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Abstract

Transportation modeling has played a key role in how decision makers and planners make decisions for transport networks and cities. With the increase in available technology, the complexity of the designed interventions is growing. To complement and inform these decisions, transportation models must develop to reflect the multidimensional scope of the impact of such interventions and the individualized responses to them. While travel has traditionally been considered a means to reach activities, the understanding of why people perform an activity is still very limited. This thesis presents an overview of activity- and agent-based transportation demand models, and argues that activity-making in these models can be improved by explicitly measuring and modelling the happiness derived from these activities. It also proposes a Dynamic Activity-making Model—and a modified version that includes happiness measures—to capture the dynamic nature of activity-planning and actuation.

To explore measuring happiness, the thesis includes a chapter on a study conducted in Melbourne, Australia. Users were asked twice daily to report on happiness for a single activity, including travel. Based on the collected data, the chapter develops a dynamic Ordinal Logit Model for measuring happiness and discusses the estimation results in the context of Hedonic Theory. The results show how different activity types (work, education, personal, discretionary, travel, staying at home, and other) affect individuals' experienced happiness. It finds that educational activities, followed by work and travel, are the most disliked. Discretionary activities—which include social activities, meals, recreation, etc.—and other activities are seen to lead to more positive experiences of happiness. The model is used to test for the presence of an intra-activity Hedonic Treadmill Effect. It is found that people remember their activities as more neutral in later reports of happiness. The implications for the measurement of happiness data are discussed.

In the following chapter, the thesis presents current efforts in the field to make agent-based modelling more dynamic and responsive to changes within a day, and
presents a modelling framework to do so based on Latent Plan Models. The Dynamic Activity-making Model has a number of advantages, namely its ability to explicitly model changes in plans, to capture the utility of a day, and to eliminate the recursive integration with a supply module, such as dynamic traffic assignment. Finally, the chapter introduces a potential framework for including one’s state of happiness into the Dynamic Activity-making Model.

Thesis Supervisor: Moshe Ben-Akiva

Title: Edmund K. Turner Professor
Acknowledgements

It has been a great pleasure to work on many of the aspects of this thesis with Moshe Ben-Akiva. His criticisms, insights, suggestions, and creativity have been extremely valuable in the creation of the content I have worked on during my two years at MIT. I am extremely grateful for Carlos Lima Azevedo's patience, insight, and collaboration—I cannot imagine what my masters would have looked like without him. Furthermore, I would like to thank Maya Abou-Zeid, who inadvertently introduced me to the most interesting subsection of transportation modelling and who has sparked my curiosity in innumerable way with her work. To the people who have shared room 1-249 with me for these last two years, thank you for the invaluable knowledge-sharing, joke-making, debate-having, and coffee-drinking.

To my friends, old, new, and even older, I am grateful for your endless support and kindness. My dear housemates at the Norfolk Nook, you have all inspired me in endless ways. My dearest partner, you have made finishing this experience possible with nothing but a smile on my face. Last but not least, thank you to my unconditionally loving parents and brother, for being always a phone call away to help with anything and everything.
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Chapter 1

Introduction

Transportation modeling has played a key role in how decision planners and politicians make decisions for transport networks and cities. With the increase in available technology, the complexity of the designed interventions is growing. To complement and inform these decisions, transportation models must develop to reflect the multidimensional scope of the impact of such interventions and the individualized responses to them. Activity-based models model travelers’ behaviors as a sequence of trips, originating and ending at home, as a consequence of activity-making outside of home. In addition, many agent-based modeling (ABM) approaches leverage personalized daily schedules for each individual to represent their activity-making throughout a day. The generated day activity schedules (DAS) are composed of a sequence of activities and travel decisions. In turn, they are used to extract aggregate demand metrics and to simulate travel behavior. While travel behavior in itself has been studied and modelled
for decades, modelling the activity generation that creates said travel is less straightforward. We have incorporated little insight of the subjective reasons why people plan and undertake activities into our modelling frameworks.

**Thesis Organization**

This thesis presents the framework of representing activity utility through the remembered happiness they generate, and then proposes a dynamic system for generating activities. It is organized as follows: Chapter 1 presents a review of current activity-based ABMs and discusses the value of looking at happiness in the context of activity-making. Chapter 2 reports on a study that discusses measuring happiness and investigates the relationship between real-time and remembered happiness. Chapter 3 proposes a modelling framework that captures the dynamic aspects of activity planning and making, and then includes happiness in the dynamic decision-making process. Chapter 4 summarizes the thesis and provides closing remarks.

**Literature Review**

*Activity-making Behavior in Agent-based Modelling*

In the applications of activity-based travel demand models, Rasouli and Timmermans (2014) identified three different approaches: (1) constraints-based models, (2) utility-maximizing models, and more recently, (3) computational process models. These three approaches mainly differ in the way individual and household activity travel patterns are modeled.

Constraints-based models are the earliest type of activity-based models. They are only designed to check whether any given activity program is feasible given spatial and temporal constraints rather than to predict travel patterns. The constraints in these
models originate from Hägerstrand's (1970) formulation of "time geography," which classifies these constraints into three categories: capability constraints, coupling constraints, and authority constraints. Besides not being able to predict activity travel patterns, these models suffer from major limitations, including the unrealistic assumption of isotropic conditions (Miller, 1991), and more importantly, their inability to deal with uncertainty as well as spatial and temporal variability.

On the other hand, utility-maximizing models utilize econometric models—mainly discrete choice models—in order to model household and individual’s travel. In the earlier applications of these models, Adler and Ben-Akiva (1979) and Recker and McNally (1986a and 1986b) proposed a multinomial logit (MNL) model to represent an individual’s choice of the optimal travel pattern, defined in terms of the tours traveled on a given day and the number of stops made within each tour.

This approach was further developed by Ben-Akiva and Bowman (1996, 1995, 1998, 2000) who proposed the daily activity schedule model. It utilizes nested logit (NL) models to represent different travel choices as a multidimensional choice with shared unobserved elements. The topmost choice within this approach is an activity pattern choice, in which the primary activity, the primary tour type, and the number and purpose of secondary tours are modeled. The number of secondary tours is restricted between zero, one, or two or more tours. Lower levels—which are conditional on the activity pattern choice—include a variety of choices, such as time-of-day, destination, and mode for primary and secondary tours. This approach also has a coarse representation of tour time-of-day decisions, which is limited to sixteen alternatives representing different combinations of four time periods: AM peak, midday, PM peak, and other. DaySim, the extension to this model implemented in Sacramento, allows for greater variability by estimating tour types and numbers separately (Bradley et al., 2010). Further extensions
and implementations of the original Bowman and Ben-Avika model have been done by Siyu (2015) in Singapore and Viegas de Lima et al. (2017) in the Greater Boston Area. These models expanded the possible trip chaining structures and made time-of-day choices more complex, by modeling it in 30-minute segments.

The Prism-Constrained Activity-Travel Simulator (PCATS) (Kitamura & Fujii, 1998) is another utility-based model which utilizes Hägerstrand’s time-space prisms. It divides the day into blocked periods in which individuals are engage in fixed activities at specific times and locations. A two-tier nested logit model is used for open periods, whereby individuals first choose between an “in-home activity,” an “activity at or near the location of the next fixed activity,” and a “general out-of-home activity.” Similarly, mode and destination choice models and activity duration models are used to develop the full patterns.

A similar approach is adopted by Bhat, et al. (2004) in the Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (CEMDAP), which divides the population into workers and non-workers. The activity patterns of workers are divided into five periods with regards to work while the patterns for non-workers consists of a sequence of home-based tours. The simulator uses a generation-allocation model to determine activity participation which includes (1) work and school activities, (2) children’s travel needs, and (3) independent activities for personal and household needs. Afterwards, a scheduling model is applied to determine the sequencing of the activities produced by the generation-allocation model.

The Comprehensive Utility-based System of Travel Options Modelling (CUSTOM, Habib, 2017) has recently been developed as an approach that considers time budgets for activity scheduling. In the prototype application, trips purpose, mode, location, and time allocation decisions are made sequentially for workers. After each activity, an individual
decides to either go home permanently, go home temporarily, or perform another activity.

A number of activity-based approaches have also been implemented in different regions of North America. Coordinated Travel-Regional Activity Modeling Platform (CT-RAMP) (Davidson et al., 2010), differentiates between non-mandatory and mandatory activities, such as work and education. It determines the frequency of mandatory tours and schedules those, and then uses the remaining time to schedule additional tours. TASHA (Miller et al., 2015), active in the Greater Toronto-Hamilton Area, generates individual projects for each individual including a start time and duration. It schedules household member’s days by adjusting the predetermined start times. For additional implementations, refer to Rasouli and Timmermans (2014)

More recently, computational process models have been utilized in developing heuristics that represent activity and travel patterns. Some examples of these applications are SCHEDULER (Gärling et al., 1989), AMOS (Pendyala et al., 1997 and Pendyala et al., 1998), and ALBATROSS (Arentze et al., 2000, 2004, 2005). On the other hand, MATSIM (Balmer et al., 2008) draws agents’ activity chains conditional on their socio-demographics from the observed distribution in the population. ActivitySim, the open-source agent-based simulator developed by Los Alamos National Laboratory, uses optimization to choose the best schedule at any point in time based on utilities, priority functions, and location functions (Galli, 2008). Other models assume a planning horizon and scheduled and unscheduled trips to be generated, such as ADAPTS (Auld and Mohammadian, 2008). However, most of these models lack behavioral interpretability compared to utility-maximizing models. For a detailed description of these three approaches, I refer the reader to Rasouli and Timmermans (2014).
Utility of an Activity

While many processes exist for generating activity, even the models that leverage utility maximization are limited in how the utility of an activity is defined. Bowman and Ben-Avika (1996, 1995, 1998, 2000), CEMDAP (Bhat et al., 2004), DaySim (Bradley et al., 2010), for example, all rely on alternative-specific constants and interactions between activity purposes. Some, to capture the effect of accessibility, include inclusive values from mode and destination models. Therefore, for example, a person who has access to more shopping locations can derive more utility from shopping. Despite these efforts, the current methodology for modelling activity utility does not actually represent the experienced utility of the activity itself by the individual.

