Bartosz Bursa

Modeling the Intra-Destination Travel Behavior of Tourists

Schriftenreihe des Arbeitsbereichs
Intelligente Verkehrssysteme der Universität Innsbruck
Verkehrsplanung und Verkehrstechnik

studia
VERLAG

Bartosz BURSA

MODELING THE INTRA-DESTINATION TRAVEL BEHAVIOR OF TOURISTS

DISSERTATION

eingereicht an der

LEOPOLD-FRANZENS-UNIVERSITÄT INNSBRUCK
FAKULTÄT FÜR TECHNISCHE WISSENSCHAFTEN

zur Erlangung des akademischen Grades

DOKTOR DER TECHNISCHEN WISSENSCHAFTEN

DOCTOR OF TECHNICAL SCIENCES

Band 3

der Schriftenreihe des Arbeitsbereichs Intelligente Verkehrssysteme
an der Universität Innsbruck

Hrsg.: Markus Mailer, Innsbruck, 2021

Arbeitsbereich Intelligente Verkehrssysteme, Institut für Infrastruktur,
Universität Innsbruck – Technikerstraße 13, A-6020 Innsbruck

Studia Verlag 2021

STUDIA Verlag
Herzog-Siegmund-Ufer 15, 6020 Innsbruck
verlag@studia.at

Printed in Austria 2021
ISBN 978-3-99105-014-8

This publication was printed with the financial support of the Vice-Rectorate for Research of the Leopold-Franzens-University Innsbruck.

Betreuungskomission
Supervising Committee

Hauptbetreuer Principal advisor	Univ.-Prof. Dipl.-Ing. Dr. techn. Markus Mailer, University of Innsbruck, Department of Infrastructure, Unit of Intelligent Transport Systems
Zweitbetreuer Co-advisor	Prof. Dr.-Ing. Kay W. Axhausen, ETH Zurich, Institute for Transport Planning and Systems

Prüfungskommission
Examination Committee

Vorsitzender Chair	Univ.-Prof. Mag. Dr. Hans-Peter Schröcker, University of Innsbruck, Department of Basic Sciences in Engineering Sciences, Unit of Geometry and Surveying
Erster Beurteiler First examiner	Univ.-Prof. Dipl.-Ing. Dr. techn. Markus Mailer, University of Innsbruck, Department of Infrastructure, Unit of Intelligent Transport Systems
Zweiter Beurteiler Seconds examiner	Univ.-Prof. Dr.-Ing. Martin Fellendorf, Graz University of Technology, Institute of Highway Engineering and Transport Planning

Vorwort des Herausgebers und Betreuers

Nachdem Band 1 der Schriftenreihe des Arbeitsbereichs Intelligente Verkehrssysteme eine Dissertation aus dem Eisenbahnwesen präsentierte, folgt mit der Doktorarbeit von Herrn Dr. Bursa, MEng in Band 3 nun innerhalb kurzer Zeit eine zweite Veröffentlichung aus der Verkehrsplanung. Mit einem Thema zu Mobilität und Tourismus ist sie einem der Forschungsschwerpunkte des Arbeitsbereichs zuzuordnen, der auch im interdisziplinären Forschungszent-rum Freizeit und Tourismus der Uni Innsbruck beteiligt ist. Bartosz Bursa war mit seiner Dissertation im dort eingerichteten Doktorratskolleg integriert. Dem Leitsatz des Arbeitsbereichs „Mobilität der Zukunft erforschen und gestalten!“ entsprechend, steht die Untersuchung und Entwicklung von Mobilitätsangeboten im Fokus, die eine nachhaltigere Mobilität im Tourismus ermöglichen.

