and extreme situations are required for users to deviate in the mode choice between PT and non-PT alternatives. Furthermore it shown that discrete choice modelling is a suitable method for analysing for this type of data.

Keywords: Integrated mobility, Mobility-as-a-Service, multi-modal journey planner, smartphone app data, revealed preference data

1. Introduction

Multimodal travel is positioned as one of the most effective ways to tackle the negative effects on urban mobility and provide people with their mobility needs [1]. The combined use of transportation modes and services is however not straightforward [2]. Different operators often require different payment methods, subscriptions and mobile applications [3]. And, integrated information and planning assistance is needed to compare and combine different modes and services for trips for multimodal travel. Because of these complexities, solving mobility issues requires a renewed organizational approach that focuses on 'integrated mobility' with improved access to different transport modes [4, 5].

This concept is also known as Mobility-as-a-Service (MaaS); a mobility distribution model that delivers a transportation need to users through one single digital interface, by integrating and bundling different transport modes into mobility packages [6].

A certain ambiguity exists surrounding the concept, its characteristics and in which way they can be addressed [7]. But the idea behind the concept is integrated and seamless mobility. Such integration can be provided through integrated mobility platforms. The functions of these platforms are provided through smartphone applications or online interfaces. The platforms improve interoperability between modes, by uniting information, and assisting in planning intermodal journeys. As such, the platforms simplify and motivate the use of multiple transportation modes [8, 9]. In the past, multiple information systems had to be consulted separately to plan a multimodal trip [10]. With integration, users are able to compare and combine any type of mode or service, and have the possibility to rationally choose the best path for their trip [1].

Because the concepts of integration and MaaS seem promising, different types of integrated mobility platforms have emerged. But, due to the novelty of the concept, researchers are only just starting to understand (and quantify) the travel behaviour of users with respect MaaS and integrated mobility platforms. Research into the travel behavior in response to the platforms is valuable as a profound understanding of this behavior can function as a guide towards designing efficient and user-friendly forms of integrated mobility platforms [11] [3].

Up until now, only a few researches exist that provide a quantifiable insight into the travel behaviour of users in multimodal environments.Most of this existing knowledge on the topic is gained through trials and surveys. As real MaaS implementations and integrated platforms were not available at the time of these researches, the necessary passive RP data for conducting these researches was also unavailable.

1.1. Stated Preference vs. Revealed Preference

A problem with these types of researches is that they cope with hypothetical bias. This bias can be avoided using revealed preference (RP) data for research. RP data is based on actual actions and represents actual choice outcomes. Using RP techniques therefore reflects travel behaviour in a real context. In RP research, data is usually collected through travel diaries of respondents. But, even RP experiments are often subject to hypothetical bias because the respondents are mostly actively recruited. Respondent already willing to join experiment or trial and this can affect results.

To overcome such issues a solution lies in collecting 'big' and passive RP data. Big data, resulting from smartphones, enables collection of large amounts of data. Passive refers to those data not collected through active solicitation [12]. They are generated for purposes that are not intended, but can potentially be used for research. The upside is that this type of data leads to a very high ecological validity, and lots of data is available [12]. However, this data type also brings along many challenges. For example, issues as multi-collinearity and self-selection occur. Also these data are mostly anonimyzed, making it difficult to determine the causation of results. Moreover, conventional travel behaviour methods have not often been applied yet to these types of data, and therefore it is unknown whether this type of data is suitable for conventional travel behaviour researches.

1.2. Objective

Given need for research on integrated mobility platforms, preferably with a passive RP data source, this research takes on a novel approach. Passive RP data is collected from a smartphone application for integrated mobility, allowing to evaluate travel behavior in integrated mobility platforms. The data collected for this research results from an app called TripGo. The app consists of a travel planner with multimodal functionalities. Therefore, the collected data consists of users' travel choices in a multimodal and integrated environment. This data allows to investigate how users actually behave in such integrated environments, with a broad variety of transportation modes available, and without being subject to hypothetical bias. Thereby, this research offers behavioural insights on integrated mobility with a high ecological validity. The main objective of this research is to create a better understanding of the choice behaviour of travellers in an integrated environment provided by a mobility platform. Simultaneously, it is experimented to apply conventional travel behaviour methods to this type of data.

1.3. Context of TripGo

The TripGo platform integrates information on private, public and intermediate modes of transportation into one digital interface. Amongst the included information is real-time traffic information, public transport schedules (also updated with real-time information), information about the seating availability in public transport, availability and costs of parking and the whereabouts of shared vehicles. Besides providing access to all this information at once, TripGo's main function is a multimodal journey planner. This planner can assist people in multimodal trip planning, both by generating complex intermodal trip plans and by allowing users to choose between a broad range of options presented side by side. Within the focus area of Sydney, an abundance of mobility services is available, and the following of these modes are integrated in TripGo:

- *Private*: car, motorcycle and bicycle

- *Public*: train, light rail, ferry, bus, tram, subway
- *Intermediate*:
  - Car rental; Swiftfleet (another platform including all participating rentals, i.e. Avis, Hertz)
  - On-demand; taxi (GoCatch, Ingogo, TaxisCombined,Mydriver), Uber, airport shuttles
  - Car-share; GoGet (station based, B2C), Car Next Door (station based, P2P)

The data provided by this platform consists of the choice sets that TripGo provides for performing trips, and the chosen alternatives.

2. Research Methodology

For this research, several methods are applied. First of all a descriptive data analysis is performed to provide an insight into the users and their usage of the platform. As such it can be explored whether the users make use of the broad variety of mobility offerings provided by the platform. Next the conventional method of discrete choice modelling is applied to gain an insight into the travel behaviour of the TripGo users.

Within descrete choice modelling, this research makes use of the Multinomial Logit model. Within this model, it is chosen to apply the theory of random utility maximization (RUM) to capture peoples decision rules. This theory implies that a decision maker always chooses the most attractive alternative from a choice set. In the MNL model, each alternative's attractiveness is represented by a utility function. It is assumed that decision makers aim at maximizing the utility they obtain from choosing an alternative, known as 'random utility maximization (RUM)[13]. The total utility from choosing an alternative is computed by based on utility functions that are formulated for each alternative.

Prior to perform these two analyses the smartphone app RP data must be prepared. As no dedicated method is available for this, a method is developed throughout the research. This method consists of two parts; a first part for transforming raw smartphone app data into RP choice data, and a second part for reducing noise from the data. For constructing choice data a set of steps and rules is developed that can be applied when transforming smartphone app data into choice data. To ensure the quality of the data for travel behaviour research, the second part of this method includes an approach for eliminating noise from the data.

2.1. Transforming Smartphone Data into RP Choice Data

Raw data from smartphone apps are the starting point of data processing. Smartphone app data often comes in massive volumes of unstructured (or semi-structured) data strings. The steps and rules described in Table A.9 provide a method for structuring this type of data into consistent tables. While applying this method, it is aimed for:

1. Consistent formulation of the choice data
2. Accurate and complete representation of information
3. Minimal size of the choice data

During the construction of choice sets, trade-offs must be made between these aims as they they are often interfering and can not all be optimal. For example, the most consistent and complete choice set formulations contribute to a large data set. While on the other hand, reducing the size of the data set requires a more inconsistent formulation or simplification of the available information.

2.2. Reducing Noise from the Choice Data

With RP data, it is important to ensure the data quality and limit the amount noise that can interfere with accurate model results. Therefore, the second part of this method offers an approach for identifying and resolving issues and errors in the data, in order to reduce noise.

The created choice data functions as a starting point for noise reduction. Firstly, issues must be identified, Table A.8 provides a guide for uncovering these. After identification of an issue, the next step is to investigate the cause of the issue, and to find a suitable solution. Different types of issues require different solutions, an approach to solving each issue type is given below:

- **Issue type 1: Double Record** A double record in the data is an invalid representation of reality. The solution therefore is to keep only the unique records.
- **Issue types 2 and 3: Missing information and invalid attribute values**
  Before deleting records with issue types 2 or 3, it must be investigated what the repercussions of deleting observations are for the data. If it appears that results are severely affected with elimination of the affected observations, it can be chosen to estimate values for the erroneous attributes (i.e. through logistic regression).
- **Issue type 4: Outliers**
  For removing outliers in this type of data, the attribute ranges are investigated and judged on the veracity of the extreme values. The aim is to only delete those observations that appear to be outliers due to measurement errors. To achieve this, the attribute ranges must be checked and it must be judged whether the maximum values seem plausible. Observations including implausible outliers must be eliminated from the dataset.

It is important to note that in this method, eliminating issues always takes place at the level of the observation, and not at level of the alternative. This way the observations are represented as accurately as possible.

3. Results

The results for this research consist of two parts. Firstly, the results from the data analysis to provide an insight into the users and usage of TripGo, and secondly the results of the discrete choice model to uncover the travel behavior that leads to the choices in the data.

3.1. Results Data Analysis

Mode name	**Availability**		**Chosen**		**Ratio**
	(#observations)	(% of observations)	(#chosen)	(% of choices)	(chosen/available)
Walk	47632	97,89%	44512	91,48%	0,93
Bus	42348	87,03%	37935	77,96%	0,90
Train	22748	46,44%	13562	27,87%	0,60
Uber	20165	41,44%	531	1,09%	0,03
Bicycle	19039	39,13%	458	0,94%	0,02
Car	18769	38,57%	528	1,09%	0,03
Taxi	8824	18,14%	92	0,19%	0,01
Motorcycle	5546	11,40%	102	0,21%	0,02
Car share (1)	2907	5,97%	11	0,02%	0,00
Ferry	1576	3,24%	714	1,47%	0,45
Schoolbus	1144	2,35%	684	1,41%	0,60
Car share (2)	1014	2,08%	3	0,01%	0,00
Tram	965	1,98%	345	0,71%	0,36
Walk (wheelchair)	530	1,09%	488	1,00%	0,92
Airport shuttle	20	0,04%	0	0,00%	0,00
Car rental	2	0,00%	1	0,00%	0,50

Table 1: Modes and occurrence in the data

Looking at the ratio between 'chosen' and 'available' in Table 1, it can be seen that walking (walk and walk-wheelchair), bus, train, ferry and schoolbus are chosen most often. Table 2 reveals information on the most often chosen alternatives in the data (¿100 chosen). Together, these statistics show that public

Alternative	Availability		Chosen		Ratio
(Mode combination in names)	(# observations)	(% of observations)	(# chosen)	(% of choices)	(% chosen/available)
bus,walk	35316	72,58%	30265	62,20%	85,70%
bus,train,walk	12099	24,87%	6067	12,47%	50,14%
train,walk	10569	21,72%	4890	10,05%	46,27%
train	1974	4,06%	1868	3,84%	94,63%
walk	28780	59,15%	926	1,90%	3,22%
bus,	879	1,81%	740	1,52%	84,19%
schoolbus,walk	909	1,87%	579	1,19%	63,70%
bus,walk (w)	417	0,86%	364	0,75%	87,29%
ferry,wal	547	1,12%	296	0,61%	54,11%
car,wal	14298	29,39%	291	0,60%	2,04%
bicycle	18475	37,97%	288	0,59%	1,56%
Uber	11669	23,98%	241	0,50%	2,07%
bus,ferry,walk	493	1,01%	200	0,41%	40,57%
Uber,train,walk	3282	6,75%	150	0,31%	4,57%
tram,walk	370	0,76%	138	0,28%	37,30%
bicycle,train	3108	6,39%	119	0,24%	3,83%
car	4723	9,71%	118	0,24%	2,50%

Table 2: Alternatives chosen more than 100 times

No.	Alternative type	Availability		Chosen		Ratio
		(# observations)	(% of observations)	(# chosen)	(% of choices)	(% chosen/available)
1.	Public Transport (PT)	47641	97,91%	45968	94,47%	96,49%
2.	Private (P)	26965	55,42%	798	1,64%	2,96%
3.	Intermediate (I)	21624	44,44%	424	0,87%	1,96%
4.	PT + P	5915	12,16%	289	0,59%	4,89%
5.	PT + P + I	1	0,00%	1	0,00%	*100,00%*
6.	PT + I	5120	10,52%	245	0,50%	4,79%
7.	P + I	2	0,00%	0	0,00%	0,00%
8.	Walking	28813	59,22%	932	1,92%	3,23%

Table 3: Occurence of Unimodal and Intermodal Alternatives

transport alternatives are chosen most by TripGo users. The share of choices for 'bus and walking' is huge, 62,2% of choices are for this alternative. The second and third largest shares go out to 'bus, train, walk' and 'train and walk' with respectively 12,5% and 10,1%. After the these alternatives, the share of choices quickly drops. Through adding up only the often chosen PT alternatives of Table 2, public transport trips already account for 95,22% of the trips. In comparison, the average Sydney mode split consists of 26,3% public transport trips.