As early as the 18th century, thinkers have equated utility with happiness. Jeremy Bentham, a moral philosopher, defined the experienced utility of an activity as the happiness that it generates, stating that, “By the principle of utility is meant that principle which approves or disapproves of every action whatsoever, according to the tendency which it appears to have to augment or diminish the happiness of the party whose interest is in question: or, what is the same thing in other words, to promote or to oppose that happiness.” Thus, an individual understands the utility of an action as the positive or negative effect that it will have on themselves. The connection between experienced utility is related directly to the happiness has been revived by behavioral economists, such as Kahneman (2000). He has argued that, while the revealed choice gives great insight into the utility of an experience, measuring the happiness from said experience generates more insight into what the real utility is. Furthermore, Ben-Akiva (2007, 2009) and Abou-Zeid (2009) have argued that people perform activities to enhance and sustain their happiness and well-being.
Chapter 2

Modelling Activity Happiness

This thesis chapter is based on a study developed for a book chapter called "Dynamic Modeling of Activity Happiness: An Investigation of the Intra-Activity Hedonic Treadmill" in Quality of Life and Daily Travel (in print). Other authors of the study include Maya Abou-Zeid, Ronny Kutadinata, Zahra Navidi, Stephan Winter, Fang Zhao, and Moshe Ben-Akiva. Kutadinata, Winter, and Navidi—affiliated with the University of Melbourne—collected the data for the study, and Navidi helped develop the descriptive statistics. Zhao, from the Singapore-MIT Alliance for Research and Technology, was instrumental in assembling the web- and phone-based data collection tool. In addition to myself, Abou-Zeid and Ben-Akiva were large contributors in the modelling framework and helped with theoretical interpretation of the results.
Introduction

Travel has traditionally been thought of as a means to reach specific activities. Within the last decade, researchers have begun looking at how these activities affect people’s well-being, which in turn helps generate individuals’ demand to perform such activities. Reaveau et al. (2015) describes how well-being has been studied by transportation researchers over time. A number of studies have looked at users’ self-reported subjective well-being associated with performed, current, or anticipated activities (Kahneman, Diener, and Schwartz; 1999). While some studies—such as Abou-Zeid and Ben-Akiva (2012), Bergstad et al. (2012), Archer et al. (2013)—measure well-being associated with activities in general, others developed measurements to understand the well-being of individuals during travel. These include studies such as Ory and Mokhtarian (2005), who modeled the additional well-being derived from travel itself; Duarte et al. (2008), who looked at leisure and work trips; Ettema et al. (2011), who looked at satisfaction with travel; and Ravulaparthy et al. (2013), who measured the well-being of elderly travel. This study adds to the first case, analyzing the subjective happiness of individuals during and after different activities.

The motivation of this study was to describe the relationship between real-time and remembered happiness, proposed by Kahneman (1999) and formalized by Abou-Zeid (2009). Figure 2.1 describes the relationship. The moment and remembered utilities are both latent and unobserved, whereas the real-time happiness and remembered happiness are observable.
The differentiated measurement of real-time and remembered happiness was explored by Raveau et al. (2015), which modeled reported happiness data collected from a convenience sample. While the study made a distinction between real-time and remembered measurements, it did not attempt to capture the relationship between the two, represented by the bolded arrow in Figure 2.1. To explore this process, this study develops a dynamic Ordinal Logit Model (OLM) using a larger sample from Melbourne, Australia, and ties its results back to the Hedonic Theory. Using happiness data collected over time for the same activities, the model is used to test whether an intra-activity Hedonic Treadmill exists. An intra-activity Hedonic Treadmill refers to the change in perception of the remembered experienced happiness for a specific activity instance over time. The model results extend the understanding that the experienced happiness changes over time from specific uncomfortable situations—such as colonoscopies.
(Redelmeier and Kahneman, 1996), inflicted pain (Ariely, 1998), and annoying noises (Ariely and Zauberman, 2000)—and travel (Pedersen et al., 2011; Abou-Zeid and Ben-Akiva, 2012), generalizing it to a number of activities in individuals’ day-to-day lives. The chapter presents a literature review of applications of Hedonic Theory in transportation, the data collection methodology and describes the sample. Then it proceeds to specify the dynamic OLM and present the model estimation. Finally, it discusses the estimation results, the implications for the measurement of happiness, and the limitations of the study.

**Literature Review**

**Data Collection Methodologies**

Data collection for transportation surveys has significantly improved in past years by leveraging the increase in smartphone ownership. By using GPS, GSM, accelerometer, and WiFi sensors, smartphone applications have the capacity to collect and process travel information without user intervention. These applications mitigate a number of issues associated with pen-and-paper travel surveys, such as under-reporting of activities and rounding of activity durations. Recent studies that have used smartphone capabilities to collect travel diaries include the *Quantified Traveler* (Jariyasunan et al., 2012), which collected travel data for 135 participants and then calculated their travel footprint. The objective of the study was to relay the personal information back to the users to modify their travel patterns and aid in more sustainable behavior. Furthermore, smartphones have also been used to collect data on happiness. Killingsworth and Gilbert (2010) developed an iPhone application called *Track Your Happiness*. The application asked users about their current happiness, their current activity, and they were thinking about
anything unrelated and, if so, what it was. The study collected data from 5,000 people from 83 different countries, leading to half a million sample points. Similarly, Baumeister et al. (2016) followed 500 people in Chicago. They were pinged throughout their day to inquire what they were thinking about and how it made them feel. Passive ways of capturing the happiness of people have become possible as well: sentiment analysis of social media reveals happiness related to activities or locations (Giachanou and Crestani, 2016; Sinnott and Cui, 2016). This study utilizes these developed capabilities.

**Understanding Happiness**

Different methods have been applied to understanding and quantifying a person’s subjective well-being. While hedonic theory is vast, a number of developed concepts apply directly to this study, mainly those pertaining to Hedonic Adaptation. Frederick and Loewenstein (1999) summarize Hedonic Adaptation as the process by which individuals adapt their expectations to reduce overly positive and overly negative experiences throughout their day. Also known as the Hedonic Treadmill Effect, the process involves both an individual’s cognitive ability to transform situations and neurochemical processes that desensitize the brain’s reaction to negative and positive stimuli. To measure this, the concept of an Adaptation Level was originally developed by Helson (1964). This Adaptation Level, also known as a Set Point, is a moving average of a person’s stimulus levels. Therefore, a person’s Hedonic State is the difference between a given stimulus and their Set Point. Parducci (1968) went on to argue that the stimulus should be compared to the range and to the median. He developed measurements for the Set Point that weighed distinct activity purposes differently and used medians. More complex models were later introduced by Ryder and Heal (1973), March (1988), and Hardie et al. (1993), among others. These models are time-dependent
and consider differences between positive and negative stimuli. Fujita and Diener (2005), on the other hand, argue that people have a stable Set Point, against which they understand their Life Satisfaction (LS). However, Diener (1984) also highlights that there are a number of issues when measuring happiness. Measurements that are done on single-item scales are easier to compare over time, yet more likely to be skewed towards happy categories (Andrews and Withey, 1976).

Another major component of hedonic theory is the concept of Duration Neglect. Kahneman (1999) distinguishes between moment-utility—the Hedonic State during an activity—and the Remembered Utility, which is the remembered Hedonic State. Kahneman cites a number of studies that show that people do not consider the whole activity when recalling their experience of an activity. Instead, they remember the feeling during the peak of the activity and the end of the activity, known as the Peak-End Rule. Furthermore, the length of an activity does not affect an individual’s perception of their Hedonic State during an activity, which is known as Duration Neglect.

Data Collection

Methodology

Data for this study was collected through the Future Mobility Sensing (FMS) mobile phone application (Cottrill et al., 2013; Raveau et al., 2015). FMS leverages increasing smartphone penetration to collect travel information and disseminate surveys. The application uses sensing technology built in phones, as well as machine learning algorithms in the backend server, to infer individual travel patterns. Data collected through mobile phone sensors are sent to the server database, where they are analyzed and stored. Users have access to their processed data for validation through web- and phone-based interfaces.
Furthermore, the user interface allows researchers to ask additional questions about users’ activities throughout the day and during validation.

The mobile application is designed to efficiently run in the background of users’ phones. Available for Android and iOS, it collects data using GPS, GSM, accelerometer, and WiFi sensors. In addition, it is designed to consume little memory. Collected data is sent to the database either by WiFi or cellular network, where they are interpreted by the backend server. Activities—such as going to work, shopping, or staying at home—and travel modes are inferred based on sensors, contextual transportation and location data, and user-specific previously validated data. The user interfaces allow individuals to validate their data over a web-based interface or on a mobile app. Validation includes confirming inferred patterns, completing missing data, correcting incorrect inferences, and indicating activity purposes when necessary.

FMS was used in this survey to collect socio-demographic characteristics through a pre-survey and daily activity information, and to disseminate questions about happiness. Users were prompted to give information on their happiness with regard to a certain activity at two different points: once throughout the day on their phone while performing the activity and once during subsequent validation of the activity. They were alerted of the question on their phone at a randomly chosen time after movement was detected at the beginning of a day and before 9:00 PM, and could answer the mobile question anytime until a new question became available the following day. If the user did not respond within 30 minutes of the mobile alert, the question that appeared on their phone was modified from “How happy are you with your current activity?” to “How happy were you with your activity ___ hours ago?”. Both questions—the one appearing on the phone and the one appearing during subsequent validation of the activity—asked users about their experienced happiness regarding the same activity in a given day, such that
each activity may have one or two happiness reports. Happiness was reported on a 7-point scale, ranging from "Very Unhappy" to "Very Happy."

**Descriptive Statistics**

The data collection took place in Melbourne, Australia, namely the University of Melbourne. To encourage participation, users who fulfilled certain requirements—such as age restriction and residence address (Roddis, 2016)—and finished a full 14-day survey were remunerated with AU$50 e-vouchers. Of the 437 registered users, participating over varying lengths of periods, 114 answered happiness questions. Table 2.1 and Table 2.2 provide summaries of the respondents' demographic and socioeconomic characteristics.

**Table 2.1 Individual demographics and socioeconomic characteristics**

<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>47%</td>
</tr>
<tr>
<td>Female</td>
<td>53%</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
</tr>
<tr>
<td>18-29</td>
<td>40%</td>
</tr>
<tr>
<td>30-49</td>
<td>51%</td>
</tr>
<tr>
<td>50-69</td>
<td>9%</td>
</tr>
<tr>
<td>70+</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
</tr>
<tr>
<td>Year 12 or under</td>
<td>19%</td>
</tr>
<tr>
<td>Bachelor</td>
<td>31%</td>
</tr>
<tr>
<td>Master’s or Postgraduate Degree</td>
<td>24%</td>
</tr>
<tr>
<td>Doctorate</td>
<td>12%</td>
</tr>
<tr>
<td>Other</td>
<td>14%</td>
</tr>
<tr>
<td><strong>Employment</strong></td>
<td></td>
</tr>
<tr>
<td>Any employment</td>
<td>80%</td>
</tr>
<tr>
<td>Not employed</td>
<td>20%</td>
</tr>
<tr>
<td><strong>Household Income (per week)</strong></td>
<td></td>
</tr>
<tr>
<td>$1-$599</td>
<td>11%</td>
</tr>
<tr>
<td>$600-$1,249</td>
<td>15%</td>
</tr>
<tr>
<td>$1,250-$1,999</td>
<td>15%</td>
</tr>
<tr>
<td>$2,000+</td>
<td>40%</td>
</tr>
<tr>
<td>Missing income</td>
<td>18%</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
</tr>
</tbody>
</table>
Table 2.2 Household characteristics

<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Household size</strong></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>14%</td>
</tr>
<tr>
<td>2</td>
<td>33%</td>
</tr>
<tr>
<td>3</td>
<td>21%</td>
</tr>
<tr>
<td>4</td>
<td>25%</td>
</tr>
<tr>
<td>5+</td>
<td>7%</td>
</tr>
<tr>
<td><strong>Number of vehicles in the household</strong></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>19%</td>
</tr>
<tr>
<td>1</td>
<td>40%</td>
</tr>
<tr>
<td>2</td>
<td>27%</td>
</tr>
<tr>
<td>3</td>
<td>9%</td>
</tr>
<tr>
<td>4</td>
<td>4%</td>
</tr>
<tr>
<td>5+</td>
<td>0%</td>
</tr>
</tbody>
</table>

The gender profile of the participants is similar to that from the local household travel survey, the Victorian Integrated Survey of Travel and Activity (VISTA) (The Victorian Department of Transport, 2011), in which 52% of the respondents are female. Being over 18 years old was a prerequisite to participate in the survey, such that there are no participants under 18. There are also no participants over 70 years old, whereas in VISTA 12% of the Melbourne participants are over 70. Since the survey was predominantly advertised to the staff and students of the University of Melbourne, most participants are between 18-59 (91%) and have a tertiary degree in their education (67%). Eighty percent of the respondents have some type of employment (e.g., full-time, part-time, or self-employed), whereas the figure is 54% for VISTA respondents. High education and employment result in high income: 55% of all users have a yearly income more than AU$65,000 (AU$1,250 per week). There are no data for education or household income in VISTA for comparison. However, since VISTA surveys a valid sample of the
population, other sources can be used to fill in. The Australian Bureau of Statistics reports an average equalized disposable household income in 2013–14 of $998 per week (2017). It also reports from the 2011 census that 18.8% of the Australian population has a tertiary degree (2011).