In diesem Kontext behandelt die vorliegende Arbeit von Bartosz Bursa einen wichtigen Aspekt, der in der bisherigen Forschung weniger Beachtung gefunden hat. Im Gegensatz zur An- und Abreise ist die Mobilität von Touristen an den Urlaubsdestinationen weniger erforscht. Dabei ist diese nicht nur für die Wahl des eigenen PKW als Verkehrsmittel für die Anreise gera-de im alpinen Tourismus oft entscheidend. Zunehmend ergeben sich durch die Überlagerung der Fahrten der Gäste mit jenen der Einheimischen auch an Werktagen kritische Verkehrsbelastungen, wie sie früher oft nur an den An- und Abreisetagen beobachtet wurden. Doch was ist für die Verkehrsmittelwahl und Zielwahl in der vor-Ort-Mobilität der Gäste entscheidend? Wie unterscheiden sich die Einflussfaktoren von jenen in der Alltagsmobilität? In seiner Arbeit ist Bartosz Bursa diesen Fragen nachgegangen und hat mit einem Discrete Choice Ansatz Modelle zur Verkehrsmittelwahl in der vor-Ort-Mobilität von Touristen entwickelt. Die Arbeit wurde von der Österreichischen Forschungsgesellschaft Straße-Schiene-Verkehr und dem österreichischen Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie (BMK) mit dem FSV-Preis ausgezeichnet.

Univ.-Prof. Dipl.-Ing. Dr. Markus Mailer, Herausgeber und Betreuer

Foreword by the editor and supervisor

Following Volume 1 of the publication series of the Unit Intelligent Transport Systems, which presented a dissertation from the field of railway engineering, the doctoral thesis of Dr. Bursa, MEng, in Volume 3 is now the second publication from the field of transport planning within a short period of time. With a topic on mobility and tourism, it can be assigned to one of the main research areas of the unit, which is also actively engaged in the interdisciplinary Research Center Tourism and Recreation at the University of Innsbruck. With his dissertation, Bartosz Bursa was involved in the doctoral program established there. According to the mission statement of the unit "Researching and designing mobility of the future!", the focus lies on the investigation and development of mobility services that will allow for a more sustainable mobility in tourism.

In this context, the present work by Bartosz Bursa addresses an important aspect that has received less attention in research to date. In contrast to long-distance travel to and from destinations, the mobility of tourists at vacation resorts has remained under-represented in academic studies. Yet this is often crucial not only for the choice of one's private car as mode of transport for travel to the destination, especially in alpine tourism. Increasingly, we are also observing tourists' on-site trips overlapping with those of residents, resulting in critical traffic congestion on weekdays, which was previously seen only on arrival and departure days. But what are the key determinants of guests' mode and destination choices in their on-site mobility? How do the influencing factors differ from those in everyday mobility? In his work, Bartosz Bursa pursued these questions and, using Discrete Choice Analysis, developed models for transport mode choice for intra-destination mobility of tourists. The work was awarded the FSV Prize by the Austrian Research Association for Roads, Railways and Transport and the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology (BMK).

Univ.-Prof. Dipl.-Ing. Dr. Markus Mailer, editor and supervisor

Acknowledgements

It is *Markus Mailer* who came up with the idea of looking specifically at the intra-destination movements of tourists. Seemingly uninteresting at the beginning, the topic turned out to be deeply intriguing, offering a great potential of underexplored research niches located at the crossroads of transportation, travel behavior, tourism, leisure and vacation studies. He has always had a good intuition and helped me avoid mistakes (though not all!) and blind alleys of the research. He also cared about optimal working conditions that allowed me to make constant progress during the course of the doctoral studies. I am very grateful for funding the participation in numerous conferences and subsidizing the courses on discrete choice at the EPFL in Lausanne and at the University of Leeds, which opened my eyes to where I am on the personal development axis and what still is to be done.

I truly appreciate *Kay Axhausen* allowing me to work with him and his team during my short stays at the IVT on ETH in Zürich. These visits were always extremely productive, resulted in huge progress in my work and the discussion we had were always an intellectual pleasure. It never ceases to amaze me how broad his knowledge is. He is *the Renaissance Man* in transportation. Chapeau bas! I am also thankful to Felix Becker who always offered advice to me, whenever I had doubts concerning modeling in R.