With this information, it can be concluded that a self-selection effect occurs for the TripGo user group. This means users select themselves into this research based on shared characteristics. In this case, their shared characteristic consists of the fact that they are public transport users with an interest in other modes of transportation. As public transport users are the type of travellers that like to plan their trips using smartphone applications, they self-select themselves as TripGo user.

Even though public transport is dominant amongst chosen trips, the fact that these users chose TripGo as their app suggest an interest in information on other modes of transportation. Otherwise, they could have chosen a conventional platform for public transport planning. The data illustrates a slight interest in non-PT modes; besides the high penetration of public transport for chosen trips, it can be seen that most other modes of transportation are still chosen daily in the data. For example, Uber is chosen 531 times in the data, this indicates TripGo is used to plan 44 rides trips per day.

When looking at the choice for non-PT modes, it appears that bicycle, car and Uber are the most chosen non-PT modes. It is noteworthy that alternatives consisting of those modes are chosen relatively more often when the mode is combined with a public transport mode. An investigation into different trips types,

	Number of users	Percentage of users	Classification
Total users	7327	100%	
· users that chose an intermodal trip (1)	5,98%		
· users that chose two unimodal different categories (2)	794	10,84%	
· users that did both (1) and (2)	111	1,51%	
· users that did either (1) or (2)	1121	15,30%	Multimodal travellers
· users that chose neither		84,70%	Public transport users

Table 4: Multi-modality of Users

reported in Table 3 also shows that combinations of public transport and private or intermediate modes are chosen more often than unimodal trips of non-PT alternatives. This finding suggests that the intermodal trips offered by TripGo are in a way valued by the users. And, the non-PT modes in the application, are more likely to be used to complement PT trips, than to substitute for PT. Furthermore, it is uncovered that the intermodal trips proposed in the platform, are chosen for trips with a trip length twice larger than average.

Multimodality is also assessed from a user perspective in Table 4. From a user perspective it is seen that 15,30% of users makes use of TripGo's multimodal offerings even though only a small portion of the chosen trips include non-PT alternatives (or PT combinations). On a user level, users make use of multimodal offerings through either choosing intermodal trips or altering their trip types for different travels.
With the information from this chapter, it can be argued that the described that the TripGo platform can provide public transport users with an extension on their mobility options.

3.2. Choice Model Results

To specify the best possible choice model for this research, utility functions are created for each of the 421 alternatives in the data. These functions capture only the systematic utility of an alternative, and therefore take on the following general form:

$$V_i = ASC^{mode} + \sum_m \beta_m \cdot x_{im} + \sum_{p=1...P} D_p \cdot P_{ijp} \quad (1)$$

where: V_i systematic utility of alternative i

ASC^{mode} Alternative Specific Constant for a specific mode

β_m taste parameter for attribute m

x_{im} the attribute level of attribute m in alternative i

D_p Ordering dummy for position p

$$P_{ijp} = \begin{cases} 1 & \text{if alternative i is on position p in observation j} \\ 0 & \text{otherwise} \end{cases}$$

The derived estimation results of the the model are reported in Table 5 and 6. The estimation report shows a Rho-square compared to the null model of 0,486. This indicates that this model is able to explain about 50% of the decision making process that leads to the choices recorded in the data. Considering the noisiness of the data, and the complex decision making process that is aimed to be captured this is a very acceptable model fit.

Significance of parameter estimates

The robust t-tests of the parameter estimates in Table 6 are consulted to check the precision of the estimated values. It can be seen that only two parameters in this model appear to be statistically insignificant for a

Number of estimated parameters:	40
Sample size:	38.927
Init log likelihood:	-56.365
Final log likelihood:	-28.956
Likelihood ratio test for the null model:	54.818
Rho-square for the null model:	0,486

Table 5: Estimation report

99% significance level.

Sensibility of parameter estimates

Looking at the estimated values of the parameters, it appears that all of the parameters are of the expected sign, except for $\beta_{Tparking}$. This parameter is positive, indicating that an increase in parking time has a positive effect on utility. Intuitively, this is an incorrect representation of actual travel behavior. Yet, this can be explained by the fact that this model does not only capture travel behaviour. The model also, and more specifically, captures the travel behaviour in response to an information system. In the TripGo app, not all car trips are administered with information on parking times and location. As most car trips do require parking, it is likely that users choose a car trip with parking information over one without it. This leads to a positive parameter estimate for the parking parameter.

Choice Behaviour

Through interpreting the estimated parameters of the model, choice behavior of TripGo users can be derived. Users' choices for alternatives are largely determined by the alternative specific constants in the model. It is notable that the differences in ASC values between PT and non-PT are relatively large compared to the potential impact of the taste parameters. Therefore, especially in the choice between PT and non-PT trips or intermodal trips, the variable attributes values are unlikely to make a difference. The estimated constants of the choice model strongly benefit public transport modes, with values much higher than for other constants.

Table 7 shows that differences in walking time and the number of modes in an alternative, provoke the largest impact on utility. They therefore also have the most potential to influence the choice between PT and non-PT. For trips between less well-connected OD pairs, public transport is often accompanied with larger walking times and multiple modes required to perform the trip. In such cases the utility of all PT alternatives deteriorates while other modes are less affected by these factors. This results in a higher choice probability of the non-PT alternatives that are less or not affected by these factors. Also combinations between PT and non-PT modes may be considered in this case, as a trade-off may occur between the number of modes and transfers needed for a PT trip, and including a low-ASC mode to avoid those transfers.

However, in the majority of choice situations, public transport dominates the mode choice. In particular, for trips between accessible locations, the variability of the measured attributes over different alternatives is too small to influence the choice between PT and non-PT. For the different modes of public transportation, the values of the related ASCs are close. Therefore the choice between different public transport alternatives is largely determined by the values of the measured attributes. Trips with minimal modes in the alternative, and minimal walking, in-vehicle and transfer times appear most attractive. And, as a final comment, the order in which alternatives are presented in the choice set also affect an alternative's probability of being chosen. The further it is placed down the choice set, the lower the probability of being chosen.

The choice behavior inferred from the model results is related to the effect of user group self-selection. From the data analysis it is uncovered that the group of TripGo users consists largely of public transport users. This presumably occurs because the TripGo app mostly appeals to PT users, and therefore mostly draws this user type into the user group. The findings for choice behavior, inclusive of preferences for public

Name	**Value**	**Robust t-test**
ASC_bicycle	-3,66	*-32,81*
ASC_car	-3,72	*-23,52*
ASC_bus	0	
ASC_car-s	-3,09	*-5,95*
ASC_ferry	1,87	*15,90*
ASC_motor	-4,25	*-25,38*
ASC_schoolbus	0,962	*9,31*
ASC_shuttle	-8,52	*-12,24*
ASC_taxi	-3,21	*-18,05*
ASC_train	0,901	*14,78*
ASC_tram	1,16	*9,83*
ASC_uber	-2,45	*-19,14*
ASC_walk	-0,145	*-1,99*
ASC_walkbus	1,04	*18,37*
BETA_TT	-0,0303	*-18,18*
BETA_TTransfer	-0,0547	*-15,49*
BETA_TTwalk	-0,084	*-29,4*
BETA_Tcollect	-0,297	***-1,04***
BETA_Tparking	0,215	*4,46*
BETA_Twait	-0,0637	*-3,35*
BETA_calories	-0,0017	*-2,89*
BETA_carbon	-0,144	*-2,72*
BETA_combine	-1,36	*-20,47*
BETA_TC	-0,0234	*-4,85*
D_p1	0	
D_p2	-0,466	*-26,13*
D_p3	-0,837	*-35,34*
D_p4	-1	*-33,89*
D_p5	-0,986	*-26,11*
D_p6	-0,918	*-17,87*
D_p7	-0,939	*-13,39*
D_p8	-0,942	*-9,92*
D_p9	-1,19	*-8,59*
D_p10	-1,1	*-5,44*
D_p11	-1,46	*-4,55*
D_p12	-1,23	*-3,18*
D_p13	-1,97	*-2,91*
D_p14	-0,941	***-1,49***
D_p15	-5,76	*-10,41*
D_p16	-4,59	*-10,29*
D_p17	-1,75	*-2,01*
D_p18	-1,14	*-2,00*
D_p19	0	

Table 6: Parameter Estimates

Attribute	75th percentile	Unit	Parameter estimate	Relative Importance
Calories	64	*kcal*	-0,0017	-0,109
Carbon	1,1	*kg CO2*	-0,144	-0,158
Collecting time	2	*min*	-0,297	-0,594
Combine	3	*modes*	-1,360	-4,080
In-vehicle time	55,78	*min*	-0,030	-1,690
Parking time	4	*min*	0,215	0,860
Transfer time	11,78	*min*	-0,055	-0,645
Travel cost	6,69	*AUS$*	-0,023	-0,156
Waiting time	8	*min*	-0,062	-0,496
Walking time	26,01	*min*	-0,145	-3,771

Table 7: Relative importance of parameter estimates

transport, are in line with the revealed self-selection effect.

The constants that capture the preference for public transport represent unobserved factors related to the transportation modes. These unobserved factors can include many different considerations that cause users to tilt towards PT. These unobserved factors can consist of several explanations such as habit execution and barriers or obstructions for using the other modes in the app. Here it can be thought resistance from memberships required to use Uber or car sharing.

Even though these preferences exist amongst the TripGo users, it is also seen that non-PT alternatives, or combined alternatives do make an appearance amongst the chosen alternatives. This is seen in the data analysis, and the choice model results allow to sketch the situation for which this is most likely to occur. Namely, when PT is at a disadvantage, for example for OD pairs that are not well-connected. This can occur either when the trip is planned from and/or to an inaccessible location, or when the trip is planned outside of the operating hours of public transport services.

4. Usability of Smartphone App RP Data for Discrete Choice Analysis

Discrete choice analysis is suitable for several purposes. These include the explanation of travel behaviour, economic appraisal and predicting future choices. To answer this research questions, it is therefore commented on the usability of the data for these three purposes.

From the previous section, it can be concluded that choice models can be informative of decision making process in smartphone applications. With the best possible model having a proper fit, behavioural factors can be identified that explain travel choices. To uncover the underlying mechanisms that lead to these factors, a deep understanding of the data is required. Many of the explanations provided for the model results are based on an intuition that is created with the thorough data analysis. Inherent in this data source is that no knowledge is available on the user group. All knowledge on the case context has to be inferred from the data and use of the application. Therefore, it is essential to perform a thorough data analysis and understand how the contents of the data relate to the use of the app. Doing this allows users to substantiate findings in the model results with well-reasoned arguments and retrieve accurate explanations of behavior.