More than 90% of the participants come from small households (4 or fewer) and 86% of them have 2 or fewer cars in their households. The household structure proves to be highly similar to that of VISTA, with 91% of the respondents being from small households and 92% of the households having 2 or fewer vehicles.

In total, 1733 valid responses were recorded from the 114 users who answered the happiness questions for 1213 different activities. Table 2.3 presents a summary of the activity purposes for which happiness was reported and how they were grouped for analysis. They are further divided to indicate if the response was collected through the mobile phone or the web interface. Most of the responses were recorded at home (39%) or at work (29%). This confirms that many of the respondents were among the staff of the university, in comparison to students, since high income level and high education level were also observed in the sample.
Table 2.3 Activity purpose breakdown

<table>
<thead>
<tr>
<th>Activity Purpose</th>
<th>Phone Count</th>
<th>Phone Percent</th>
<th>Web Count</th>
<th>Web Percent</th>
<th>Total Count</th>
<th>Total Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>356</td>
<td>35%</td>
<td>328</td>
<td>46%</td>
<td>684</td>
<td>39%</td>
</tr>
<tr>
<td>Home</td>
<td>347</td>
<td>34%</td>
<td>323</td>
<td>45%</td>
<td>670</td>
<td>39%</td>
</tr>
<tr>
<td>Other Home</td>
<td>9</td>
<td>1%</td>
<td>5</td>
<td>1%</td>
<td>14</td>
<td>1%</td>
</tr>
<tr>
<td>Work</td>
<td>302</td>
<td>30%</td>
<td>209</td>
<td>29%</td>
<td>511</td>
<td>29%</td>
</tr>
<tr>
<td>Work</td>
<td>276</td>
<td>27%</td>
<td>187</td>
<td>26%</td>
<td>463</td>
<td>27%</td>
</tr>
<tr>
<td>Work-Related Business</td>
<td>26</td>
<td>3%</td>
<td>22</td>
<td>3%</td>
<td>48</td>
<td>3%</td>
</tr>
<tr>
<td>Education</td>
<td>91</td>
<td>9%</td>
<td>40</td>
<td>6%</td>
<td>131</td>
<td>8%</td>
</tr>
<tr>
<td>Education</td>
<td>91</td>
<td>9%</td>
<td>40</td>
<td>6%</td>
<td>131</td>
<td>8%</td>
</tr>
<tr>
<td>Discretionary</td>
<td>160</td>
<td>16%</td>
<td>81</td>
<td>11%</td>
<td>241</td>
<td>14%</td>
</tr>
<tr>
<td>Meal/Eating Break</td>
<td>32</td>
<td>3%</td>
<td>18</td>
<td>3%</td>
<td>50</td>
<td>3%</td>
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<tr>
<td>Social</td>
<td>66</td>
<td>6%</td>
<td>43</td>
<td>6%</td>
<td>109</td>
<td>6%</td>
</tr>
<tr>
<td>Entertainment</td>
<td>8</td>
<td>1%</td>
<td>2</td>
<td>0%</td>
<td>10</td>
<td>1%</td>
</tr>
<tr>
<td>Recreation</td>
<td>40</td>
<td>4%</td>
<td>7</td>
<td>1%</td>
<td>47</td>
<td>3%</td>
</tr>
<tr>
<td>Sports/Exercise</td>
<td>14</td>
<td>1%</td>
<td>11</td>
<td>2%</td>
<td>25</td>
<td>1%</td>
</tr>
<tr>
<td>Personal</td>
<td>34</td>
<td>3%</td>
<td>27</td>
<td>4%</td>
<td>61</td>
<td>4%</td>
</tr>
<tr>
<td>Personal Errand/Task</td>
<td>11</td>
<td>1%</td>
<td>6</td>
<td>1%</td>
<td>17</td>
<td>1%</td>
</tr>
<tr>
<td>Shopping</td>
<td>21</td>
<td>2%</td>
<td>21</td>
<td>3%</td>
<td>42</td>
<td>2%</td>
</tr>
<tr>
<td>Medical/Dental (Self)</td>
<td>2</td>
<td>0%</td>
<td>0</td>
<td>0%</td>
<td>2</td>
<td>0%</td>
</tr>
<tr>
<td>Travel</td>
<td>53</td>
<td>5%</td>
<td>18</td>
<td>3%</td>
<td>71</td>
<td>4%</td>
</tr>
<tr>
<td>Travelling</td>
<td>40</td>
<td>4%</td>
<td>0</td>
<td>0%</td>
<td>40</td>
<td>2%</td>
</tr>
<tr>
<td>Change Mode/Transfer</td>
<td>13</td>
<td>1%</td>
<td>18</td>
<td>3%</td>
<td>31</td>
<td>2%</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>2%</td>
<td>11</td>
<td>2%</td>
<td>16</td>
<td>1%</td>
</tr>
<tr>
<td>To Accompany</td>
<td>7</td>
<td>1%</td>
<td>2</td>
<td>0%</td>
<td>9</td>
<td>1%</td>
</tr>
<tr>
<td>Someone</td>
<td>7</td>
<td>1%</td>
<td>2</td>
<td>0%</td>
<td>9</td>
<td>1%</td>
</tr>
<tr>
<td>Pick Up/Drop Off</td>
<td>3</td>
<td>0%</td>
<td>4</td>
<td>1%</td>
<td>7</td>
<td>0%</td>
</tr>
<tr>
<td>Other</td>
<td>13</td>
<td>1%</td>
<td>5</td>
<td>1%</td>
<td>18</td>
<td>1%</td>
</tr>
<tr>
<td>Total</td>
<td>1019</td>
<td></td>
<td>714</td>
<td></td>
<td>1733</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.2 shows the breakdown of reported happiness for each activity type. In general, the majority (71%) of the responses were in happy levels, regardless of activity purpose. Discretionary and other activity purposes had the highest level of happiness, with only 4% of the responses in unhappy levels. Meanwhile, education had the highest level of unhappiness, with 38% of the answers in unhappy levels. Participants reported being
unhappy at work only 12% of the time. Overall, the response distribution follows the trend highlighted by Diener (1984): single-item scales of well-being responses are often concentrated in happy categories.

![Count](count)  

**Home**  
**Work**  
**Education**  
**Personal**  
**Discretionary**  
**Travel**  
**Other**  

- Very Unhappy  
- Unhappy  
- Slightly Unhappy  
- Neutral  
- Slightly Happy  
- Happy  
- Very Happy

**Figure 2.2** Reported happiness by activity purpose

This high level of happiness is fascinating compared to previous studies (Raveau *et al.*, 2015). This can be explained by the context in which data was collected. Melbourne has been reported the most livable city in the world for seven consecutive years by the Economist Intelligence Unit (2017). This ranking considers factors such as safety, health care, educational resources, infrastructure, and the environment, meaning that people in Melbourne have a high standard of living. Thus, it can be assumed to be generally happier than other countries in which the same Happiness Survey has taken place before, such as Chile, China, Singapore, and United States (Raveau *et al.*, 2015)—although others
have shown that the economic impact on happiness is marginal (Oswald, 1997). The same study also showed that the average reported happiness between countries is significantly different, which points to cultural reasons as well. Moreover, according to the World Happiness Report 2017 (Helliwell et al., 2017), Australians are the ninth happiest nation of the world. Therefore, observing a high level of happiness is not surprising in Melbourne.

Figure 2.3 shows the distribution of the duration for the reported activities. Seventy-five percent of all activities are less than 12.6 hours long, and 90% are less than 21.5 hours long. Longer activities tended to be home-based. Figure 2.4 shows the distribution of time before the different reports for the activities. Seventy-five percent and 90% of all responses occurred within 9.5 hours and 24.2 hours of the end of the activity respectively, while 43% occurred within one hour of the activity itself. Responses occurring after 24 hours were mostly done through the web-based interface.

![Figure 2.3 Distribution of activity duration](image)
Model Specification

To account for potential inter-user discrepancy in the use of the happiness scale—a Slightly Happy to one person may have been comparable to another person’s Slightly Unhappy—instead of modeling individuals’ reported happiness, individuals’ deviation from their own Set Point, or their Hedonic State, is modeled. To do so, two major assumptions are made. The first is that the study is conducted throughout a two-week period that is quotidian, such that the activities selected for reporting happiness are representative of the users’ day-to-day lives. Since all activities are recurring and the extent of the activities collected is insignificant compared to what has accumulated for an individual throughout a lifetime, a single activity does not significantly affect the Set Point. Therefore, instead of using a moving average or moving median, the Set Point is assumed to be the overall median across all activities. This is especially useful because of the limited number of sample points available for each user. The Set Point is rounded to the nearest integer to limit the available alternatives for the developed model. Note that
the Set Point could have been activity purpose-specific, yet there are not enough observations of different activity purposes for each individual.

Secondly, since the individual’s Set Point is stable for the period of time the data is collected, a user’s Hedonic State is the difference between their reported happiness and their established Set Point. Table 2.4 shows the counts for the different Hedonic States across all users. Unlike the happiness responses, the Hedonic States are accumulated around the Set Point. Furthermore, 44% of the Hedonic States are actually 0, which translates to each individual’s median.