I am grateful to *Martin Fellendorf* for undertaking the role of the second evaluator. I hope we'll have more occasions to work together in the future.

Furthermore, I would like to thank my working colleagues in Innsbruck for friendly atmosphere over the last four years. Special thanks goes to *Stephan Tischler* for introducing me in the world of backcountry skiing and for these few tours that we made together. Hoping for more!

Emma Komarek receives my thanks for her laborious work on questionnaire digitalization and data cleaning.

The biggest appreciation deserves my beloved girlfriend *Patrycja* who suffered at least as much as I did and survived even more. She took the responsibility of the graphic design of the PAPI questionnaires and was always at hand with her creativity

and excellent graphic design skills. She was a steadfast supporter in the tough time and a peaceful soul alleviating the unnecessary stress, rush and chaos I used to notoriously produce. Your dedication in the last months was worth one's weight in gold.

Me working on this thesis was surely not the only thing bothering my *mum* during the past four years. I would not have reached this level of education, had she not strived for better chances for me as a single parent many years ago. Thank you for that.

This endeavor is also for my *grandma,* who passed away last winter, for keeping her fingers crossed for me all her life.

It has been intensive time – hectic, exhausting and formidable but also challenging, stimulating and rewarding. The pandemics that swept over the world in the spring of 2020 right at the moment of finishing the thesis, the precariousness of working in the academia and the entire scientific world evolving uncontrollably in different directions did not make it easier either. Fortunately, living in Innsbruck compensates for these hardships with interest. I have never really expected that I could live in the Alps, even though, as someone who loves mountaineering, climbing, cycling, etc., it has always been running through my mind. I can still remember the moment I came across the job posting of the University in Innsbruck and the discussions we had at home before taking the bold decision to jump ship and leave London.

All in all, given that I embarked upon this scientific journey having only vague idea of how the academia works, being unaware of research methods and even having very mediocre knowledge about statistics, the sole fact that I reached the finish line, can be called a lifetime accomplishment.

KURZFASSUNG

Angesichts der ständig steigenden touristischen Nachfrage in den Alpenländern, des damit verbundenen Verkehrsaufkommens und der daraus resultierenden negativen Externalitäten sowie der sozialen und ökologischen Kosten ist es dringend notwendig, eine Verkehrspolitik zu entwerfen, die in der Lage ist, den Tourismusverkehr effizient zu steuern und in Anbetracht der begrenzten finanziellen, räumlichen und ökologischen Ressourcen umsichtig in die Verkehrssysteme und die Infrastruktur zu investieren. Während es ein deutliches Forschungsinteresse an Fernreisen und Ankunfts-/Abreisemustern von Touristen gibt, sind Forschungsarbeiten zur touristischen Mobilität während des Aufenthalts in der Urlaubsdestination leider so gut wie nicht vorhanden. Dies erschwert es den politischen Entscheidungsträgern, fundierte Entscheidungen zu treffen, die durch wissenschaftliche Erkenntnisse gestützt sind. Die vorliegende Dissertation versucht, diese Forschungslücke zu schließen und ein "analytisches" Licht auf das Reiseverhalten von Touristen am Reiseziel zu werfen.

Zunächst wird dazu der Stand des Wissens in der Verkehrs- und Tourismusliteratur recherchiert und zusammengefasst, um Faktoren zu identifizieren, die potenziell Einfluss auf Mobilitätsentscheidungen von Touristen haben könnten. Der Überblick über den Forschungsstand in den drei elementaren Wahlkomponenten im Reiseverhalten, der Ziel-, Verkehrsmittel- und Routenwahl sowie der Theorie der gemeinsamen Entscheidungen und den Auswirkungen des Wetters dient als Grundlage für die Gestaltung einer mehrteiligen, maßgeschneiderten Befragung zum Verkehrsverhalten. Weiteres wird über die durchgeführte Feldforschung basierend auf einer Umfrage, die in den Jahren 2018 und 2019 in drei Tourismusregionen im österreichischen Bundesland Tirol durchgeführt wurde, berichtet.