To assess the choice model's performance in economic appraisal and predicting future choices, additional tests with the model are performed. For economic appraisal the Value-of-Time is computed, a trade-off between money and time that is computed as following:

$$\text{Value-of-Time} = \frac{\beta_{TT}}{\beta_{TC}} = \frac{\delta V/\delta TT}{\delta V/\delta TC} = \frac{\delta TC}{\delta TT}$$

From the specified model the retrieved VoT amounts to 77,69 AUS $/. This value is unexpectedly high judging from comparison to peers. Government guidelines in the state of New South Wales state a value of travel time of $16.26 per hour applicable to private car occupants, on-board train time, on-board bus time, ferry travel, cycling time and walking time [14]. The VoT resulting from this research lies far out of this range, and is therefore unreliable. From further investigation of choice models it appears that a reliable value for this VoT can be retrieved from a basic model with only travel time and travel costs. The VoT resulting from that model amounts to $20,38/hour, but the model fit is however much poorer ($\rho^2 = 0,149$).

From further investigating choice models, trying different formulations and inspecting correlations the following line of reasoning appears. When the aim is to capture travel behavior, as much information as possible is taken into account in the model. However, for economic appraisal this approach is not most suitable, as with RP data the model parameters start correlating. These correlations hamper the derivation of 'pure' trade offs between pairs of parameters, as other subtleties get caught up in the trade-off. In this case, a solution lies within the formulation of a basic model. This model shows it is possible to retrieve a reliable monetary trade-off from the data.
Therefore, economic appraisal with this type of data as an input for choice models is less straightforward, but not impossible. It is seen that a different modelling approach can be used to derive a suitable VoT.

Finally, the predictive capabilities of the model are assessed through deriving the hitrate in a validation dataset. To compute the hitrate, observed choices in the validation data are compared to predicted choices of a model for each observation. The percentage of correct predictions is called the hitrate.
A predicted choice is specified as the alternative with the highest probability of being chosen in a choice set. With this formulation it can be seen that the choice model application is able to predict with a hitrate of 70%. Therefore, it can be concluded from this research that choice models based on RP data are suitable for predicting future choices.

To conclude, discrete choice modeling is an appropriate method for analysing smartphone app RP data. Specifically for understanding travel behaviour and predicting future choices the method is well-suited. For travel behavior, analysts are however limited in their knowledge on users. Therefore the discrete choice analysis is recommended to be complemented by a general data analysis. For economic appraisal, a more investigative and pragmatic approach should be applied to infer reliable values.

5. Conclusion

Given the self-selection that creates this user group, it is found that that 95,22% of the chosen trips consists of pure public transport alternatives. It can therefore be said that the broad range of transportation modes is not made use of to the fullest extent. However, a certain interest exists in the information on other modes. This is sensible because travellers could have chosen a conventional app for public transportation without multimodal offerings. The data shows that modes other than PT are still chosen on a daily basis, even though they make up for a small portion of the total amount trips.

With the information provided from the data analysis and choice model, it can be argued that the described that the TripGo platform is mainly used for public transport, but it can provide public transport users with an extension on their mobility options.

But, as explained in Section 1, integrated mobility is an important enabler for multimodal travel, which aim is to provide people with an attractive alternative to private car use. Based on this idea MaaS is often promoted as a sustainable concept, but in reality it could also lead to greater congestion with more vehicles on the road [15]. With the rise of MaaS and integrated mobility platforms, current PT users will also gain easier access to car-based services [16]. This could ignite a modal shift from PT to car instead of vice versa, and therefore increase the total number of car trips.

From a sustainability point of view, this identified risk is also a relevant issue with TripGo. If the app currently attracts PT users, it basically exposes PT users to alternative modes. As such, this application could only evoke a modal shift away from PT. At this point results of this study however show that the risk of this negative effect is limited. Even if PT users are exposed to other modes, they are unlikely to opt out of PT. This is an interesting finding as public transport users will eventually also be exposed to MaaS offerings. For this application to evoke a modal shift away from car, ways should be explored to get users of private vehicles to engage with the app.

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Appendix A. Appendix

No.	Issue Type	Description	Identification Method
1.	Double records	These consist of identical observations are recorded into the data multiple times	Inspect rows for duplicates
2.	Missing information	Occurs when a value for one or more attributes of an alternative is missing	Inspect cells for empty cells
3.	Invalid attribute value	Occurs when attribute values are of unexpected sign (i.e. negative travel time)	Inspect attribute levels: · compute range [min,max] · compute boxplots
4.	Outliers	Attrribute values that are distant from other observations due to measurement errors	Inspect attribute levels

Table A.8: Issue Identification

Goal	Step	Rules
Understand data	**1. Understand raw data** a. Investigate small number of strings (2-5) b. Identify what information is provided in the strings c. Identify consistent and inconsistent part(s) of strings	· Consistent information is present and equally sized for each observation · Inconsistent information is absent in some observations and/or different stringsize in different observations
	2. Define what information to include in the choice data	· Choice data must at least consist of choice sets and choices
Design choice set framework		· The framework consists of a table, in which each row represents an observation · Each column represents ordered category that includes the same information for each observation
Determine size framework	**3. Determine number of alternatives in the choice data** a. Identify number of modes in the data b. Determine modes to include in choice model c. Identify number of mode combinations in the data, to uncover the number of unique alternatives d. Identify where to accommodate for double alternatives e. Create mode labels	· To exclude modes from the data, delete all observations they occur in · If total number of observations becomes too small, extract more data · If too many mode combinations exist in the data (i.e. >500), simplify: Simplify option 1: neglect order of combined modes Simplify option 2: merge double occurring modes in combinations · Identify for each alternative the maximum number of times it occurs in one observation, these are doubles · The total number of alternatives in the choice data equals the sum of unique alternatives and their doubles.
Determine size framework	**4. Determine representation of alternatives** a. Select attributes to include for each alternative b. Determine how to represent inconsistent attributes	· Each alternative represented with same number of columns · Each alternative is provided with same information · If desired attribute/component is not directly recorded in the data might be possible to compute that attribute manually · Starting point for inconsistent attributes: create a column for each existing attribute for each alternative. If the number of columns gets too large: Simplify option: identify the number of columns needed to accommodate for the alternative with maximum number of attributes required. · Represent each alternative with identified number of columns. · If attributes are now presented inconsistently per alternative, record inconsistency in alternative label
Compute choice data	**5. Create framework for choice data table** a. Create table b. Create table header	· Create columns for each element defined in step 2. For choice sets create columns for each alternative and their attributes. (#alternatives * #attributes) · For each column in the data, define category name representing what the column contains
	6. Store data from strings into framework	· Store information of strings in columns they belong, add zero's to columns that do not apply to information in the string
	7. Attribute scaling	· Scale attributes to unit such that the scales are somewhat within the same range (i.e. all attributes ranges within 10-1000)

Table A.9: Method for constructing smartphone data into RP choice data

B
Alternative Table

	Combination in names	Availablility		Chosen		Ratio
		(# observations)	(% of observations)	(# chosen)	(% of choices)	(chosen/available)
1	bus,walking,	35316	72,58%	30265	62,20%	85,70%
2	walking,	28780	59,15%	926	1,90%	3,22%
3	bicycle,	18475	37,97%	288	0,59%	1,56%
4	car,walking,	14298	29,39%	291	0,60%	2,04%
5	bus,train,walking,	12099	24,87%	6067	12,47%	50,14%
6	Uber,	11669	23,98%	241	0,50%	2,07%
7	train,walking,	10569	21,72%	4890	10,05%	46,27%
8	Uber,walking,	7462	15,34%	97	0,20%	1,30%
9	motorcycle,	4845	9,96%	89	0,18%	1,84%
10	taxi,	4788	9,84%	28	0,06%	0,58%
11	car,	4723	9,71%	118	0,24%	2,50%
12	taxi,walking,	3665	7,53%	25	0,05%	0,68%
13	Uber,train,walking,	3282	6,75%	150	0,31%	4,57%
14	bicycle,train,	3108	6,39%	119	0,24%	3,83%
15	car share,walking,	2741	5,63%	9	0,02%	0,33%
16	train,	1974	4,06%	1868	3,84%	94,63%
17	car,train,walking,	1873	3,85%	57	0,12%	3,04%
18	taxi,train,walking,	1331	2,74%	28	0,06%	2,10%
19	car share (2),walking,	942	1,94%	1	0,00%	0,11%
20	schoolbus,walking,	909	1,87%	579	1,19%	63,70%
21	bus,	879	1,81%	740	1,52%	84,19%
22	motorcycle,walking,	621	1,28%	4	0,01%	0,64%
23	ferry,walking,	547	1,12%	296	0,61%	54,11%
24	bus,ferry,walking,	493	1,01%	200	0,41%	40,57%
25	car,train,	436	0,90%	21	0,04%	4,82%
26	bus,walking (w),	417	0,86%	364	0,75%	87,29%
27	car,bus,walking,	394	0,81%	13	0,03%	3,30%
28	tram,walking,	370	0,76%	138	0,28%	37,30%
29	Uber,bus,walking,	287	0,59%	13	0,03%	4,53%
30	bus,tram,walking,	275	0,57%	92	0,19%	33,45%
31	Uber,train,	275	0,57%	8	0,02%	2,91%
32	ferry,train,walking,	230	0,47%	77	0,16%	33,48%
33	motorcycle,train,walking,	228	0,47%	4	0,01%	1,75%
34	bicycle,train,walking,	226	0,46%	9	0,02%	3,98%
35	train,tram,walking,	201	0,41%	66	0,14%	32,84%