<table>
<thead>
<tr>
<th>Differences</th>
<th>Phone Count</th>
<th>Percent</th>
<th>Web Count</th>
<th>Percent</th>
<th>Total Count</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4</td>
<td>14</td>
<td>1%</td>
<td>1</td>
<td>0%</td>
<td>15</td>
<td>1%</td>
</tr>
<tr>
<td>-3</td>
<td>28</td>
<td>3%</td>
<td>18</td>
<td>3%</td>
<td>46</td>
<td>3%</td>
</tr>
<tr>
<td>-2</td>
<td>68</td>
<td>7%</td>
<td>25</td>
<td>4%</td>
<td>93</td>
<td>5%</td>
</tr>
<tr>
<td>-1</td>
<td>213</td>
<td>21%</td>
<td>136</td>
<td>19%</td>
<td>349</td>
<td>20%</td>
</tr>
<tr>
<td>0</td>
<td>414</td>
<td>41%</td>
<td>352</td>
<td>49%</td>
<td>766</td>
<td>44%</td>
</tr>
<tr>
<td>1</td>
<td>238</td>
<td>23%</td>
<td>162</td>
<td>23%</td>
<td>400</td>
<td>23%</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
<td>3%</td>
<td>19</td>
<td>3%</td>
<td>54</td>
<td>3%</td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>1%</td>
<td>1</td>
<td>0%</td>
<td>10</td>
<td>1%</td>
</tr>
</tbody>
</table>

To understand how different activity attributes and socio-demographic characteristics affect an individual’s Hedonic State, a dynamic Ordinal Logit Model (OLM) was estimated. OLM models are a subset of Random Utility Maximization models. These models assume that individuals make choices that maximize their utility. While one’s utility can be explained through a number of personal and situational characteristics, there is a part of the utility that is random, such that an individual’s choice is probabilistic in nature. OLM models specifically recognize that there is an underlying order to the discrete choices. Table 2.5 outlines the different variables used in the developed model.
### Table 2.5 Model variables

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual</td>
<td>$n$</td>
<td>--</td>
</tr>
<tr>
<td>Activity</td>
<td>$a$</td>
<td>--</td>
</tr>
<tr>
<td>Observation</td>
<td>$k$</td>
<td>${1,2}$</td>
</tr>
<tr>
<td>Real-time</td>
<td>$\delta_{\text{realtime}, na1}$</td>
<td>binary</td>
</tr>
<tr>
<td>Multiple Observations</td>
<td>$\delta_{\text{MultiObs}, na}$</td>
<td>binary</td>
</tr>
<tr>
<td>Time Until Observation</td>
<td>$\text{ObsTime}_{nak}$</td>
<td>continuous</td>
</tr>
<tr>
<td>Duration of Activity</td>
<td>$\text{Dur}_{na}$</td>
<td>day</td>
</tr>
<tr>
<td>Activity Purpose</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td>$\delta_{i, na}$ for $i \in I$</td>
<td>binary</td>
</tr>
<tr>
<td>Work</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal</td>
<td>$\delta_{j, na}$ for $j \in J$</td>
<td>binary</td>
</tr>
<tr>
<td>Discretionary</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekend</td>
<td>$\delta_{\text{Weekend}, na}$</td>
<td>binary</td>
</tr>
<tr>
<td>Socioeconomic binaries</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female - fixed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full-time - fixed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part-time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td>$\delta_{j, n}$ for $j \in J$</td>
<td>binary</td>
</tr>
<tr>
<td>Self-employed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single - fixed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household Income</td>
<td>$\text{Income}_{n}$</td>
<td>midpoint of income range</td>
</tr>
<tr>
<td>Missing Income</td>
<td>$\delta_{\text{missingIncome}, n}$</td>
<td>binary</td>
</tr>
<tr>
<td>Hedonic State</td>
<td>$d_{nak}$</td>
<td></td>
</tr>
</tbody>
</table>

Note that observation $k$, which refers to a happiness response for a specific activity instance, can take on the value of 1 if an individual answered the happiness question on their phone yet not on the web interface (during validation) or 2 if the individual answered both happiness questions for the same activity. $\delta_{\text{MultiObs}, na}$ indicates if an activity $a$ for individual $n$ has multiple observations. While a phone-based response is
judged to have been real-time if the individual responded before the end of the activity, the web-based response was always after the end of the activity because it was completed during validation. $\text{ObsTime}_{nak}$ is the time between the end of the activity and the response. It is set to zero if the response was real-time. These attributes, along with the activity duration, $\text{Dur}_{na}$, were extracted from the user's activities from the FMS database.

As mentioned, the calculated Hedonic State, $d_{nak}$, reflects an individual's latent happiness, $h_{nak}$, such that

$$d_{nak} = \begin{cases} 
-4 & -\infty < h_{nak} \leq \tau_{-3} \\
-3 & \tau_{-3} < h_{nak} \leq \tau_{-2} \\
-2 & \tau_{-2} < h_{nak} \leq \tau_{-1} \\
-1 & \tau_{-1} < h_{nak} \leq \tau_{-0} \\
0 & \tau_{-0} < h_{nak} \leq \tau_{+0} \\
1 & \tau_{+0} < h_{nak} \leq \tau_{1} \\
2 & \tau_{1} < h_{nak} \leq \tau_{2} \\
3 & \tau_{2} < h_{nak} < +\infty 
\end{cases}$$

where the $\tau$'s are the thresholds for the latent happiness. This is further described in Figure 2.5. $d_{nak} = 0$ is centered between $\tau_{-0}$ and $\tau_{+0}$. Centering $d_{nak} = 0$ allows for clearer interpretation of variables.

![Figure 2.5 Hedonic State thresholds](image)

Furthermore, the second happiness response $h_{na2}$ for the same activity $na$ is dependent on the first happiness response $h_{na1}$. Their causal relationship, together with the actualized Hedonic States $d_{na1}$ and $d_{na2}$, are described in Figure 2.6.
Figure 2.6 Relationship between $h_{na1}$ and $h_{na2}$

$h_{na1}$ is specified as follows:

$$h_{na1} = \beta_{\text{realtime}} \cdot \delta_{\text{realtime,na1}} + \beta_{\text{obstime}} \cdot \text{ObsTime}_{na1}$$

$$+ \sum_{i \in I} (\beta_{i,\text{dur}} \cdot \text{Dur}_{na} + \beta_{i,\text{dur2}} \cdot \text{Dur}_{na}^2) \cdot \delta_{i,na}$$

$$+ \sum_{i \in I} \beta_{i,\text{weekend}} \cdot \delta_{i,na} \cdot \delta_{\text{weekend,na}} + \sum_{i \in I} \beta_{i,\text{weekday}} \cdot \delta_{i,na} \cdot (1 - \delta_{\text{weekend,na}})$$

$$+ \sum_{j \in J} \beta_{j} \cdot \delta_{j,n} + \beta_{\text{missingincome}} \cdot \delta_{\text{missingincome,n}} + \beta_{\text{income,n}}$$

$$\cdot (1 - \delta_{\text{missingincome,n}}) \cdot \text{Income}_n + \eta_n + \omega_{na1} + \epsilon_{na1}$$

$$h_{na1} = \beta' X_{na1} + \eta_n + \omega_{na1} + \epsilon_{na1}$$

where

$$\eta_n \sim \mathcal{N}(0, \sigma^2_\eta)$$

$$\omega_{na1} \sim \mathcal{N}(\mu, \sigma^2_\omega)$$

$$\epsilon_{na1} \sim \text{logistic}(0,1).$$

The specification includes components for the response being real-time and for the time elapsed between the end of the activity and the response. For each activity purpose, a
quadratic function of duration is included, as well as an intercept. The intercept distinguishes between the activity being performed during a weekday or the weekend. Socioeconomic variables are included linearly. \( \eta_n \) is a panel effect to account for inter-individual heterogeneity and intra-individual unobserved correlation. \( \omega_{na1} \), on the other hand, is an error term included in the phone-based happiness response equation to account for potential mistakes when selecting an answer on the screen. Including it also makes the estimation computationally easier. Finally, the model includes the random error, which is logistically distributed for OLM. Note that the \( \beta \)'s for weekday-home activities, full-time, and single are fixed to zero for estimation.

For simplicity, let \( h_{na1} \) be decomposed as follows:

\[
h_{na1} = h_{na1} + \epsilon_{na1}.
\]

Such that \( h_{na1} \) is composed of all of the components of the first but the logistical error term. As previously mentioned, \( h_{na2} \), the second happiness response for the activity \( na \), is a function of \( h_{na1} \) and is defined as

\[
h_{na2} = \beta_{h1} \cdot h_{na1} + \beta_{ObsTime} \cdot \text{ObsTime}_{na2} + \epsilon_{na2}.
\]

Since both happiness reports are made by the same individual \( n \) about the same activity instance \( a \), the only difference in activity attributes between the first and second reports are the time elapsed since the end of the activity. Therefore, \( h_{na2} \) includes a scaled component of \( h_{na1} \) and the observation time, as well as a random error \( \epsilon_{na2} \), distributed similar to \( \epsilon_{na1} \).
The error term for \( k = 2 \) is logistically distributed with position 0 and mean 1, such that the probability of the observed \( d_{na2} = y_2 \) for \( y_2 \in \{-4, \ldots, 3\} \), conditional on the individual panel effect, \( \eta_n \), and the phone-based error, \( \omega_{na1} \), is the difference of logistics.

\[
P(d_{na2} = y_2 | \eta_n, \omega_{na1}) = \left( F_{\varepsilon_2}(\mathcal{h}_{na2} - \tau_{y_2-1}) - F_{\varepsilon_2}(\mathcal{h}_{na2} - \tau_{y_2}) \right)^{\delta_{\text{MultObs,na}}}
\]

where

\[
\mathcal{h}_{na2} = \beta_1 \cdot \mathcal{h}_{na1} + \beta_{\text{obstime}} \cdot \text{ObsTime}_{na2}
\]
is the systematic component of \( h_{na2} \).

The conditional probability of \( d_{na2} = y_2 \) is raised to the power of \( \delta_{\text{MultObs,na}} \) so that the term is expressed when there are multiple observations, but is 1 when there is only one observation for activity \( a \) for individual \( n \)—that is, \( d_{na2} \) does not exist.

Similarly, the conditional probability for \( d_{na1} = y_1, y_1 \in \{-4, \ldots, 3\} \), is

\[
P(d_{na1} = y_1 | \eta_n, \omega_{na1}) = F_{\varepsilon_1}(\mathcal{h}_{na1} - \tau_{y_1-1}) - F_{\varepsilon_1}(\mathcal{h}_{na1} - \tau_{y_1})
\]

where

\[
\mathcal{h}_{na1} = \beta' X_{na1} + \eta_n + \omega_{na1}.
\]
The joint probability for individual \( n \) and activity \( a \), conditional on both \( \eta_n \) and \( \omega_{na1} \), is

\[
P(d_{na1} = y_1 | \eta_n, \omega_{na1})P(d_{na2} = y_2 | \eta_n, \omega_{na1}).
\]
The joint probability must be integrated over the density of \( \omega_{na1} \) to make the joint probability only conditional on the individual panel effect \( \eta_n \), resulting in the probability of an activity \( a \) for individual \( n \).

\[
\int_\omega P(d_{na1} = y_1 | \eta_n, \omega_{na1})P(d_{na2} = y_2 | \eta_n, \omega_{na1}) f_\omega(\omega_{na1}) d\omega_{na1}
\]
To account for the individual panel effect, the product of the above expression for all activities \( a \) for individual \( n \) must be integrated over the density of \( \eta_n \).
This results in the joint probability for the sequence of activities for an individual \( n \). The likelihood, \( L \), is the product of the individual likelihood over all individuals.

\[
L = \prod_{n} \int_{\eta} \left( \prod_{a} \int_{\omega} P(d_{na1} = y_1 | \eta_n, \omega_{na1}) P(d_{na2} = y_2 | \eta_n, \omega_{na1}) f_\omega(\omega_{na1}) d\omega_{na1} \right) f_\eta(\eta_n) d\eta
\]

And the log likelihood, \( \mathcal{L} \), is the sum of the log of the joint probability for the sequence of activities for an individual \( n \), over all individuals.

\[
\mathcal{L} = \sum_{n} \log \left( \int_{\eta} \left( \prod_{a} \int_{\omega} P(d_{na1} = y_1 | \eta_n, \omega_{na1}) P(d_{na2} = y_2 | \eta_n, \omega_{na1}) f_\omega(\omega_{na1}) d\omega_{na1} \right) f_\eta(\eta_n) d\eta \right)
\]

**Model Estimation**

A number of other specifications were also estimated. These included models that repeated the variables from \( h_{na1} \) in \( h_{na2} \) and different inclusions of \( \text{ObsTime}_{na2} \) in \( h_{na2} \).