Nach der deskriptiven Auswertung der Befragungsdaten, die auch die Unterschiede zwischen Sommer- und Wintersaison hervorhebt, werden in der Dissertation ökonometrische Wahlmodelle für die Analyse von Entscheidungen über die Verkehrsmittelwahl von Touristen eingesetzt. Anhand der Wege und Aktivitäten

der Befragten, ergänzt durch Daten aus externen Quellen, werden mittels Multinomial- und Nested-Logit-Spezifikationen die Einflussfaktoren ermittelt und deren Effektgröße in der erhobenen Stichprobe geschätzt.

Darauf aufbauend werden die vorgeschlagenen Wahlmodelle zur Berechnung der Indikatorwerte für politische Maßnahmen verwendet. Dabei werden für alle Alternativen Elastizitäten auf Änderungen in der Reisezeit und den Reisekosten geschätzt. Darüber hinaus wird der Wert der Reisezeitersparnis (VTTS) von Touristen für Reisen mit dem Auto und mit dem öffentlichen Verkehr berechnet. Sowohl die Elastizitäten als auch die VTTS von Touristen werden mit den in österreichischen und internationalen Studien berichteten Werten für die Mobilität der ansässigen Bevölkerung verglichen.

Abschließend fasst die Dissertation die Ergebnisse zusammen und diskutiert ihre Implikationen für Wissenschaft, Wirtschaft und Politik. Sie resümiert die Leistungen der entwickelten Modelle und gibt klare Empfehlungen für ihre Anwendung unter Berücksichtigung der Grenzen aller Forschungsphasen. Zudem werden Lücken in der Wissenschaft identifiziert und weitere Aufgaben formuliert, die die Forschung zur touristischen Mobilität über den Rahmen dieser Arbeit hinaus voranbringen können.

Abstract

In the face of a continuous increase in tourism demand in the Alpine countries, the associated traffic volumes, and the resulting negative externalities as well as social and environmental costs, there is an urgent need to design policies capable of managing tourist traffic efficiently and to invest in transport systems and infrastructure wisely, given the limited financial, spatial and environmental resources. Unfortunately, while there is a considerable research interest in long-distance travel and arrival/departure patterns of tourists, research on tourist mobility during the stay at the destination is almost non-existent. This prevents policy-makers from making informed decisions backed by scientific evidence. The dissertation attempts to fill this research gap and shed an "analytical" light on travel patterns of tourists at the destinations.

In the first instance, the transportation and tourism literature are researched and synthesized in order to identify factors that might be potentially influential on tourist decisions. The overview of the state of research on the three elementary choice components in travel behavior, destination, mode and route choice, the theory of joint decisions and the impact of weather serves as a basis for the design of a multipart bespoke travel-activity survey. A field report from the survey conducted in 2018 and 2019 in three tourist regions in the Austrian province of Tyrol is provided.

Following the descriptive analysis of the survey data highlighting differences between the summer and winter seasons, the thesis employs econometric models of choice for the analysis of tourist transport mode decisions. Based on the trips and activities of the respondents, and supplemented by data from external sources, Multinomial and Nested Logit specifications are used to find the impactful factors and measure their effect size within the collected sample.

Next, the proposed choice models are used to calculate values of the indicators for policy measures. Elasticities with respect to changes in travel time and travel cost are estimated for all alternatives. Furthermore, the Value of Travel Time Savings (VTTS) of tourist visitors are calculated for travel by car and on transit. Both the

elasticities and VTTS of tourists are compared to values of local residents reported in Austrian and international studies.

Finally, the thesis recapitulates the findings and discusses their implications for science, economy and policy. It summarizes the performance of the models developed and provides clear recommendations for their application, taking into account the limitations at all stages of the research. In addition, new gaps in science are identified and further tasks are formulated that could advance the research on tourist mobility beyond the scope of this thesis.