	Combination in names	Availablility (# observations)	(% of observations)	Chosen (# chosen)	(% of choices)	Ratio (chosen/available)
36	car share,bus,walking,	196	0,40%	2	0,00%	1,02%
37	schoolbus,bus,walking,	192	0,39%	50	0,10%	26,04%
38	bicycle,ferry,	173	0,36%	14	0,03%	8,09%
39	taxi,bus,walking,	173	0,36%	4	0,01%	2,31%
40	Uber,ferry,walking,	151	0,31%	6	0,01%	3,97%
41	bicycle,bus,walking,	121	0,25%	12	0,02%	9,92%
42	train,walking (w),	116	0,24%	59	0,12%	50,86%
43	Uber,bus,train,walking,	107	0,22%	5	0,01%	4,67%
44	taxi,train,	100	0,21%	1	0,00%	1,00%
45	bus,ferry,train,walking,	99	0,20%	25	0,05%	25,25%
46	car,walking (w),	98	0,20%	7	0,01%	7,14%
47	bus,train,tram,walking,	91	0,19%	25	0,05%	27,47%
48	motorcycle,train,	88	0,18%	0	0,00%	0,00%
49	bicycle,walking,	86	0,18%	1	0,00%	1,16%
50	car,bus,train,walking,	79	0,16%	4	0,01%	5,06%
51	car share,train,walking,	77	0,16%	0	0,00%	0,00%
52	bus,train,walking (w),	75	0,15%	36	0,07%	48,00%
53	ferry,	73	0,15%	69	0,14%	94,52%
54	Uber,walking (w),	68	0,14%	1	0,00%	1,47%
55	car share (2),bus,walking,	67	0,14%	0	0,00%	0,00%
56	taxi,ferry,walking,	65	0,13%	3	0,01%	4,62%
57	car,ferry,walking,	62	0,13%	6	0,01%	9,68%
58	bicycle,bus,train,walking,	61	0,13%	2	0,00%	3,28%
59	taxi,tram,walking,	54	0,11%	0	0,00%	0,00%
60	Uber,bus,	49	0,10%	0	0,00%	0,00%
61	Uber,ferry,train,walking,	48	0,10%	2	0,00%	4,17%
62	taxi,bus,train,walking,	43	0,09%	0	0,00%	0,00%
63	car share,bus,train,walking,	42	0,09%	0	0,00%	0,00%
64	car,schoolbus,walking,	41	0,08%	2	0,00%	4,88%
65	taxi,train,tram,walking,	39	0,08%	2	0,00%	5,13%
66	bicycle,bus,	38	0,08%	0	0,00%	0,00%
67	taxi,ferry,train,walking,	38	0,08%	0	0,00%	0,00%
68	schoolbus,	37	0,08%	36	0,07%	97,30%
69	car share (2),	35	0,07%	0	0,00%	0,00%
70	walking (w),	33	0,07%	6	0,01%	18,18%
71	taxi,walking (w),	33	0,07%	0	0,00%	0,00%
72	schoolbus,train,walking,	31	0,06%	3	0,01%	9,68%
73	Uber,schoolbus,walking,	31	0,06%	1	0,00%	3,23%
74	bicycle,schoolbus,walking,	29	0,06%	6	0,01%	20,69%
75	Uber,tram,walking,	28	0,06%	3	0,01%	10,71%
76	Uber,train,tram,walking,	28	0,06%	2	0,00%	7,14%
77	car,train,tram,walking,	26	0,05%	4	0,01%	15,38%
78	car share,	26	0,05%	0	0,00%	0,00%
79	taxi,bus,	26	0,05%	0	0,00%	0,00%
80	car share (2),train,walking,	24	0,05%	0	0,00%	0,00%
81	company shuttle,walking,	22	0,05%	21	0,04%	95,45%
82	bus,train,	22	0,05%	9	0,02%	40,91%
83	ps_shu,	20	0,04%	0	0,00%	0,00%
84	car,tram,walking,	19	0,04%	1	0,00%	5,26%
85	bicycle,tram,	18	0,04%	2	0,00%	11,11%
86	motorcycle,bus,walking,	18	0,04%	1	0,00%	5,56%
87	car,ferry,train,walking,	18	0,04%	1	0,00%	5,56%
88	taxi,schoolbus,walking,	17	0,03%	0	0,00%	0,00%
89	car share,walking (w),	16	0,03%	0	0,00%	0,00%
90	company shuttle,train,walking,	15	0,03%	7	0,01%	46,67%
91	motorcycle,schoolbus,ferry, tram,walking,	14	0,03%	3	0,01%	21,43%
92	bicycle,ferry,train,walking,	14	0,03%	2	0,00%	14,29%
93	car,train,walking (w),	13	0,03%	0	0,00%	0,00%
94	Uber,train,walking (w),	12	0,02%	2	0,00%	16,67%
95	motorcycle,bus,train,walking,	12	0,02%	0	0,00%	0,00%
96	bicycle,tram,walking,	11	0,02%	1	0,00%	9,09%
97	car,bus,	11	0,02%	0	0,00%	0,00%
98	bicycle,ferry,walking,	11	0,02%	0	0,00%	0,00%
99	bicycle,ferry,train,	9	0,02%	1	0,00%	11,11%
100	car pool,walking,	9	0,02%	0	0,00%	0,00%

	Combination in names	Availablility (# observations)	(% of observations)	Chosen (# chosen)	(% of choices)	Ratio (chosen/available)
101	taxi,train,walking (w),	8	0,02%	1	0,00%	12,50%
102	ferry,tram,walking,	8	0,02%	0	0,00%	0,00%
103	ferry,walking (w),	7	0,01%	6	0,01%	85,71%
104	car share (2),bus,train,walking,	7	0,01%	1	0,00%	14,29%
105	bicycle,schoolbus,	7	0,01%	0	0,00%	0,00%
106	motorcycle,bus,	7	0,01%	0	0,00%	0,00%
107	car share,tram,walking,	7	0,01%	0	0,00%	0,00%
108	motorcycle,ferry,walking,	7	0,01%	0	0,00%	0,00%
109	car,schoolbus,train,walking,	7	0,01%	0	0,00%	0,00%
110	motorcycle,train,tram,walking,	7	0,01%	0	0,00%	0,00%
111	car share (2),walking (w),	6	0,01%	0	0,00%	0,00%
112	company shuttle,bus,walking,	5	0,01%	3	0,01%	60,00%
113	schoolbus,bus,train,walking,	5	0,01%	1	0,00%	20,00%
114	bicycle,train,tram,walking,	5	0,01%	0	0,00%	0,00%
115	tram,walking (w),	4	0,01%	2	0,00%	50,00%
116	motorcycle,schoolbus,	4	0,01%	1	0,00%	25,00%
117	car share,ferry,walking,	4	0,01%	0	0,00%	0,00%
118	motorcycle,ferry,train,walking,	4	0,01%	0	0,00%	0,00%
119	ferry,train,tram,walking,	4	0,01%	0	0,00%	0,00%
120	car,ferry,	3	0,01%	2	0,00%	66,67%
121	bus,ferry,walking (w),	3	0,01%	1	0,00%	33,33%
122	car,schoolbus,	3	0,01%	0	0,00%	0,00%
123	car share (2),train,	3	0,01%	0	0,00%	0,00%
124	bicycle,schoolbus,bus,walking,	3	0,01%	0	0,00%	0,00%
125	car,bus,tram,walking,	3	0,01%	0	0,00%	0,00%
126	motorcycle,schoolbus,tram, walking,	3	0,01%	0	0,00%	0,00%
127	tram,	2	0,00%	2	0,00%	100,00%
128	car rental,walking,	2	0,00%	1	0,00%	50,00%
129	car,schoolbus,tram,walking,	2	0,00%	1	0,00%	50,00%
130	schoolbus,train,	2	0,00%	0	0,00%	0,00%
131	bicycle,bus,train,	2	0,00%	0	0,00%	0,00%
132	car,bus,walking (w),	2	0,00%	0	0,00%	0,00%
133	Uber,bus,walking (w),	2	0,00%	0	0,00%	0,00%
134	bicycle,schoolbus,train,walking,	2	0,00%	0	0,00%	0,00%
135	car share,bus,tram,walking,	2	0,00%	0	0,00%	0,00%
136	taxi,schoolbus,train,walking,	2	0,00%	0	0,00%	0,00%
137	Uber,schoolbus,train,walking,	2	0,00%	0	0,00%	0,00%
138	Uber,bus,ferry,walking,	2	0,00%	0	0,00%	0,00%
139	company shuttle,bus,train,walking,	2	0,00%	0	0,00%	0,00%
140	schoolbus,walking (w),	1	0,00%	1	0,00%	100,00%
141	car share (2),train,walking (w),	1	0,00%	1	0,00%	100,00%
142	train,tram,walking (w),	1	0,00%	1	0,00%	100,00%
143	bicycle,company shuttle,train, walking,	1	0,00%	1	0,00%	100,00%
144	car share,train,	1	0,00%	0	0,00%	0,00%
145	Uber,schoolbus,	1	0,00%	0	0,00%	0,00%
146	schoolbus,bus,	1	0,00%	0	0,00%	0,00%
147	car,taxi,walking (w),	1	0,00%	0	0,00%	0,00%
148	car,company shuttle,walking,	1	0,00%	0	0,00%	0,00%
149	car share,schoolbus,walking,	1	0,00%	0	0,00%	0,00%
150	car share (2),bus,walking (w),	1	0,00%	0	0,00%	0,00%
151	motorcycle,schoolbus,walking,	1	0,00%	0	0,00%	0,00%
152	taxi,bus,walking (w),	1	0,00%	0	0,00%	0,00%
153	Uber,ferry,walking (w),	1	0,00%	0	0,00%	0,00%
154	schoolbus,train,walking (w),	1	0,00%	0	0,00%	0,00%
155	bus,tram,walking (w),	1	0,00%	0	0,00%	0,00%
156	ferry,train,walking (w),	1	0,00%	0	0,00%	0,00%
157	bicycle,bus,ferry,walking,	1	0,00%	0	0,00%	0,00%
158	car,company shuttle,train,walking,	1	0,00%	0	0,00%	0,00%
159	car share,schoolbus,bus,walking,	1	0,00%	0	0,00%	0,00%
160	motorcycle,company shuttle, train,walking,	1	0,00%	0	0,00%	0,00%
161	taxi,company shuttle,train,walking,	1	0,00%	0	0,00%	0,00%
162	taxi,bus,train,walking (w),	1	0,00%	0	0,00%	0,00%
163	Uber,schoolbus,train,walking (w),	1	0,00%	0	0,00%	0,00%
164	Uber,bus,train,walking (w),	1	0,00%	0	0,00%	0,00%
165	Uber,ferry,train,walking (w),	1	0,00%	0	0,00%	0,00%
166	bus,train,tram,walking (w),	1	0,00%	0	0,00%	0,00%
167	motorcycle,bus,ferry,train,walking,	1	0,00%	0	0,00%	0,00%
168	bus,ferry,train,tram,walking,	1	0,00%	0	0,00%	0,00%

Table B.1: Unique alternatives that occur in the data

C

Descriptive Data Appendix

C.1. Users and Data Processing

Data	Number of users	Observations per user mean	Observations per user maximum
Original data (*100.000 obs*)	8.483	4	295
Processed data (*48.657 obs*)	7.327	3	129

Table C.1: Users in the data

As Table C.1 shows, the original data set contains 8.483 unique users. In data processing, about 50% of the observations were deleted because of noise. This is not proportional to the amount of users deleted in this process, as only 13,6% of the users were deleted.
Through checking the amount of users and observations during this process, it appeared that many groups of more than 200 observations belonging to the same ID were deleted because of noise. This indicates that errors occur in the data that are related to certain users, or devices. Also, 200 observations for one user seems like an implausible amount of trips to plan in 12 days. Given that most deleted observations belong to Android users, it is expected that users of this platform is causing the erroneous records in the data.

C.2. Multicollinearity

A challenge with revealed preference data is that it can be noisy, and that multicollinearity can arise if attributes do not sufficiently vary. A basic example of this issue is that a longer trip also includes larger costs. In this case, the parameters for travel time and travel costs show covariance. In a model, it then becomes difficult to assign choices to either one of the attributes. For this reason, a simple inspection is performed by checking the distribution of attribute levels of attributes that are expected to covary.

In Figure C.1, it is seen that travel time and travel cost are well distributed and capture a broad range of possibilities. Some lines can be recognized in this pattern, these indicate a certain mode, for which increasing travel time indeed leads to increased costs.