The mentioned specification was chosen so that \( \beta_{h1} \) could be treated as a scaling factor of \( h_{na1} \), but \( \text{ObsTime}_{na2} \) was still accounted for. The model was estimated using Python Biogeme (Bierlaire and Fetiarison, 2009) with numerical integration. The resulting estimated model is presented in Table 2.6.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Activity Purpose</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekday</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td>0</td>
<td>fixed</td>
</tr>
<tr>
<td>Work</td>
<td>-0.816</td>
<td>0.581</td>
</tr>
<tr>
<td>Education</td>
<td>0.111</td>
<td>0.0729</td>
</tr>
</tbody>
</table>

39
<table>
<thead>
<tr>
<th>Activity</th>
<th>Discretionary</th>
<th>Personal</th>
<th>Travel</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekend</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td>0.349</td>
<td>0.295</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work</td>
<td>-0.553</td>
<td>0.502</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.0512</td>
<td>0.0737</td>
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<td></td>
</tr>
<tr>
<td>Discretionary</td>
<td>0.623</td>
<td>0.668</td>
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<td></td>
</tr>
<tr>
<td>Personal</td>
<td>-1.14</td>
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<td></td>
</tr>
<tr>
<td>Travel</td>
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<td>0.725</td>
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<td></td>
</tr>
<tr>
<td>Other</td>
<td>-0.0388</td>
<td>1.32</td>
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### Duration of Activity

<table>
<thead>
<tr>
<th>Activity</th>
<th>Duration (days)</th>
<th>Duration (days²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>2.61</td>
<td>0.678</td>
</tr>
<tr>
<td>Work</td>
<td>-0.972</td>
<td>0.973</td>
</tr>
<tr>
<td>Education</td>
<td>-0.667</td>
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</tr>
<tr>
<td>Discretionary</td>
<td>5.53</td>
<td>1.04</td>
</tr>
<tr>
<td>Personal</td>
<td>4.98</td>
<td>3.03</td>
</tr>
<tr>
<td>Travel</td>
<td>3.77</td>
<td>1.77</td>
</tr>
<tr>
<td>Other</td>
<td>-1.62</td>
<td>5.68</td>
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### Time of Response

<table>
<thead>
<tr>
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<th>Real-time</th>
<th>Time Until Observation (days)</th>
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<tbody>
<tr>
<td></td>
<td>0.314</td>
<td>0.0156</td>
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### Personal Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
<th>Fixation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0</td>
<td>fixed</td>
</tr>
<tr>
<td>Male</td>
<td>-0.211</td>
<td>0.189</td>
</tr>
<tr>
<td>Household Income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (AU$1000 / week)</td>
<td>-0.133</td>
<td>0.113</td>
</tr>
<tr>
<td>Missing Income</td>
<td>-0.542</td>
<td>0.351</td>
</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>0</td>
<td>fixed</td>
</tr>
<tr>
<td>Married</td>
<td>-0.136</td>
<td>0.223</td>
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<tr>
<td>Divorced</td>
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<td>0.489</td>
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<td>Employment</td>
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<tr>
<td>Full-time</td>
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<td>fixed</td>
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<tr>
<td>Part-time</td>
<td>-0.286</td>
<td>0.250</td>
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<tr>
<td>Self-employed</td>
<td>0.0904</td>
<td>0.432</td>
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40
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Unemployed</td>
<td>-0.224</td>
<td>0.291</td>
</tr>
<tr>
<td>Retired</td>
<td>-0.509</td>
<td>0.889</td>
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**Panel Effects**

<p>| | | |</p>
<table>
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<tr>
<td>Individual Error</td>
<td>0.471</td>
<td>0.118</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phone-based Error</td>
<td>-0.241</td>
<td>0.349</td>
</tr>
<tr>
<td>Mean (μ)</td>
<td></td>
<td></td>
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<tr>
<td>Phone-based Error</td>
<td>1.77</td>
<td>0.140</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td></td>
<td></td>
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</table>

**Effect of First Observation on Second**

**Response**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{na1}$</td>
<td>0.739</td>
</tr>
<tr>
<td></td>
<td>0.0675</td>
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**Thresholds**

<p>| | | |</p>
<table>
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<tr>
<th></th>
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<tbody>
<tr>
<td>$\tau_{-3}$</td>
<td>-6.66</td>
<td>0.270</td>
</tr>
<tr>
<td>$\tau_{-2}$</td>
<td>0.89</td>
<td>0.134</td>
</tr>
<tr>
<td>$\tau_{-1}$</td>
<td>-3.52</td>
<td>0.119</td>
</tr>
<tr>
<td>$\tau_{-0}$</td>
<td>-1.47</td>
<td>0.0665</td>
</tr>
<tr>
<td>$\tau_{+0}$</td>
<td>1.47</td>
<td>0.0665</td>
</tr>
<tr>
<td>$\tau_{1}$</td>
<td>4.53</td>
<td>0.175</td>
</tr>
<tr>
<td>$\tau_{2}$</td>
<td>6.96</td>
<td>0.346</td>
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</table>

**Number of Happiness**

<table>
<thead>
<tr>
<th>Observations</th>
<th>1733</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood</td>
<td>-2494.231</td>
</tr>
<tr>
<td>$\hat{\rho}^2$</td>
<td>0.259</td>
</tr>
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</table>

When comparing between activity purposes, a distinction between weekday and weekend is made. Figure 2.7 and Figure 2.8 plot the effect of duration of each activity type on the latent happiness $h_{nak}$ for weekday and weekend activities, respectively, and use activity purpose-specific values as intercepts.
The weekday plot shows that discretionary and other activities have the highest positive effect on Hedonic State compared to staying at home on a weekday, and the effect is monotonically increasing for discretionary activities. This aligns with the category itself;
it includes meals, socializing, recreation, entertainment, and exercise, all of which are activities that people typically do for pleasure. Similar results were found in Kahneman et al. (2004) for the positive effects of meals, exercising, and socializing. Education is the only other activity that has a positive weekday coefficient, yet it is considerably small in scale. While the coefficient for staying at home is fixed at zero, travel, personal, and work all have negative coefficients, with work being the most negative. This can be interpreted as work having the most negative effect on an individual’s Hedonic State. These findings also agree with those of Kahneman et al. (2004), which associate work with one of the worst net effects, second only to individuals’ morning commute.

The weekend plot, on the other hand, shows a bigger spread. While discretionary activities still contribute significantly more to a more positive Hedonic State, staying at home on weekends has a positive effect compared to staying at home on weekdays. Education has half of the positive effect, yet remains similar in magnitude compared to other activities. Curiously, work on weekends is less negative than work on weekdays. On weekends, however, personal activities contribute the most negatively to Hedonic State. This can be attributed to the nature of the category, which includes running errands, shopping, and medical and dental appointments.

The shape of the curves in both plots tells a lot about the value of the activities. Discretionary activities have the most rapidly increasing value, which means performing discretionary activities for longer periods of time contributes positively to one’s Hedonic State. The value of staying at home increases with time, yet flattens out faster than the other monotonically increasing curves, which represents the diminishing returns of spending too much time at home. Travel activities have a significant increase in positive contribution with time. This can be attributed to people enjoying longer commutes because of pleasure derived from driving on for longer, or the free time that is made
available to perform other activities during the commute, such as reading on public transport. However, the positive trend is still significant for shorter travel activities, as shown in Figure 2.9.

![Figure 2.9](image)

**Figure 2.9** Effect of duration of travel activity on utility for weekday and weekend

Reasons for enjoying travel activities, discussed by and modeled by Ory and Mokhtarian (2004), include independence, exposure to environment, buffer between activities, conquest, and physical exercise—all which may have contributed to the observed curve. However, since literature (Kahneman *et al.*, 2004; Kahneman and Krueger, 2006) has shown that people do not enjoy commuting, it may also indicate the value of taking longer trips, such as a day trip out of the city. Activities labeled as other have the most distinct curve, yet it is not possible to exactly know why. With regards to accompanying people and escorting people—activities which tend to take a short amount of time—duration does not seem to have a very significant effect. Finally, education and work activities have the flattest curves. This indicates that duration has little effect on the added utility of work and educational activities. Overall, since 75% of activities are performed...
under 12.6 hours, the activity purpose itself has a greater effect on happiness than the
duration, which aligns with the developed theories of Duration Neglect.

The personal characteristics give insight into the skewness of the distribution of
individuals’ Hedonic States. Men’s average Hedonic State tends to be below their
median—or their Set Point—compared to women’s. Furthermore, married and divorced
individuals have an average Hedonic State that is below their Set Point compared to
single individuals. In terms of employment, part-time, unemployed, and retired persons
reported lower average Hedonic States compared to full-time employed people. On the
other hand, self-employed individuals have an average that is slightly more positive than
employed people—however, the difference is an order of magnitude smaller. Income
appears to contribute negatively to average Hedonic State. However, this may be
attributed to the non-representative number of high income individuals in the sample. It
is worth noting that all of the personal characteristics have very high standard errors of
their parameter estimates. This means that they are not as significant towards explaining
Hedonic State. This makes sense because the Hedonic State was calculated around
personal medians, such that it is expected that there be less variation across individuals
and the sample, as previously shown in Table 2.4.

With regards to the response time, activities reported in real-time tend to have a
more positive Hedonic State. The fact that the constant is significant and has a
considerable parameter magnitude compared to activity purpose variables and
socioeconomic variables may be a demonstration of the distinction between moment
utility and remembered utility. Since the end of the activity has not happened, a
happiness response reported in real-time is considered a single measurement of moment
utility, which by itself is not necessarily predictive of how people remember the activity
(Kahneman, 1999). Similar positive effects of real-time measurements have been seen in
Pedersen et al. (2011), who found that private vehicle users report higher satisfaction when riding public transport than they later remember. The time until observation is also significant, however, the magnitude of its effect is considerably smaller. Since approximately 90% of the activities are under one full day, the time before reporting has a small effect on the Hedonic State itself.

The individual and the phone-based panel effects both have significant standard deviations, yet the mean for $\omega_{na1}$ has a high standard error. This means that the added utility, in this case negative, to responding on the phone is not significant.

Finally, the coefficient of the systematic part of the $h_{na1}$, $\beta_{h1}$, is positive and less than one. A t-test can be performed to compare the estimate to one. The standard error, adjusted for the sample size of 714 activity instances with a second happiness report, is 0.0647, leading to a t-score of $-3.87$. For such sufficiently large sample size, the t distribution approaches the standard normal distribution, such that the p-value is $5.4 \times 10^{-5}$, or 0.00. Therefore, $\beta_{h1}$ is significantly different than one for our sample size. This result for $\beta_{h1}$ indicates that the second happiness response for a given activity $a$ for an individual $n$ is closer to the Set Point. $\beta_{h1}$ is, therefore, a damping effect of $h_{na1}$. Recall that $h_{na1}$ is the first happiness response for a specific activity $a$ for an individual $n$ collected over the mobile phone, and that $h_{na2}$ is the second response collected during the web-based validation. This may be interpreted as an intra-activity Hedonic Treadmill, where the individual’s perception of the happiness towards an activity instance is likely to be more neutral as time goes by. Like the Hedonic Treadmill described in Frederick and Loewenstein (1999), an intra-activity Hedonic Treadmill shows that remembered happiness also tends to become less accentuated, such that individuals’ memories of their activity become more neutral in later reports. This would show that one’s memory of
their happiness is not objective; instead, it is susceptible to changes. This finding is in accordance with a number of studies which highlight that one’s remembered well-being becomes more neutral, such as Abou-Zeid and Ben-Akiva (2012) and Pedersen et al. (2011), who found that car users’ positive real-time report of satisfaction in public transport becomes less positive in memory. Furthermore, the finding that the second report of happiness is a moderated version of the first report aligns with Ariely’s (1998) conclusions that self-reporting throughout an experience moderates the evaluations made retrospectively.