CONTENTS

LIST OF FIGURES

List of Tables

GLOSSARY

AIC:	Akaike information criterion
ASC:	Alternative Specific Constant
BIC:	Bayesian information criterion
CHF:	Swiss Franc currency
CNL:	Cross-Nested Logit
DCA:	Discrete Choice Analysis
EUR:	Euro currency
GDP:	Gross domestic product
GPS:	Global Positioning System
LL:	Log-likelihood
LR:	Likelihood-ratio
MMNL:	Mixed Multinomial Logit
MNL:	Multinomial Logit
NL:	Nested Logit
RP:	Revealed preference
SD:	Standard deviation
SP:	Stated preference
UNWTO:	United Nations World Tourism Organization
VOT:	Value of Time
VTTS:	Value of Travel Time Savings

1 Introduction

1.1 Motivation

Tourism industry is an important source of income in the Alpine areas of Austria, Switzerland, Italy or France. Tourism accounts for 17.5% of direct Gross Domestic Product (GDP) in the Austrian province of Tyrol (MCI, 2014). While the average stay duration of tourists in Tyrol decreased from 5.1 nights in 2000 to 4.0 nights in 2019, the number of arrivals increased by almost 60% from around 8 million to more than 12 million over the last two decades, despite no expansion on the supply side as the number of beds dropped by 7% in this period (Statistics Austria, 2020). This is an evidence of an accelerating trend of short yet more frequent holidays (Alegre and Pou, 2006; Gössling et al., 2018; Martínez-Garcia and Raya, 2008), which unavoidably results in an increase in tourism-related travel (Schlich et al., 2004). Given the fact that almost 75% of inbound holiday trips to Austria are made by private car (Austrian National Tourist Office, 2014), the effects of this trend on traffic congestion and parking space management at the destinations can be substantial (Cullinane and Cullinane, 1999; Dickinson and Robbins, 2007, 2008; Regnerus et al., 2007). Particularly in mountainous regions, where alternative routes are limited, tourist traffic coinciding with daily commute, leisure and freight traffic leads to disturbances to local communities in high season (Langer, 1995; Ogrin, 2012; Pechlaner and Hamman, 2006; Scuttari et al., 2016; Scuttari et al., 2019; Scuttari and Isetti, 2019; Tischler and Mailer, 2014) and deteriorates residents' perception and attitudes towards tourism development (Hudson, 2005; Lindberg et al., 1999; Mason and Cheyne, 2000; McGehee and Andereck, 2004; Pegg et al., 2012).

Besides the effect on congestion and performance of transportation networks, an increase in number of car trips in tourist regions inevitably implies a negative environmental impact, which is clearly reflected in increased CO_2 emissions (Dolnicar et al., 2010; Filimonau et al., 2014; Gühnemann et al., 2021; Mailer et al., 2019; Martín-Cejas, 2015; Rendeiro Martin-Cejas and Ramirez Sanchez, 2010; Unger et al., 2016), but also other negative externalities such as higher noise levels (Barber et al., 2011; Díez-Gutiérrez and Babri, 2020; Monz et al., 2016; Pickering and Barros, 2013; Zhong et al., 2011) and higher number of accidents (Ball and Machin, 2006; Bellos et al., 2020; Castillo-Manzano et al., 2020; Wang et al., 2016).

While the problems are recognized and present also in other non-urban destinations, they have attracted only limited attention of researchers so far – a point raised by Gronau (2017b) or (Dickinson and Dickinson, 2006). Local authorities still do not have any quantitative evidence at their disposal. In effect, the policy measures are often shots in the dark, which, despite entailing considerable expenses (e.g. free transit services for tourists), lack proper evaluation and appraisal. This work aspires to make a step in filling this gap.