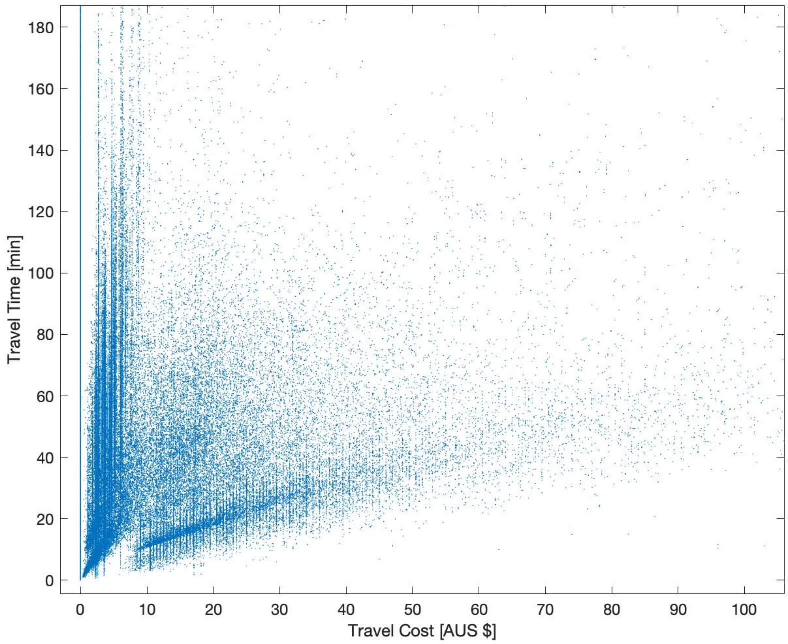

Figure C.1: Scatter plot of travel costs vs. travel time

The next check investigates the distribution of calories versus that of carbon. More active modes of transportation require more calories, but emit less carbon, therefore multicollinearity could be suspected. Nevertheless, inspection of these attributes levels (see Figure C.2) reveals that carbon and calories are also distributed over a broad range of values. Also leading to no need for suspecting multicollinearity.

The third and final check investigates the distribution of carbon emission versus that of travel costs. It can be suspected that more expensive modes of transportation emit more carbon. For example, taking an Uber is more expensive and emits more carbon than performing a trip on public transport, and of course walking is for free and emits no carbon dioxide. The scatter plot for this investigation can be found in Figure C.3. It can be seen that the distribution of these attributes do not capture an equally broad range as the two previous plots. A line pattern can be recognized of increasing costs with increasing carbon. This confirms the expectation that travel costs and carbon are slightly correlated. Nonetheless, it is expected that the spread is large enough for proper model estimation.

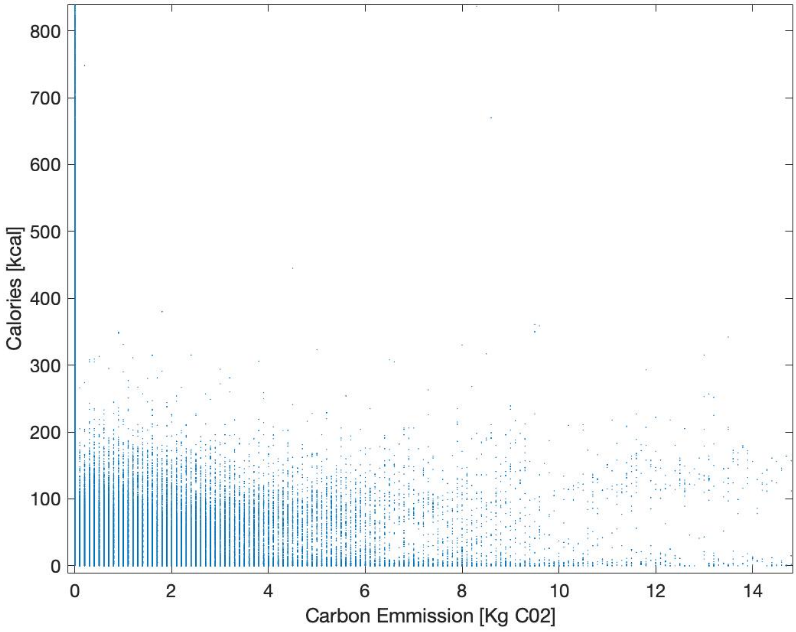

Figure C.2: Scatter plot of carbon emission vs. calories

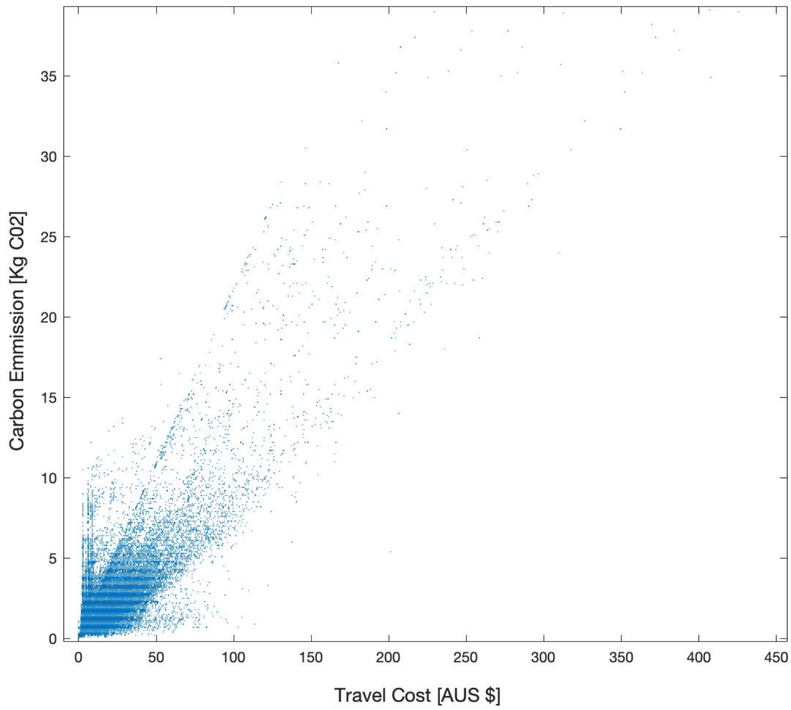

Figure C.3: Scatter plot of carbon emission vs. travel costs

D

Choice Modelling Process

This chapter elaborates on the modeling process that leads to identification of the best possible model. Each relevant intermediate model is discussed, and step-by-step improvements are explained.

D.1. Including Attributes

As a starting point, a model is formulated with ASC's for all modes, and taste parameters for travel time and travel cost. To find what other attributes to include in the choice model, this model is expanded step-by-step with additional attributes. The estimation results of the formulated models are reported in Table 3.9. It can be seen that inclusion of each of the attributes leads to a significant improvement in model fit.

The reliability of the parameters also improves over these first models. As attributes are included in the model, more parameters become significant, indicating a better model specification. At this point, 'MNLattributes-4' is perceived to be the best possible model.

D.2. Including Interaction ASC's

The information retrieved from the first models is used as a guidance to formulating better models. In the first models, it is seen that difficulties arise in assigning values to ASC's for schoolbus, tram, train and walk. As enough observations are available to determine values for these constants, the insignificances indicate a model mis-specification. Therefore, the involved ASC specifications are further explored.
An explanation for the insignificances could lie in the ASC for walking. From the first models, it can be seen that public transport modes have the highest ASC values. And, from the data analysis it is also known that public transport alternatives are chosen most in combination with walking.
To perform a public transport trip, people must mostly also include a walk in their trip, even though they might not prefer walking. This makes it difficult to assign a sensible value to the ASC for walking, because the data suggests it is chosen often. Therefore, the following model aims at capturing the interaction between public transport and walking with additional ASC's.

Four additional ASCs are explored for this next modelling step. They capture the interaction between walking and each public transport mode. The interaction ASCs are added to all alternatives that include walking and the specific public transport mode.

For ferry, tram and train, the model can not distinguish the interaction parameter from the ASC for the mode, resulting in correlations higher than 0.9. These three ASC's do lead to an improved model fit, but as they are not identifyable, they are not included in the model. The interaction ASC for walking and bus is identifyable, and also leads to an improved model fit. The parameter estimates of this model are reported in Table D.2.
The parameter estimates of model 'MNLinteraction' are more reliable, as they do not include any insignificant estimates. Also, it can be seen that the ASC for walking becomes negative. This is more in line with

	MNLattributes-1		MNLattributes-2		MNL attributes-3		MNL attributes-4	
Parameter Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-4,35	*-50,28*	-2,95	*-36,63*	-2,95	*-36,73*	-2,67	*-32,75*
ASC_bus	0		0		0		0	
ASC_car	-4,69	*-52,13*	-4	*-50,84*	-3,85	*-46,92*	-3,74	*-46,05*
ASC_car-s	-3,99	*-13,18*	-3,55	*-11,73*	-3,70	*-12*	-3,60	*-11,54*
ASC_ferry	0,204	*2,1*	0,402	*4,28*	0,601	*5,52*	0,905	*8,24*
ASC_motor	-5,82	*-34,47*	-4,92	*-33,46*	-5,01	*-31,82*	-4,84	*-30,87*
ASC_schoolbus	0,0385	*0,46*	-0,0598	*-0,71*	-0,0629	*-0,74*	0,0511	*0,6*
ASC_shuttle	-10,3	*-11,5*	-10,3	-11,86	-11,8	*-12,94*	-11,5	*-12,69*
ASC_taxi	-4,21	*-28,85*	-4,53	*-30,16*	-4,62	*-30,47*	-4,51	*-29,73*
ASC_train	-0,529	*-20,88*	-0,416	*-15,89*	-0,404	*-15,28*	-0,0576	*-1,62*
ASC_tram	0,179	*1,83*	0,0583	*0,59*	0,0685	*0,69*	0,343	*3,44*
ASC_uber	-3,57	*-40,46*	-3,82	*-41,43*	-3,79	*-40,61*	-3,69	*-39,83*
ASC_walk	-0,0256	*-0,44*	0,0505	*0,9*	0,0443	*0,79*	0,143	*2,52*
BETA_TT	-0,0904	*-54,85*	-0,0608	*-36,12*	-0,0607	*-36,08*	-0,0579	*-34,4*
BETA_calories			-0,0212	*-29,9*	-0,0213	*-30,03*	-0,0232	*-30,43*
BETA_carbon					-0,252	*-4,01*	-0,254	*-4,11*
BETA_combine							-0,562	*-14,83*
BETA_TC	-0,0535	*-14,89*	-0,0446	*-11,33*	-0,0262	*-4,94*	-0,0267	*-5,03*
Number of estimated parameters:	14		15		16		17	
Sample size:	38927		38927		38927		38927	
Init log likelihood:	-56.366		-56.366		-56.366		-56.366	
Final log likelihood:	-32.143		-30.764		-30.745		-30.618	
Rho-square for the init, model:	0,43		0,454		0,455		0,457	
LRS compared to previous	31.645		2.757		39		253	
VoT (AUS$ / hour)	101,38		81,79		139,01		130,11	
Relative Importance								
BETA_TC	-1,10		-0,92		-0,54		-0,55	
BETA_TT	-7,92		-5,33		-5,32		-5,07	
BETA_calories			-3,10		-3,11		-3,39	
BETA_carbon					-0,58		-0,58	
BETA_combine							-1,69	

Table D.1: Choice models for finding what attributes to include

expectation, as it can be expected that busses are preferred over walking. Therefore, this model also improves the interpretability of the parameters.

D.3. Formulating Specific Travel Time Parameters

In the data, the travel time formulated for each different mode or segment. This offers the opportunity for more detail in the model, by splitting up the travel time parameter. As a first step, the total travel time is split up in time spent on parking, waiting, transfers and collecting vehicles is separated from the in-vehicle time. Another model is formulated that includes a breakdown of the travel time parameter for each mode.

The estimation results of these models are provided in Table D.3. Model ‘MNLtraveltimes-1’, with the in-vehicle time separated, shows an improvement in model fit, but does include an insignificant parameter for collecting time, and unexpected sign for parking time. Nevertheless, the explanatory ability of the model is not hampered by these issues. And therefore, this model is positioned as best possible model at this point.

The other model, ‘MNLtraveltimes-2’ shows a slight additional improvement in model fit, but it contains many uninterpretable and unreliable parameter estimate. Therefore, it is not chosen as best possible model.