Discussion

Summary

Overall, the conducted study contributes to the literature of applied models of happiness by analyzing an individual’s Hedonic State using a dynamic Ordinal Logit Model, and by testing an intra-activity Hedonic Treadmill for a variety of day-to-day activities. Through the data collection platform, FMS, happiness data was collected over a varying period of time through phone- and web-based interfaces. The provided data was processed such that each individual was given a Set Point and the Hedonic State was calculated for each happiness observation. The dynamic OLM model showed that, while socioeconomic characteristics were less significant in modifying individuals’ average happiness compared to their median, activity attributes—such as purpose, duration, and if it was performed during the weekend or a weekday—were more significant in explaining Hedonic State. Furthermore, the model demonstrated that the second report of happiness is a dampened version of the first report, implying that there exists an intra-activity Hedonic Treadmill.
Happiness Measurement Implications

The developed understanding of an intra-activity Hedonic Treadmill leads to a number of implications on how well-being is measured. Satisfaction surveys for an event, for example, could be significantly different if conducted directly after or a week after said event. If one’s memory of their happiness with an activity becomes more neutral with time, data collection efforts can be planned to attain information that is relevant to the purpose of analysis. Real-time measurements of well-being when driving or in public transport can be used to improve the actual user experience. On the other hand, knowing that the remembered utility of an activity dampens with time may lead to better measurements for predictive purposes. Since people rely mostly on their memories of activities to decide whether to engage in the activity again (Wirtz et al., 2003), it becomes more relevant to understand people’s remembered utility instead of their moment utility to predict future behavior. Further understanding how the intra-activity Hedonic Treadmill varies for different types of activities could give researchers even more insight as to when to conduct happiness measurements.

Limitations and Further Work

The major limitation of the model provided is the small number of happiness observations for each individual. On average, each individual had 15.2 happiness recordings on 10.6 activities. Since these were not enough to establish a proper moving Set Point, assumptions were made in order to determine individuals’ Hedonic States. Ideally, if individuals had collected data for longer periods of time, the Set Point could have been a moving average or median. Furthermore, more data points could have resulted in more elaborate calculations of a Set Point, such as those described in Parducci
One example would have been to create activity purpose-specific Set Points for each individual. Another approach that could have been used, independent of data size, is to model the Set Point itself as a latent variable. Alternative specifications could include creating two distinct scaling effects, $\beta_{h_1^+}$ and $\beta_{h_1^-}$, such that the effect is different for activities with positive Hedonic States and negative Hedonic States, or non-linear scaling effects with time. These would be based on an additional binary latent variable for the sign of $h_{na1}$. Finally, given more data, the Hedonic Treadmill Effect, as described in Frederick and Loewenstein (1999) among a progression of activities, could be tested.

With more available data, it would have been possible to test more elaborate specifications of activity duration. They could, for example, have been specific to weekdays or weekends, or be interacted with socioeconomic variables. This would lead to more understanding of what affects different users' Hedonic State. Moreover, other specifications may be tested to account for non-linear effects of the duration.

Data collection can also be improved with better inference from sensors. As an emerging methodology for collecting daily activity behavior, FMS still requires user input in fixing inferred activities and validating one's day. Despite eliminating a number of biases from traditional activity reporting, the methodology may still affect data quality, such as activity duration (Ghorpade et al., 2015). As reported, activity durations tended to be very large, especially with regards to travel activities. These may have been the result of incorrect reporting of activities between travel. Improvements in the data collection methodology should be investigated in further research.

Additionally, the model could be elaborated by including variables that take into account sequences of activities. This can be done with solely the reported activities, where the previous activity, $n(a - 1)k$, and the current activity, $nak$, are interacted. However,
since FMS provides information on all of the user’s activities throughout the day, the interaction can be based on the previous activity or activity pattern, even if an individual did not report on the happiness of said activity. Information on activities preceding and following the activity reported on could have also informed a distinction between commuting and other types of travel. This would allow for a difference in the categorization of travel and possibly eliminate the multiple interpretations of the travel curve. Furthermore, given information on what activity the user is performing while answering the happiness question retrospectively, the damping effect could be modified to understand the how different activities affect how an individual remembers happiness during a previous activity. This could illuminate mechanisms of the proposed intra-activity Hedonic Treadmill.
Chapter 3

Dynamic Activity-making Model

Introduction

This chapter discusses the advancements that have been done in transportation modelling to account for the dynamic nature of activity-making. It highlights an overview of how different agent-based modelling frameworks have included rescheduling modules, and then discusses the Latent Base Plan model approach to dynamic modelling. It then proposes a Dynamic Activity-making Model framework, develops the likelihood function for it, and possible implementation. The estimation of this framework is an ongoing project, such that the chapter does not present estimation results.
Literature Review

Dynamic Responses in Agent-Based Modelling

Modelling dynamic choices in transportation has become increasingly more popular and has been implemented in different capacities and different scales. Timmermans et al. (2014), divides the different horizons of dynamic responses into three categories: (1) long-term, (2) mid-term, and (3) short-term. Long-term effects include those derived from lifestyle changes as a result of resource availability—such as owning a car—and land-use. Mid-term horizons are based on day-to-day learning of the effects of activities performed throughout a day and their effect, such that “successful” patterns are reinforced. Short-term dynamics are concerned with travel and activity-making responses to real-time conditions of travel networks and activity availabilities. These dynamic responses have been captured in a variety of experiments and models (Timmermans et al., 2014).

Qualitative Analysis of Dynamic Behavior

A number of studies have looked at how people change their behaviors in the short-term. In addition to those summarized by Timmermans et al. (2014), García-Jiménez et al. (2014), for example, looked at how individuals deviated from their planned behavior. Through a study conducted in València, Spain, researchers collected plans for the following week for 166 users. They then collected their activities in real-time using a mobile app, and followed up with an interview at the end of the week. They qualified the reasons why people canceled activities, which were namely temporal and social.

Thorhague et al. (2016) also looked at how people reschedule their planned trips. The Danish study collected data for a 24-hour period and included a stated preference survey. The study used Shannon’s Entropy to measure the complexity of trips and found
that trips chains before and after work, and thus constrained by work times, were the least flexible when simulating a ring toll policy in Copenhagen.

**Frameworks for Dealing with Rescheduling**

In addition to qualitatively understanding how individuals dynamically change their activity-making behavior, a number of frameworks have been developed to model said patterns. Thorhague et al. (2016) also proposed a modelling framework for the probability of developing schedules based on multinomial logits (MNL). The probability of a schedule is the product of the probabilities of scheduling said activities, yet without any interaction terms. In addition, a measurement of the complexity of the trip chain, based on Shannon’s Entropy, was used to penalize rescheduling of activities in a trip.

Joh et al. (2002 and 2003) proposed that a scheduling framework should take in a current schedule and perform sequential operations on it until it some form of equilibrium is met. Implemented for AURORA, operations include adjusting departure time, arrival time, duration, adding, deleting, and swapping activities. To account for the burden of finding an equilibrium—both computationally and in an individual’s planning process—penalties are applied for the number of iterations performed and the number of activities considered. Balac and Axhausen (2016) implemented addition, exclusion, and swapping of activities in MATSIM. The operations were done iteratively until the added utility of each activity cannot be improved for an individual, such that their schedule is optimal.

Other modules have been introduced to existing agent-based models. As an addition to FEATHERS, Bladel et al. (2009) use a mixed binary logit approach to determine if an activity would be rescheduled. Dimensions for rescheduling include timing, location, and cancelation. Knapen et al. (2013) later introduced a module to
modify agents' arrival and departure times given information on accidents. By modelling accidents as reduced road capacities, activities were expanded and shrunk in response to travel times provided by a dynamic traffic assignment (DTA) module.

Iterations with DTA modules have also been seen in Xiang et al. (2017) and Halat et al. (2017). By minimizing the gap between expected travel time in the ABM schedule and experienced travel time based on a DTA, the modules change activity duration and cancel activates, respectively. They work by recursively updating agents' schedules until realistic patterns are reached, and penalize changes to the schedule throughout iterations.

While the previous models depended on changing existing plans to match conditions provided DTA modules, dynamic models for planning and executing activities have been proposed. In scheduling, Auld and Mohammadian (2012) proposed that activity generation, planning, and scheduling should be treated separately and then connected. The model, created for Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS), plans and schedules activities in real-time using information provided by a DTA, cutting out the recursive part of the process. However, as a computational process model, it does not use utility maximization.

**Latent Plan Models**

Including dynamic decision-making into utility-based choice modelling has been proposed before. Latent Plan Models, proposed by Ben-Akiva et al. (2007), suggest that observable actions are based on unobservable plans, which is conditional on the current state, which in turn is conditional on the previous action. This relationship is described in Figure 3.1.
Choudhury et al. (2009) proposed that, in a dynamic scenario, the decision processes are broken down into two layers: a plan layer and an action layer. These, in turn are interdependent, and follow the assumptions of a Markov Decision Process (Bellman, 1957) such that the current state is only dependent on the one directly before it. This dynamic process was applied to lane changing on highways. The plan to change lanes, and the possible types of lane changes—normal, courtesy, and forced merging—was actuated as one of the three merge styles or no merging at all.

**Dynamics of Happiness in Modelling**

The integration of happiness in latent plan models has also been proposed with respect to travel. Abou-Zeid (2009), developed the framework for understanding how the real-time and remembered utility of an activity are measurable through their reported happiness, further postulated that the remembered happiness effects the following decision of an individual. The framework is simplified and adapted in Figure 3.2.
Motivation

Understanding how individuals change their behavior from their initial plan is essential to creating informative tools for policy- and decision-makers. While the dynamics of activity-planning have been modelled in real-time using computational process models, ABMs that leverage on utility-maximization are still relying on recursive scheduling with DTAs to achieve feasible schedules and account for potential changes in networks. Overall, convergence in these methods are either hard to reach or computationally costly: SimMobility (Adnan et al., 2015), for example, relies on day-to-day learning to adjust the travel time and time cost used in planning, yet still has a hard time generating feasible schedules for all individuals. The module developed by Balac and Axhausen (2016),
which iteratively improves individuals’ schedules, added 10% extra computation time when tested with only 0.1% of the Zurich population. The framework proposed in this chapter describes a Dynamic Activity-making Model, which can be integrated with a DTA in real-time to capture changes in people’s behavior in response to the network. Furthermore, the framework poses other advantages, which are discussed later on.

**Framework Specification**

Let us assume that everyone, at the beginning of a day, has some sort of plan for their day—even if it is highly unknown and stochastic even to them, such that they are not sure about what they will do—which eventually gets actuated into different performed activities. An individual may have their whole day planned out down to the minute, decided on where they are going, when they are going, or how they are getting there. At each step of the day, they do exactly what they had planned, and their plans remain the same. On the other side of the spectrum, an individual may have no concrete plans for the day and decide as they go along. Whatever an individual’s plan is, these plans are unknown to the modeler, yet the activities that are performed are not. Therefore, let us consider a person’s daily behavior as a sequence of plans and activities, shown in Figure 3.3. A proposal for what a plan could be defined as will be presented in the following section, yet for not allow the plan to be abstract.
Figure 3.3 Dynamic Plan and Activity Framework

Here, a person \( n \) has an initial latent plan at the beginning of the day, \( p_{n0} \), and that plan may or may not change throughout the day as the person performs activities. A plan at any time-step \( k \), \( p_{nk} \), is unobservable, and effects the activity at \( k \), \( a_{nk} \). In turn, we assume that at the end of the activity, the individual \( n \) has the opportunity to change their plan to \( p_{n(k+1)} \), which is a function of the performed activities and previous plans. In addition, every activity \( a_{nk} \) and \( p_{nk} \) is a function of network traits at time-step \( k \). If we make the First Order Markovian assumption, \( p_{n(k+1)} \) is only a function of \( a_{nk} \) and \( p_{nk} \), such that there are two probabilities of interest.

The first is the probability of individual \( n \) performing an activity given the previous plan.

\[
P(a_{nk} \mid p_{nk})
\]

The second is the probability of a plan at time step \( k \) given the previous plan at \( k - 1 \) and the previous activity \( a_{n(k-1)} \).

\[
P(p_{nk} \mid p_{n(k-1)}, a_{n(k-1)})
\]

Therefore, since the plan \( p_{nk} \) is unknown, the probability of an action \( a_{nk} \) becomes the sum over all of the possible plans.
\[
P(a_{nk}|p_{n(k-1)}) = \sum_{p_{nk} \in P_{nk}} P(a_{nk}|p_{nk})P(p_{nk}|p_{n(k-1)}, a_{n(k-1)})
\]

where \( P_{nk} \) is the choice set of possible plans for individual \( n \) at time-step \( k \). \( P_{nk} \) is defined based on individual-specific characteristics and previous activities. For example, education is part an individual’s choice set if they are enrolled in an academic institution.

The size of \( P_{nk} \) is determined by how the modeler decided to measure the plan. If a person has performed \( K_n \) total activities, the likelihood of their activity pattern, including their unobserved plans and conditional on an individual-specific error, is

\[
P(a_{n1}, ..., a_{nK_n}, p_{n1}, ..., p_{nK_n}|\eta_n)
\]

\[
= P(a_{n1}|p_{n1}, \eta_n) ... P(a_{nK_n}|p_{nK_n}, \eta_n)P(p_{n0}|\eta_n)P(p_{n1}|p_{n0}, \eta_n)P(p_{n2}|p_{n1}, \eta_n) ... P(p_{nK_n}|p_{n(K_n-1)}, \eta_n)
\]

where

\[
\eta_n \sim \mathcal{N}(0, \sigma^2).
\]

Such is attained as a product of all of the activities and plans. Since the plans for each time-step between \( k = 0 \) and \( k = K_n \) are unknown, by summing over all possible plans, \( P_{n0} \) to \( P_{K_n} \), we get the individual likelihood of the observed activity pattern conditional on the individual-specific error.

\[
P(a_{n1}, ..., a_{nK_n}|\eta_n) = \sum_{p_{n1} \in P_{n1}} ... \sum_{p_{nK_n} \in P_{nK_n}} P(a_{n1}, ..., a_{nK_n}, p_{n1}, ..., p_{nK_n}|\eta_n)
\]

Rearranged, the conditional likelihood takes on the following form:

\[
P(a_{n1}, ..., a_{nK_n}|\eta_n)
\]

\[
= \sum_{p_{nK_n} \in P_{nK_n}} P(a_{nK_n}|p_{nK_n}, \eta_n) \sum_{p_{n(K_n-1)} \in P_{n(K_n-1)}} P(p_{nK_n}|p_{n(K_n-1), a_{n(K_n-1)}, \eta_n})P(a_{n(K_n-1)}|p_{n(K_n-1)}, \eta_n)
\]

\[
... \sum_{p_{n1} \in P_{n1}} P(p_{n2}|p_{n1}, a_{n1}, \eta_n)P(a_{n1}|p_{n1}, \eta_n) \sum_{p_{n0} \in P_{n0}} P(p_{n1}|p_{n0}, \eta_n)P(p_{n0}|\eta_n)
\]
If we integrate over the individual-specific error, we get the likelihood for an individual's activity pattern:

\[ L_n = P(a_{n1}, ..., a_{nK}) = \int \eta \, P(a_{n1}, ..., a_{nK}, \eta) f_\eta(\eta) \, d\eta. \]

Finally, the likelihood of activity patterns for all individuals \( N \) is

\[ L = \prod_n L_n \]

such that the log likelihood is

\[ \mathcal{L} = \sum_n \log L_n. \]

The convenience of this modeling architecture is that both \( P(a_{nk} | p_{nk}) \) and \( P(p_{nk} | p_{n(k-1)}, a_{n(k-1)}) \) can take on as complicated or as simple as a form as the modeler desires. In the following section, a few proposals are made.

**Framework Advantages**

1. **Modeling behavioral shift between plans**

   The proposed framework models the behavioral shift that happens internally when an individual is triggered to change their daily plan. Their modified plan, in turn, affects the performed activities. In addition to capturing the effect of network conditions on certain activities, it also captures its effect on how deterministic a pattern is. For example, we could get a measure of how much a plan changed by doing the root mean square difference of the probabilities for a given plan from time-step \( k \) to \( k + 1 \). This can measure how much an incentive may destabilize one's plan.
2. Measurement of the utility of a day

In addition to measuring stability of plans throughout an individual’s day, the proposed framework also allows modelers to measure and compare the utility of an individual’s day. By summing the utility of the performed activities, a measurement of the day can be achieved. This, for example, can be used to compare the value to the user of specific incentives and nudges.

The approach has a few advantages compared to existing frameworks. Consider framework proposed by Siyu (2015). If one were to consider the logsum of the full set of choices as a measure of an individual’s utility of their day, it would be static despite the simulation outcome. Alternatively, if the utility were based on just the activity purposes chosen, it would not consider different possible how these activities were performed, namely the duration, location, and mode. This issue arises because the utility of a specific activity is not measured. Other approaches, such as the one proposed by Bhat et al. (2004), measure the utility of an activity though Discrete Continuous Models or Multiple Discrete Continuous Models, yet they are not able to capture the interactions between activities or the utility of the sequence.

3. Real-time response to supply and network

While many ABMs for demand exist, most are disconnected from the supply and rely on multiple iterations with traffic assignment before generating a feasible schedule for every individual. The proposed framework can be integrated with supply, such as a DTA, in real-time, eliminating the need for multiple iterations. Furthermore, it removes the assumption that an equilibrium between supply and demand can exist.
4. **Eliminates hierarchal assumptions between activities**

Many proposed modeling frameworks require some level of assumptions to be made in terms of how people plan and schedule activities. SimMobility, for example, assumes a static order for what activity purposes are modeled first (Viegas de Lima *et al.*, accepted). Similarly, TASHA, active in the Greater Toronto-Hamilton Area, prioritizes work and educational activities (Miller *et al.*, 2015). While one approach that has been done is to model the order of scheduling (Auld and Mohammadian, 2012). The structure proposed here, on the other hand, does not require any prior knowledge or assumption on the order in which people schedule activities.

5. **Models are interchangeable**

More interestingly, the proposed modeling framework can be used for a variety of model specifications. The Plan Model \( P(p_{nk}|p_{n(k-1)}, a_{n(k-1)}) \) and the Activity Model \( P(a_{nk}|p_{nk}) \) can take on almost any form. The only requirement is that there be a measurement of the plan in the activity model and of the previous plan in the current plan.

**Model Specification**

\[
\text{Plan Model} \mid P(p_{nk}|p_{n(k-1)}, a_{n(k-1)})
\]

The concept of what a plan is can take on multiple dimensions: what activities do you plan on doing? How many times do you plan to do each activity? What time of day will they be performed? Who will be joining you? Therefore, the Plan Model can include a number of dimensions and complexity. It may, for example, include the purpose of the activity and the exact times at which they will be performed. For the sake of simplicity,
assume that the Plan Model takes on the structure of the Day Pattern Tours Model, as specified in Viegas de Lima et al. (accepted). In this model, the purposes an individual will pursue in a day are explicitly modelled as binary variables, and no distinction is made with regard to how many times an activity purpose will be performed, nor when it they will be performed. The model is a multinomial logit (MNL), where the choice set includes a combination of each the available activity purposes. The limit on the number of activity purposes in the combinations is empirically determined.

**Main Structure**

Consider a choice set where the plan in constructed of binary variables for each possible activity purpose, including loops,

\[ p_{nk} = \{(\delta_1, ..., \delta_i, ..., \delta_l)\} \]

where

\[ \delta_i = \begin{cases} 1 & i \in p_{nk} \\ 0 & \text{otherwise} \end{cases} \]

for each activity purpose \( i \). If all plans are available, an individual can have up to

\[ \sum_{x=0}^{l} \binom{l}{x} \]

alternative plans, which is the size of the choice set. Alternatively, if we cap the number of alternatives based on the data to \( l_{\text{max}} \), we have

\[ \sum_{x=0}^{l_{\text{max}}} \binom{l}{x} \]

alternatives. Note that, instead of a binary variable, we could have the number of each activity \( i \), or that each activity \( i \) could have been interacted with a specific time of the day, all leading to a higher number of dimensions.
The systematic utility of each plan, \( U_{pnk} \), includes:

- **Purpose-specific constants**
  \[
  \sum_{i=1}^{l} \beta_i \delta_i
  \]
  Captures the utility of a specific activity purpose in any combination.

- **Purpose-interaction constants**
  \[
  \sum_{i=1}^{l} \sum_{l \neq l'} \beta_{il} \delta_i \delta_{l'}
  \]
  Captures the added utility of having two different activity purposes in the plan.

- **Individual-specific binary variables for socio-demographic characteristics, \( \delta_{nj} \)**
  \[
  \sum_{i \in 1,...,l} \sum_{j \in J} \beta_{ij} \delta_i \delta_{nj}
  \]
  where \( J \): set of socio-demographic variables
  Captures the purpose-specific utility based on sociodemographic characteristics. Note that the specification can also be modified to account for non-binary socio-demographic variables.

- **Coefficients for the count of activity purposes in plan, \( \delta_m \)**
  \[
  \sum_{m} \beta_m \delta_m
  \]
  for
  \[
  \delta_m = \begin{cases} 
  1 & \sum_{i} \delta_i = m \\
  0 & \text{otherwise}
  \end{cases}
  \]
  where \( m = 1, ..., I_{max} \)
  Captures the utility of having a specific number purposes in the plan compared to having 0 purposes in the plan.
• Logsum of Mode-Destination Model, $L_{nki}^M$

\[
\sum_{i=1,\ldots,l} \beta_{Mi} L_{nki}^M
\]

Captures utility of the different modes and destinations on including an activity purpose $i$ in a plan, given the real-time network conditions at time-step $k$.