	MNL attributes-4		MNLinteraction	
Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-2,67	*-32,75*	-2,23	*-25,54*
ASC_bus	0		0	
ASC_car	-3,74	*-46,05*	-3	*-31,67*
ASC_car-s	-3,6	*-11,54*	-2,66	*-8,64*
ASC_ferry	0,905	*8,24*	1,68	*14,43*
ASC_motor	-4,84	*-30,87*	-4,19	*-26,21*
ASC_schoolbus	0,0511	*0,6*	0,91	*9,11*
ASC_shuttle	-11,5	*-12,69*	-10,1	*-11,21*
ASC_taxi	-4,51	*-29,73*	-3,61	*-22,65*
ASC_train	-0,0576	*-1,62*	0,725	*12,93*
ASC_tram	0,343	*3,44*	1,16	*10,51*
ASC_uber	-3,69	*-39,83*	-2,83	*-25,66*
ASC_walk	0,143	*2,52*	-0,138	*-2,17*
ASC_walkbus			0,917	*17,41*
BETA_TT	-0,0579	*-34,4*	-0,0573	*-33,94*
BETA_calories	-0,0232	*-30,43*	-0,0198	*-23,58*
BETA_carbon	-0,254	*-4,11*	-0,199	*-3,33*
BETA_combine	-0,562	*-14,83*	-1,37	*-23,29*
BETA_TC	-0,0267	*-5,03*	-0,0342	*-6,22*
Number of estimated parameters:	17		18	
Sample size:	38927		38927	
Init log likelihood:	-56.366		-56.366	
Final log likelihood:	-30.618		-30.427	
Rho-square for the init, model:	0,457		0,46	
LRS compared to previous			383	
VoT (AUS$ / hour)	130,11		100,53	
Relative importance				
BETA_TC	-0,55		-0,70	
BETA_TT	-5,07		-5,02	
BETA_calories	-3,39		-2,89	
BETA_carbon	-0,58		-0,46	
BETA_combine	-1,69		-4,11	

Table D.2: Choice Model with interaction ASC

D.4. Ordering Effects

For this next modelling step the so-called ordering effect is taken into account. It is suggested that the order in which alternatives are presented influences the choice.
This effect is captured by estimating a dummy for each position in the choice set. The estimation results of the model with ordering dummies can be seen in Table D.4.

Firstly, it can be seen that including these parameters leads to a significant improvement in model fit. From the estimated position dummies it can be seen that order indeed matters for decision-making. In general it applies that the more an alternative moves towards the end of the choice set, the more negative the utility associated with the alternative.

Through checking the t-test values, some of the dummy estimates appear to be insignificant. To solve this, the position dummy for position 19 is set to 0, and not estimated by the model. Furthermore, the dummy for position 14 shows to be insignificant. However, this insignificance does not form an obstruction for model interpretation or reliability. Therefore, the 'MNLordering-1' model is seen selected the best possible model.

Furthermore, no severe correlations exist between the parameters in the model. And, the model is well-able to disentangle effects of ordering from travel behaviour parameters.

D.5. User Frequency

As a last step for model improvement, it is explored whether user frequency has an influence on choice behavior.
To do this with a multinomial logit model, the model is estimated on two different segments of the training data. The first segment contains the observations frequent users (≥5 observations/user), the second segment contains the observations belonging to non-frequent users (<5 observations/user). It is then investigated whether the estimated parameters of the model differ over the two segments of users.

The estimation results for the complete data sample, and the two segments are reported in Table D.5. Overall, the differences between the estimated parameter values resulting from the three data sets are negligible. The largest differences in parameter estimates compared to the complete data sample are observed for BETA_Tcollect and D_p15. Especially, for BETA_Tcollect, a large difference is observed in the relative importance of the parameter. As a result, the parameter has a much larger negative influence on non-frequent users' utility of alternatives.
Overall, the rho-squares and the estimated parameter values on the segmented data are very similar to the estimates complete data. Also, the correlations between the estimated parameters look similar. Estimating the model on the two different data segments does elicit more insignificant parameter estimates. This could be a result of the reduced number of observations available in the segments as opposed to the complete sample. Because no new insights are gained, and the model fits are similar, no need arises for segmenting the data to accommodate for these two different user groups.

Table D.3: Choice Models with Specific Travel Time Parameters

	MNL interaction		MNLtraveltimes-1 in-vehicle time		MNLtraveltimes-2 all spec. times	
Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-2,23	*-25,54*	-3,66	*-30,34*	-3,38	*-23,99*
ASC_bus	0		0		0	
ASC_car	-3	*-31,67*	-3,9	*-25,33*	-4,46	*-24,57*
ASC_car-s	-2,66	*-8,64*	-3,12	*-6,05*	-4,07	*-5,38*
ASC_ferry	1,68	*14,43*	1,67	*14,19*	0,898	*5,07*
ASC_motor	-4,19	*-26,21*	-4,71	*-28,68*	-4,94	*-20,62*
ASC_schoolbus	0,91	*9,11*	0,835	*8,12*	0,563	*3,73*
ASC_shuttle	-10,1	*-11,21*	-8,78	*-9,83*	-0,0219	*0*
ASC_taxi	-3,61	*-22,65*	-3,52	*-19,85*	-4,48	*-17,54*
ASC_train	0,725	*12,93*	0,813	*13,33*	0,564	*8,53*
ASC_tram	1,16	*10,51*	1,09	*9,63*	0,561	*2,54*
ASC_uber	-2,83	*-25,66*	-2,8	*-21,5*	-2,61	*-16,9*
ASC_walk	-0,138	*-2,17*	-0,146	*-2,06*	-0,127	*-1,83*
ASC_walkbus	0,917	*17,41*	0,857	*15,33*	0,892	*16,18*
BETA_TT	-0,0573	*-33,94*	-0,0433	*-26,46*		
BETA_TTbicycle					-0,117	*-9,8*
BETA_TTbus					-0,0483	*-27,44*
BETA_TTcar					-0,0251	*-3,71*
BETA_TTcars					-0,0195	*-1,37*
BETA_TTferry					-0,00425	*-0,66*
BETA_TTmotor					-0,0479	*-4,74*
BETA_TTransfer			-0,0625	*-17,99*	-0,0606	*-17,29*
BETA_TTschoolbus					-0,03	*-3,46*
BETA_TTshuttle					-0,412	*-1,4*
BETA_TTtaxi					0,0286	*1,8*
BETA_TTtrain					-0,0307	*-15,12*
BETA_TTtram					-0,00749	*-0,51*
BETA_TTuber					-0,0482	*-4,3*
BETA_TTwalk			-0,103	*-35,61*	-0,129	*-27,17*
BETA_Tcollect			-0,317	*-1,11*	-0,227	*-0,74*
BETA_Tparking			0,159	*3,66*	0,165	*4,35*
BETA_Twait			-0,0832	*-4,3*	-0,0725	*-3,67*
BETA_calories	-0,0198	*-23,58*	-0,00391	*-5,33*	0,0062	*3,42*
BETA_carbon	-0,199	*-3,33*	-0,163	*-2,81*	-0,407	*-5,12*
BETA_combine	-1,37	*-23,29*	-1,34	*-20,5*	-1,29	*-20,09*
BETA_TC	-0,0342	*-6,22*	-0,0389	*-7,19*	-0,0349	*-5,54*
Number of estimated parameters:	18		23		34	
Sample size:	38927		38927		38927	
Init log likelihood:	-56.366		-56.366		-56.366	
Final log likelihood:	-30.427		-30.036		-29.904	
Rho-square for the init, model:	0,46		0,467		0,469	
LRS compared to previous			782		263	
VoT (AUS$ / hour)	100,53		66,79			
Relative importance						
BETA_TC	-0,70		-0,80		-0,72	
BETA_TT	-5,02		-3,79		-	
BETA_calories	-2,89		-0,57		0,91	
BETA_carbon	-0,46		-0,37		-0,94	
BETA_combine	-4,11		-4,02		-3,87	
BETA_TTransfer	-		-1,13		-1,10	
BETA_TTwalk	-		-7,16		-8,96	
BETA_Tcollect	-		-0,63		-0,45	
BETA_Tparking	-		0,64		0,66	
BETA_Twait	-		-0,67		-0,58	

Table D.4: Choice Models that Capture the Order of the Choice Set

	MNLtraveltimes-1 in-vehicle time		MNLordering-1		MNLordering-2 only the order	
Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-3,66	*-30,34*	-3,66	*-32,81*		
ASC_bus	0		0			
ASC_car	-3,9	*-25,33*	-3,72	*-23,52*		
ASC_car-s	-3,12	*-6,05*	-3,09	*-5,95*		
ASC_ferry	1,67	*14,19*	1,87	*15,9*		
ASC_motor	-4,71	*-28,68*	-4,25	*-25,38*		
ASC_schoolbus	0,835	*8,12*	0,962	*9,31*		
ASC_shuttle	-8,78	*-9,83*	-8,52	*-12,24*		
ASC_taxi	-3,52	*-19,85*	-3,21	*-18,05*		
ASC_train	0,813	*13,33*	0,901	*14,78*		
ASC_tram	1,09	*9,63*	1,16	*9,83*		
ASC_uber	-2,8	*-21,5*	-2,45	*-19,14*		
ASC_walk	-0,146	*-2,06*	-0,145	*-1,99*		
ASC_walkbus	0,857	*15,33*	1,04	*18,37*		
BETA_TT	-0,0433	*-26,46*	-0,0303	*-18,18*		
BETA_TTransfer	-0,0625	*-17,99*	-0,0547	*-15,49*		
BETA_TTwalk	-0,103	*-35,61*	-0,084	*-29,4*		
BETA_Tcollect	-0,317	*-1,11*	-0,297	*-1,04*		
BETA_Tparking	0,159	*3,66*	0,215	*4,46*		
BETA_Twait	-0,0832	*-4,3*	-0,0637	*-3,35*		
BETA_calories	-0,00391	*-5,33*	-0,0017	*-2,89*		
BETA_carbon	-0,163	*-2,81*	-0,144	*-2,72*		
BETA_combine	-1,34	*-20,5*	-1,36	*-20,47*		
BETA_TC	-0,0389	*-7,19*	-0,0234	*-4,85*		
D_p1			0		0	
D_p2			-0,466	*-26,13*	-0,537	*-42,61*
D_p3			-0,837	*-35,34*	-1,07	*-64,82*
D_p4			-1	*-33,89*	-1,43	*-67,18*
D_p5			-0,986	*-26,11*	-1,72	*-61,46*
D_p6			-0,918	*-17,87*	-1,98	*-49,92*
D_p7			-0,939	*-13,39*	-2,26	*-40,63*
D_p8			-0,942	*-9,92*	-2,48	*-31,3*
D_p9			-1,19	*-8,59*	-2,73	*-23,2*
D_p10			-1,1	*-5,44*	-2,96	*-17,08*
D_p11			-1,46	*-4,55*	-3,23	*-11,99*
D_p12			-1,23	*-3,18*	-2,92	*-9,15*
D_p13			-1,97	*-2,91*	-3,49	*-6,01*
D_p14			-0,941	*-1,49*	-2,61	*-5,15*
D_p15			-5,76	*-10,41*	-6,95	*-65,89*
D_p16			-4,59	*-10,29*	-6,52	*-42,67*
D_p17			-1,75	*-2,01*	-6,33	*-17,85*
D_p18			-1,14	*-2,00*	-5,86	*-13,05*
D_p19			0		-5,35	*-9,23*
Number of estimated parameters:	23		40		18	
Sample size:	38927		38927		38927	
Init log likelihood:	-56.366		-56365,548		-56.366	
Final log likelihood:	-30.036		-28.956		-49.354	
Rho-square for the init, model:	0,467		0,486		0,124	
LRS compared to previous			2.159			
VoT (AUS$ / hour)	66,79		77,69		-	
Relative importance						
BETA_TC	-0,80		-0,48			
BETA_TT	-3,79		-2,65			
BETA_calories	-0,57		-0,25			
BETA_carbon	-0,37		-0,33			
BETA_combine	-4,02		-4,08			
BETA_TTransfer	-1,131875		-0,990617			
BETA_TTwalk	-7,15644		-5,83632			
BETA_Tcollect	-0,634		-0,594			
BETA_Tparking	0,636		0,86			
BETA_Twait	-0,6656		-0,5096			

Table D.5: Choice Models for Frequent and Non-Frequent Users

	MNLordering-1					
	Complete Data Sample		Data Segment with Frequent Users		Data Segment with Non-Frequent Users	
Parameter Name	**Value**	***Robust t-test***	**Value**	***Robust t-test***	**Value**	***Robust t-test***
ASC_bicycle	-3,66	*-32,81*	-3,71	*-26,77*	-3,63	*-17,51*
ASC_car	-3,72	*-23,52*	-3,88	*-18,22*	-3,48	*-16,60*
ASC_car-s	-3,09	*-5,95*	-2,88	*-5,31*	-3,33	*-2,99*
ASC_ferry	1,87	*15,9*	1,81	*13,35*	1,94	*8,66*
ASC_motor	-4,25	*-25,38*	-4,24	*-21,75*	-4,07	*-13,33*
ASC_schoolbus	0,962	*9,31*	1,04	*8,73*	0,908	*4,50*
ASC_shuttle	-8,52	*-12,24*	-7,97	*-10,65*	-8,58	*-7,25*
ASC_taxi	-3,21	*-18,05*	-3,15	*-15*	-3,25	*-9,35*
ASC_train	0,901	*14,78*	0,9	*12,42*	0,946	*8,36*
ASC_tram	1,16	*9,83*	1,17	*8,76*	1,11	*4,68*
ASC_uber	-2,45	*-19,14*	-2,36	*-15,69*	-2,61	*-10,79*
ASC_walk	-0,145	*-1,99*	-0,118	*-1,31*	-0,0301	*-0,23*
ASC_walkbus	1,04	*18,37*	1,06	*15,69*	1,02	*9,31*
BETA_TT	-0,0303	*-18,18*	-0,0293	*-15,29*	-0,0296	*-9,32*
BETA_TTransfer	-0,0547	*-15,49*	-0,0517	*-10,33*	-0,048	*-8,96*
BETA_TTwalk	-0,084	*-29,4*	-0,0837	*-25,5*	-0,0777	*-12,63*
BETA_Tcollect	-0,297	*-1,04*	-0,423	*-1,46*	-3,71	*-6,54*
BETA_Tparking	0,215	*4,46*	0,272	*4,03*	0,192	*4,83*
BETA_Twait	-0,0637	*-3,35*	-0,0822	*-3,38*	-0,0501	*-1,44*
BETA_calories	-0,0017	*-2,89*	-0,00104	*-1,41*	-0,000981	*-0,89*
BETA_carbon	-0,144	*-2,72*	-0,114	*-1,88*	-0,0939	*-1,09*
BETA_combine	-1,36	*-20,47*	-1,37	*-17,2*	-1,37	*-11,31*
BETA_TC	-0,0234	*-4,85*	-0,0219	*-4,14*	-0,0199	*-2,24*
D_p1	0		0		0	
D_p2	-0,466	*-26,13*	-0,467	*-22,29*	-1	*-14,89*
D_p3	-0,837	*-35,34*	-0,851	*-30,61*	-0,905	*-19,25*
D_p4	-1	*-33,89*	-0,979	*-28,43*	-1,13	*-18,89*
D_p5	-0,986	*-26,11*	-1,03	*-23,24*	-1,11	*-14,66*
D_p6	-0,918	*-17,87*	-0,979	*-16,06*	-0,988	*-10,14*
D_p7	-0,939	*-13,39*	-0,94	*-11,3*	-1,21	*-9,01*
D_p8	-0,942	*-9,92*	-1,06	*-9,52*	-1,3	*-6,73*
D_p9	-1,19	*-8,59*	-1,26	*-7,37*	-1,15	*-4,64*
D_p10	-1,1	*-5,44*	-1	*-4,30*	-1,08	*-3,20*
D_p11	-1,46	*-4,55*	-1,180	*-2,83*	-2	*-3,33*
D_p12	-1,23	*-3,18*	-0,963	*-2,12*	-0,735	*-1,40*
D_p13	-1,97	*-2,91*	-1,69	*-2,04*	-1,69	*-1,83*
D_p14	-0,941	*-1,49*	-0,802	*-1,05*	-1,52	*-1,50*
D_p15	-5,76	*-10,41*	-6,01	*-11,62*	-7,92	*-14,87*
D_p16	-4,59	*-10,29*	-4,47	*-14,37*	-6,32	*-11,25*
D_p17	-1,75	*-2,01*	-1,3	*-2,18*	-3,4	*-3,13*
D_p18	-1,14	*-2,00*	-2,26	*-4,31*	0	
D_p19	0		0		0	
Number of estimated parameters:	40		40		40	
Init log likelihood:	-56.366		-41.299		-15.019	
Final log likelihood:	-28.956		-21.297		-7.718	
Rho-square for the init, model:	0,486		0,484		0,486	
VoT (AUS$ / hour)	77,69		80,27		89,25	
Relative importance						
BETA_TC	-0,48		-0,45		-0,41	
BETA_TT	-2,65		-2,57		-2,59	
BETA_calories	-0,25		-0,15		-0,14	
BETA_carbon	-0,33		-0,26		-0,22	
BETA_combine	-4,08		-4,11		-4,11	
BETA_TTransfer	-0,990617		-0,936287		-0,86928	
BETA_TTwalk	-5,83632		-5,815476		-5,398596	
BETA_Tcollect	-0,594		-0,846		-7,42	
BETA_Tparking	0,86		1,088		0,768	
BETA_Twait	-0,5096		-0,6576		-0,4008	

E

Choice Models for Economic Appraisal

E.1. Best Possible Model

Table E.1 shows the largest correlations (>0.5) between parameters of the best possible model. For the VoT computation it is looked for correlations with the travel time and travel cost parameter. From this table it can be seen that the carbon parameter and the travel cost parameter are confounded (correlation=-0.726).

Parameter 1	**Parameter 2**	**Correlation**
ASC_train	ASC_walkbus	0.795
ASC_taxi	ASC _uber	0.568
ASC _train	BETA _combine	-0.857
ASC _car-s	BETA _Tcollect	-0.809
ASC _walkbus	BETA _combine	-0.789
BETA _carbon	BETA _TC	-0.726
BETA _TTwalk	BETA _calories	-0.637
ASC _car	BETA _Tparking	-0.608
ASC _uber	BETA _Twait	-0.588

Table E.1: Correlations (>0.5) in Best Possible Model

To ensure the VoT computation becomes an as clean as possible trade of between pure travel time and travel cost, the parameters are estimated again with the carbon parameter fixed to 0. The estimation results of this model are reported in Table E.2. As carbon is fixed to zero, the importance of the travel cost parameter increases. This results in an improved trade off between cost and time. The new VoT derived from this model amounts to $53,18.

	MNLordering-1		MNLordering-1 *without carbon*	
Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-3,66	-32,81	-3,67	-32,83
ASC_bus	0		0	
ASC_car	-3,72	-23,52	-3,83	-24,82
ASC_car-s	-3,09	-5,95	-3,03	-5,72
ASC_ferry	1,87	15,9	1,77	16,17
ASC_motor	-4,25	-25,38	-4,2	-26
ASC_schoolbus	0,962	9,31	0,978	9,45
ASC_shuttle	-8,52	-12,24	-7,11	-11,5
ASC_taxi	-3,21	-18,05	-3,12	-17,94
ASC_train	0,901	14,78	0,906	14,8
ASC_tram	1,16	9,83	1,17	9,89
ASC_uber	-2,45	-19,14	-2,43	-18,93
ASC_walk	-0,145	-1,99	-0,157	-2,14
ASC_walkbus	1,04	18,37	1,06	18,56
BETA_TT	-0,0303	-18,18	-0,0304	-18,35
BETA_TTransfer	-0,0547	-15,49	-0,0547	-15,5
BETA_TTwalk	-0,084	-29,4	-0,0845	-29,55
BETA_Tcollect	-0,297	-1,04	-0,286	-0,99
BETA_Tparking	0,215	4,46	0,225	4,66
BETA_Twait	-0,0637	-3,35	-0,069	-3,67
BETA_calories	-0,0017	-2,89	-0,0014	-2,39
BETA_carbon	-0,144	-2,72	0	
BETA_combine	-1,36	-20,47	-1,37	-20,6
BETA_TC	-0,0234	-4,85	-0,0343	-9,8
D_p1	0		0	
D_p2	-0,466	-26,13	-0,466	-26,16
D_p3	-0,837	-35,34	-0,837	-35,36
D_p4	-1	-33,89	-1	-33,89
D_p5	-0,986	-26,11	-0,987	-26,13
D_p6	-0,918	-17,87	-0,919	-17,88
D_p7	-0,939	-13,39	-0,939	-13,4
D_p8	-0,942	-9,92	-0,941	-9,92
D_p9	-1,19	-8,59	-1,19	-8,61
D_p10	-1,1	-5,44	-1,1	-5,44
D_p11	-1,46	-4,55	-1,45	-4,51
D_p12	-1,23	-3,18	-1,23	-3,19
D_p13	-1,97	-2,91	-1,96	-2,91
D_p14	-0,941	-1,49	-0,929	-1,49
D_p15	-5,76	-10,41	-5,24	-9,83
D_p16	-4,59	-10,29	-4,18	-9,32
D_p17	-1,75	-2,01	-1,37	-1,55
D_p18	-1,14	-2,00	-0,797	-1,41
D_p19	0		0	
Number of estimated parameters:	40		39	
Init log likelihood:	-56.366		-56.366	
Final log likelihood:	-28.956		-28.964	
Rho-square for the init, model:	0,486		0,486	
LRS	15			
VoT (AUS$ / hour)	77,69		53,18	

Table E.2: The Best Possible Model adjusted for VoT computation

E.2. Full Model

Name	Value	Robust t-test
ASC_bicycle	-3,38	*-26,69*
ASC_bus	0	
ASC_car	-4,16	*-22,22*
ASC_car-s	-4,04	*-5,18*
ASC_ferry	1,18	*6,53*
ASC_motor	-4,4	*-21,33*
ASC_schoolbus	0,676	*4,4*
ASC_shuttle	0	
ASC_taxi	-3,94	*-15,96*
ASC_train	0,719	*10,8*
ASC_tram	0,674	*2,91*
ASC_uber	-2,21	*-14,85*
ASC_walk	-0,117	***-1,6***
ASC_walkbus	1,05	*18,84*
BETA_TTbicycle	-0,105	*-9,07*
BETA_TTbus	-0,0334	*-18,41*
BETA_TTcar	-0,021	*-3,2*
BETA_TTcars	-0,0131	***-0,88***
BETA_TTferry	0,00175	***0,27***
BETA_TTmotor	-0,0412	*-5,13*
BETA_TTransfer	-0,0532	*-14,93*
BETA_TTschoolbus	-0,0151	*-1,71*
BETA_TTshuttle	-0,53	*-18,61*
BETA_TTtaxi	0,0128	***0,86***
BETA_TTtrain	-0,0222	*-10,69*
BETA_TTtram	0,00156	***0,1***
BETA_TTuber	-0,0483	*-4,49*
BETA_TTwalk	-0,112	*-23,11*
BETA_Tcollect	-0,199	***-0,63***
BETA_Tparking	0,212	*4,22*
BETA_Twait	-0,0518	*-2,67*
BETA_calories	0,00923	*5,13*
BETA_carbon	-0,302	*-4,12*
BETA_combine	-1,31	*-20,06*
BETA_TC	-0,0173	*-2,99*
D_p1	0	
D_p2	-0,457	*-25,47*
D_p3	-0,827	*-34,58*
D_p4	-0,994	*-33,28*
D_p5	-0,978	*-25,62*
D_p6	-0,904	*-17,47*
D_p7	-0,917	*-12,94*
D_p8	-0,917	*-9,6*
D_p9	-1,16	*-8,32*
D_p10	-1,09	*-5,39*
D_p11	-1,43	*-4,41*
D_p12	-1,23	*-3,19*
D_p13	-1,98	*-2,93*
D_p14	-0,93	***-1,58***
D_p15	-5,47	*-10,69*
D_p16	-4,47	*-7,37*
D_p17	-1,91	*-2,07*
D_p18	-1,2	*-2,05*
D_p19	0	

Table E.3: Parameter estimates

A full model is estimated to investigate the WtP per mode. The estimation results of the model can be found in Table E.3 and E.4. The resulting WtPs are reported in Table E.5. From the results it can be concluded that the full model WtPs are unreliable due to correlations in the model, the highest of these correlations are reported in Table E.7.