• Logsum of Duration Model, $L_{nki}^D$

\[
\sum_{i=1,\ldots,l} \beta_{Di} L_{nki}^D
\]

Captures utility of the different possible durations on including an activity purpose $i$ in a plan, given the real-time network conditions at time-step $k$.

• Binary variable from having the activity purpose in the previous plan, defined as $\delta_i$

\[
\sum_{i=1,\ldots,l} \sum_{l=1,\ldots,l} \beta_{ii} \delta_i \delta_i'
\]

Captures the effect that having a specific purpose $i$ in the previous plan has on having all other purposes in the current plan. This is how $p_{nk}$ is dependent on $p_{n(k-1)}$.

Therefore, the systematic utility becomes

\[
V_{p_{nk}} = \sum_{i=1,\ldots,l} \left( \beta_i \delta_i + \sum_{i=1,\ldots,l} \beta_{ii} \delta_i \delta_i' + \sum_{j=1,\ldots,l} \beta_{ij} \delta_i \delta_{ij} + \beta_{Mi} L_{nki}^M + \beta_{Di} L_{nki}^D + \sum_{l=1,\ldots,l} \beta_{ii} \delta_i \delta_i' \right) + \sum_{m} \beta_m \delta_m
\]

Availabilities

The different plans are available to individuals based on two different factors.

• Previously performed activities
As the day progresses the availability of certain plans is limited by previous activities. The only plans available become those that include activities that have already been performed. For example, if an individual has already gone to work, only plans that include work are available. This is the effect $a_{n(k-1)}$ and $p_{n(k-1)}$ have on $p_{nk}$.

- Individual-specific sociodemographic

Certain individuals may not be allowed to perform certain activities. For example, if a person is not enrolled in an educational institution, they may not perform an education activity. On the other hand, if the person is not employed full-time, part-time, or self-employed, plans that include work are unavailable to them.

Activity Model $| P(a_{nk}|p_{nk})$

The Activity Model as a whole should encompass the key traits of an activity: the purpose, the mode, the destination, and the duration. The breakdown, however, can be accomplished in a number of ways. A discrete-continuous model, for example, could be used to couple the activity purpose and duration, and include logsum values for the mode and destination. On the other hand, the choice could be made multi-dimensional with discrete time and include all decisions at once. The proposal described below is one of the options on how to model this set of choices. It follows the structure proposed in Figure 3.4. In this figure, $b_{nk}$ shows the purpose, $M_{nki}$ represents the mode and destination for a purpose $i$ in $b_{nk}$, and $D_{nki}$ the duration for purpose $i$. 
Purpose

Main Structure

The main structure of the Activity Model can be thought of as an MNL. Each individual can choose between a predefined number of activity purposes according to their personal characteristics. In addition, the individual may also choose to go home or to do a loop activity, such as going for a drive or a walk. The choice set becomes

\[ b_{nk} = \{1, \ldots, I, \text{home}\}. \]

Note that we now include home in available set because individuals may decide to go home. Alternative specifications may also include in-home activities in the plan and activity purpose sets. The systematic utility for each of the purposes includes:

- Purpose-specific constants

\[ \sum_{i=1,\ldots,I,\text{home}} \beta_i \delta_i \]

*Captures the utility of a specific activity purpose in any combination.*

- Individual-specific binary variables for socio-demographic characteristics, \( \delta_{nj} \)
\[
\sum_{i \in 1, \ldots, I, \text{home}} \sum_{j \in J} \beta_{ij} \delta_i \delta_n j
\]

where \( J \): set of socio-demographic variables

- Time already spent on each activity, \( t_{nki} \), a non-negative continuous variable, which should be non-linear
  \[
  \sum_{i = 1, \ldots, I, \text{home}} \beta_{t1_i} t_{nki} + \sum_{i = 1, \ldots, I, \text{home}} \beta_{t2_i} t_{nki}^2
  \]
  \( i = 1, \ldots, I, \text{home} \)
  
  Captures the non-linear effects of performing an activity for more time.

- Count of time for each activity has already been performed, \( c_{nki} \), a non-negative integer
  \[
  \sum_{i = 1, \ldots, I, \text{home}} \beta_{c1_i} c_{nki}
  \]
  \( i = 1, \ldots, I, \text{home} \)
  
  Captures the utility of performing an activity more than once.

- Remaining time in day, \( t_r \), a positive continuous variable
  \[
  \sum_{i = 1, \ldots, I, \text{home}} \beta_{t1_r} t_r + \sum_{i = 1, \ldots, I, \text{home}} \beta_{t2_r} t_r^2
  \]
  \( i = 1, \ldots, I, \text{home} \)
  
  Captures the utility of the day coming to an end.

- Logsum of Mode-Destination Model, \( L_{nki}^M \)
  \[
  \sum_{i = 1, \ldots, I, \text{home}} \beta_{M_l} L_{nki}^M
  \]
  \( i = 1, \ldots, I, \text{home} \)
  
  Captures utility of the different modes and destinations at the time-step \( k \).

- Logsum of Duration Model, \( L_{nki}^D \)
  \[
  \sum_{i = 1, \ldots, I, \text{home}} \beta_{D_l} L_{nki}^D
  \]
  \( i = 1, \ldots, I, \text{home} \)
  
  Captures utility of the different possible durations at the time-step \( k \).

- Binary variable from having the activity purpose in the plan, \( \delta_i \)
  \[
  \sum_{i = 1, \ldots, I} \sum_{l \in 1, \ldots, l} \beta_{ll} \delta_i
  \]
Captures the effect that having a specific purpose \( i \) in the plan has on performing any activity. This is how \( a_{nk} \) is dependent on \( p_{nk} \).

Therefore, the systematic utility of performing an activity is

\[
V_{a_{nk}} = \sum_{i=1,...,l} (\beta_i \delta_i + \sum_{j \in j} \beta_{ij} \delta_{nj} + \beta_{t1i} t_{nk1} + \beta_{t2i} t_{nk2}^2 + \beta_{c1i} c_{nk1} + \beta_{t1r} t_r + \beta_{t2r} t_r^2 + \beta_{M1} M_{nk1} \\
+ \beta_{D1} D_{nk1} + \sum_{l \in 1,...,l} \beta_{li} \delta_l)
\]

**Availabilities**

As previously mentioned, the availabilities are limited by the personal characteristics of the individuals. For example, a person enrolled in an educational institution would have education available, while someone who is employed full-time, part-time, or self-employed has work available. An example set is:

\( i \in \{ \text{work, education, personal, recreation, shop, escort, loop, home} \} \)

**Mode-Destination**

Mode and destination are modeled jointly, such that the final choice set includes all combinations of modes and destinations. Destinations are usually the traffic analysis zones (TAZ) in the modeled region. The model includes travel times and costs for each mode when relevant. For each possible destination, size variables, such as area, employment, population, and central business district (CBD) dummy, are included. They are incorporated using the aggregate spatial method outlined by Ben-Akiva and Watanatada (1981). The model is estimated as a MNL or a nested logit (NL), where the order of nesting is determined empirically.
Duration
The duration model, for the purpose of simulation, will take on the same format as the Time-of-Day model. The continuous 24-hour day is discretized into 48 half-hour segments. The full choice set includes all of the possible combinations of start and end times, leading to 1,176 alternatives. However, yet the available alternatives are limited to the ones starting at the time for time-step \( k \). The alternative specific constants follow a continuous and cyclical form outlined by Ben-Akiva and Abou-Zeid (2013) using a trigonometric utility functional form. Activity duration, travel times, and travel costs are also included.

Integrating Happiness in Dynamic Activity-making
While the model developed in this chapter accounts for a number of limitations that exist in agent-based models (ABMs) today, it still lacks the behavioral complexity discussed in Chapter 2. To integrate happiness into the Dynamic Activity-making Model, we can look at the dynamic relationship proposed by Abou-Zeid (2009). Namely, the model can be modified to include a latent measurement of remembered happiness or of the modified Hedonic State after the activity, which affects the plan at a future stage. This proposed framework is expressed in Figure 3.5.
By including happiness in this model, the model now accounts for the subjective well-being that may be generated from an activity in the decision process to make it. Furthermore, by taking into account the happiness state after the activity in the plan, the model may capture how people’s Hedonic State may determine how they make plans and react to changes, as suggested by Archer et al. (2003).

**Estimation**

Estimation of the proposed model is an ongoing effort. Because the model requires only the observed done activities, it can be estimated through a regional travel survey. A preliminary model is being estimated using the derived maximum likelihood for the 2010 Massachusetts Travel Survey. Additionally, a data collection effort in the Greater Boston Area is being conducted using the web- and phone-based platform Future Mobility Sensing (Cottrill et al., 2013). This data includes well-being measurements, which can be used for estimating the second model, which includes happiness.
Conclusion

This chapter proposed a Dynamic Activity-making Model. In reviewing the existing literature on additions that have been developed for existing agent-based simulators, it highlights the precedent and need for developing ABM that are dynamic and responsive to real-time conditions. It introduces the Latent Plan Model and discusses precedents for using it to model transportation decisions, namely lane change. It then presents the model framework for activity-making. This model relies on two main probabilities: an observed activity model, $P(a_{nk}|p_{nk})$, which is a function of the plan $p_{nk}$ at time-step $k$, and a plan model, $P(p_{nk}|p_{n(k-1)}, a_{n(k-1)})$, which is a function of the activity and plan from the previous time-step, $k - 1$. The chapter and derives its associated likelihood function. Although estimation for the model is ongoing, the paper presents an outline of a potential specification for the probabilities $P(a_{nk}|p_{nk})$ and $P(p_{nk}|p_{n(k-1)}, a_{n(k-1)})$. Furthermore, it discusses the theoretical advantages of the proposed framework: the explicit modelling of behavioral shifts between plans; the ability to get a straightforward measurement of the utility of a day for an individual; the real-time response to networks and supply; the elimination of activity hierarchy; and the interchangeability of the models themselves. Finally, it proposes a framework for including measurements of happiness into activity-making. These models, in turn, can be used in regional simulators for testing a variety of scenarios. By adding more layers of behavioral complexity, they may be able to reflect individuals' reactions to more complex interventions.
Chapter 4

Conclusion

Summary

The thesis focuses on advancing the behavioral complexity of activity-making in agent-based modelling (ABM). Chapter 1 starts by highlighting the types of ABMs that exist in transportation simulation for agent schedule generation. It then discusses their limitations with regards to how the utility of an activity is modelled, and proposes that happiness, or subjective-wellbeing, is a measurement of the remembered utility of a performed activity.

Based on this concept, Chapter 2 presents a study which modelled an individual’s remembered happiness based on their real-time happiness. It discusses how well-being and happiness have been explored in transportation, introduces key concepts in Using a Dynamic Ordinal Logit model, it found that the remembered happiness is a dampening of the real-time happiness, such that it represents an Intra-activity Hedonic Treadmill.
Chapter 3 focuses on the behavioral enrichment of activity-based ABMs by making agent behavior more dynamic to change. It presents an overview of modules that have been developed for existing ABMs. It then discusses that Latent Plan Model approach under Markov Decision Process assumptions, and how it has been applied. The chapter then proposes a framework for the Dynamic Activity-making Model, and discusses its advantages. A proposal for the model specification is also outlined. Finally, the chapter integrates the concept of happiness by adding an additional latent layer of happiness states, which inform the proceeding plan.
References