Number of estimated parameters:	50
Sample size:	38.927
Init log likelihood:	-56.365
Final log likelihood:	-28.865
Likelihood ratio test for the null model:	55.001
Rho-square for the null model:	0,488

Table E.4: Estimation report

Mode	**AUS $ / hour**	**Reference value**	**Source**
bus	115,84	$8.36/hr	Douglas and Jones (2018)
car	72,83	$15.58/hr	NSW Government (2016)
car share	45,43	*$6.40/hour*	Ho et al. (2017)
ferry	-6,00	$14.19/hr	Douglas and Jones (2018)
motorcycle	142,89		
schoolbus	52,37		
shuttle	1.824,28		
taxi	-44,39		
train	76,99	$12.33/hr	Douglas and Jones (2018)
tram	-5,41	$20.69/hr	Douglas and Jones (2018)
Uber	167,51		
bicycle	364,16		
collect	690,17		
parking	-735,26		
transfer	184,51		
walk	388,44		
wait	179,31		

Table E.5: Willingness-to-Pay for 1 hour reduction in Travel Time on the Mode

Parameter Name	**Relative Importance**
BETA_TC	-0,12
BETA_calories	0,59
BETA_carbon	-0,33
BETA_combine	-3,93
BETA_TTransfer	-0,62687156
BETA_TTwalk	-2,91312
BETA_Tcollect	-0,398
BETA_Tparking	0,848
BETA_Twait	-0,4136

Table E.6: Relative Importance of Full Model Taste Parameters

Parameter 1	Parameter 2	Correlation
BETA_TTbicycle	BETA_TTwalk	0,901
ASC_train	ASC_walkbus	0,712
BETA_TTcar	BETA_TTuber	0,558
BETA_TTcar	BETA_TTmotor	0,533
BETA_TTbus	BETA_TTtrain	0,508
ASC_shuttle	BETA_TTshuttle	-0,998
BETA_TTwalk	BETA_calories	-0,945
BETA_TTbicycle	BETA_calories	-0,924
ASC_tram	BETA_TTtram	-0,860
ASC_train	BETA_combine	-0,798
ASC_walkbus	BETA_combine	-0,782
ASC_schoolbus	BETA_TTschoolbus	-0,770
ASC_car-s	BETA_Tcollect	-0,720
ASC_ferry	BETA_TTferry	-0,706
BETA_TTcar	BETA_carbon	-0,570
ASC_taxi	BETA_TTtaxi	-0,552
ASC_car	BETA_Tparking	-0,535
ASC_motor	BETA_TTmotor	-0,509

Table E.7: Correlations in the Full Model

E.3. Basic Model and ASC's

	Basic Model		MNLattributes-1	
Parameter Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle			-4,35	*-50,28*
ASC_car			-4,69	*-52,14*
ASC_car-r			-1,93	*-2,27*
ASC_car-s			-4,04	*-12,76*
ASC_ferry			0,204	*2,1*
ASC_motor			-5,82	*-34,45*
ASC_schoolbus			0,0385	*0,46*
ASC_shuttle			-10,4	*-11,54*
ASC_taxi			-4,22	*-28,86*
ASC_train			-0,529	*-20,88*
ASC_tram			0,179	*1,83*
ASC_uber			-3,57	*-40,47*
ASC_walk			-0,0261	*-0,45*
BETA_TT	-0,0377	-72,97	-0,0904	*-54,85*
BETA_calories				
BETA_carbon				
BETA_combine				
BETA_TC	-0,111	-71,06	-0,0534	*-14,87*
Number of estimated parameters:	2		15	
Init log likelihood:	-56.366		-56.366	
Final log likelihood:	-47.965		-32.142	
Rho-square:	0,149		0,43	
LRS compared to previous			31.646	
VoT (AUS$ / hour)	20,38		101,57	

Table E.8: Basic Model, and first modelling steps; adding the ascs

Parameter 1	Parameter 2	Correlation
ASC_uber	BETA_TC	-0.574
ASC_taxi	BETA_TC	-0.364
ASC_car-s	BETA_TC	-0.198
ASC_car	BETA_TC	-0.155
ASC_bicycle	ASC_walk	0.643
ASC_car	ASC_uber	0.332
BETA_TT	BETA_TC	0.325
ASC_uber	ASC_walk	0.321
ASC_car	ASC_walk	0.314

Table E.9: Correlation MNLattributes-1

E.4. Intermediate Models

For exploring if a model exists with a good model fit, and a reliable VoT value, several 'intermediate' models are explored that make use of a simplified ASC structure. The specified ASCs and the modes they capture are reported in Table E.10. The intermediate models that are estimated differ in the beta's they take into account. An overview of the tested models and the parameters they account for is provided in Table E.11. The estimation results of these models can be found in Table E.12 and E.13.

Constant	Modes represented
ASC_bicycle	bicycle
ASC_car	car, motorcycle
ASC_PT	bus, train, tram, ferry, schoolbus
ASC_intermediate	car share, taxi, Uber, car rental
ASC_walk	walk, wheelchair

Table E.10: Simplified ASCs

	Parameters											
Model Name	ASCs	TT	TC	carb.	cal.	comb.	TTwalk	Tcoll.	Ttransf.	Tpark.	Twait	Pos.
MNLintermediate1	x	x										
MNLintermediate2	x	x	x	x	x							
MNLintermediate3	x	x	x	x	x	x		x	x	x	x	
BestPossible												
· *simple ASCs*	x	x	x	x	x	x	x	x	x	x	x	x
·*no carbon*	x	x		x	x	x	x	x	x	x	x	x

Table E.11: Intermediate Models Estimated
TT=travel time, TC=travel cost, carb=carbon, cal=calories, comb=combine, Tcoll=collecting time, Ttransf =transfer time, Tpark= parking time, pos=position

	MNLintermediate1		MNLintermediate2		MNLintermediate3	
Parameter Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-4,21	*-48,64*	-2,6	*-32,48*	-2,73	*-30,6*
ASC_car	-4,73	*-53,6*	-4,02	*-50,88*	-4,17	*-33,13*
ASC_PT	0		0		0	
ASCintermediate	-3,62	*-42,79*	-3,84	*-42,96*	-3,28	*-28,16*
ASC_walkPT	-		-		0,911	*19,26*
ASC_walk	0,0483	*0,82*	0,212	*3,76*	-0,619	*-8,01*
BETA_TT	-0,0903	*-54,63*	-0,0578	*-34,59*	-0,0561	*-32,16*
BETA_calories			-0,0231	*-32,84*	-0,0207	*-25,16*
BETA_carbon			-0,0257	*-0,56*	0,0312	*0,69*
BETA_combine			-0,571	*-20,54*	-0,587	*-19,2*
BETA_TC	-0,0507	*-13,6*	-0,0417	*-8,78*	-0,0472	*-9,51*
BETA_TTransfer					-0,0621	*-17,97*
BETA_Tcollect					-0,286	*-1,52*
BETA_Tparking					0,23	*5,51*
BETA_Twait					-0,11	*-6,22*
Number of estimated parameters:	6		9		14	
Init log likelihood:	-56.366		-56.366		-56.366	
Final log likelihood:	-32.432		-30.719		-30.410	
Rho-square:	0,425		0,455		0,46	
LRS compared to previous			3.424		619	
VoT (AUS$ / hour)	106,86		83,17		71,31	

Table E.12: Intermediate Models without Ordering Dummies

	Best possible Simple ASC's		Best Possible Simple ASCs nocarbon	
Parameter Name	**Value**	**Robust t-test**	**Value**	**Robust t-test**
ASC_bicycle	-4,32	*-38,68*	-4,32	*-38,68*
ASC_car	-4,76	*-36,15*	-4,78	*-36,43*
ASC_walk	0,194	*2,95*	0,192	*2,92*
ASCintermediate	-3,52	*-33,13*	-3,52	*-33,07*
BETA_TT	-0,0299	*-17,89*	-0,0299	*-17,94*
BETA_TTransfer	-0,0577	*-16,36*	-0,0577	*-16,35*
BETA_TTwalk	-0,0926	*-33,77*	-0,0928	*-34,01*
BETA_Tcollect	-0,522	*-2,95*	-0,512	*-2,92*
BETA_Tparking	0,192	*4,32*	0,192	*4,32*
BETA_Twait	-0,0726	*-4,28*	-0,0738	*-4,36*
BETA_calories	-0,00241	*-3,6*	-0,00235	*-3,51*
BETA_carbon	-0,0361	*-0,86*	0	
BETA_combine	-0,383	*-11,71*	-0,385	*-11,8*
BETA_TC	-0,0287	*-6,83*	-0,0314	*-9,81*
D_p10	-1,18	*-6,08*	-1,17	*-6,05*
D_p11	-1,51	*-4,79*	-1,51	*-4,77*
D_p12	-1,27	*-3,44*	-1,27	*-3,43*
D_p13	-2,04	*-3,05*	-2,02	*-3,05*
D_p14	-0,915	*-1,65*	-0,909	*-1,63*
D_p15	-5,19	*-10,94*	-5,2	*-10,99*
D_p16	-4,12	*-10,35*	-4,16	*-10,09*
D_p17	-2,13	*-2,31*	-2,15	*-2,33*
D_p18	-1,2	*-2,1*	-1,2	*-2,1*
D_p2	-0,432	*-24,89*	-0,432	*-24,89*
D_p3	-0,785	*-34,58*	-0,785	*-34,59*
D_p4	-0,955	*-33,39*	-0,954	*-33,4*
D_p5	-0,952	*-25,83*	-0,952	*-25,83*
D_p6	-0,913	*-18,18*	-0,913	*-18,17*
D_p7	-0,954	*-14,08*	-0,954	*-14,07*
D_p8	-0,986	*-10,79*	-0,984	*-10,78*
D_p9	-1,23	*-9,14*	-1,23	*-9,13*
Number of estimated parameters:	31		30	
Init log likelihood:	-56365,548		-56365,548	
Final log likelihood:	-29255,58		-29256,181	
Rho-square:	0,481		0,481	
VoT	62,518		57,13	

Table E.13: Intermediate Models with Ordering Dummies
Best Possible model with simple ASC structure, with variable and fixed carbon parameter

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