In terms of vacation travel, we know much about travel decisions of people from census data and studies on travel behavior conducted in origin countries. Moreover, governments and international organizations collect aggregate data on tourism economy, global markets and produce statistics on travelers moving between and within countries. It is however rational and legitimate to assume that the travel behavior of tourists at the destination is not only different from how they behave on daily basis at home (Guiver et al., 2008; Prillwitz and Barr, 2011), but also from the behavior of residents in the regions they visit (Kinsella and Caulfield, 2011; Lumsdon, 2006). It also may not be in line with the data available at the aggregate level. Yet, current research in this field is limited and concentrates merely on international tourism demand and long-distance trips (Christensen and Nielsen, 2018; Gerike and Schulz, 2018; Janzen et al., 2018). It still remains mostly unexplored how tourists travel on-site at the destinations, which is of greater importance for local authorities and communities than for central or federal governments. Moreover, as noticed by LaMondia and Bhat (2013) most of research studies on tourists' travel behavior up to now are descriptive and therefore incapable of predicting.

1.2 RESEARCH OBJECTIVE AND RESEARCH QUESTIONS

The fundamental goal of the thesis is to develop a comprehensive scientific approach to the analysis of tourist travel behavior at the destination. It will inform tourism practitioners, transport planners and policy-makers working in tourist regions about data collection procedures, modeling methods and implications for policy-making. With a focus on the transport mode choice, the thesis will deliver methods scientific in nature but capable of solving practical problems, where other approaches, successfully used for modeling daily travel, fail.

Driven by the above objective and based on a detailed review of the existing literature, following detailed research questions have been defined:

1. What factors determinate travel decisions of tourists staying in alpine regions in terms of mode choice?
2. Is there a substantial impact of the accompanying party size and composition?

3. Is there a substantial impact of weather conditions?
4. How do tourists valuate their travel time savings depending on transport mode?
5. How might tourists respond to policy measures aiming to change the modal split in tourist regions?

1.3 OUTLINE

The thesis is comprised of six chapters with chapter 1 providing an introduction to the topic, describing the motivation and setting the objectives for the research.

Chapter 2 provides a broad background for next chapters. It starts from defining the terminology. Next, it reviews the literature on data collection methods and travel decisions, with a particular focus on tourists in vacation setting. Finally, the state of research in Discrete Choice Analysis (DCA) is described followed by applications of DCA in tourism and large-scale transportation models.

Chapter 3 covers the survey work. First, the conceptual framework of tourist travel at the destination is presented. Next, a detailed description of survey methodology and design is given, followed by response behavior statistics. The last part of this chapter is a broad descriptive analysis of the collected data.

Chapter 4 deals with the second core part of the thesis – the modeling work. The data preparation process is precisely described. Afterwards, model specifications and estimation results of Multinomial Logit (MNL), Nested Logit (NL) and Cross-Nested Logit (CNL) models along with their interpretation are provided.

Chapter 5 synthesizes the results and formulates the answers to research questions stated in chapter 1. The findings are critically discussed and potential implications for science, economy and policy are proposed. Limitations of the research are clearly highlighted.

Chapter 6 provides an outlook on future research and suggests prospective study topics that could either be an extension of the research described in this thesis or could resolve some of its limitations.

2 State of research on travel behavior of tourists

2.1 Definitions

As noticed by Arce and Pisarski (2009), there are many future challenges in describing tourists' mobility that are caused by i.e. data unavailability, different levels of analysis or inconsistencies in definitions. In particular, they highlight the following:

1. *"Distinguishing between international versus domestic tourists and their travel behaviour;*
2. *Distinguishing between visitors versus others who are not residents (immigrants, border workers, refugees, transit passengers, etc.) and their travel behaviour and impact on urban areas;*
3. *Distinguishing between overnight visitors (tourists per UNWTO) versus same-day visitors and their travel patterns and impacts;*
4. *Distinguishing between business versus leisure travel and their travel patterns and impacts;*
5. *Defining and investigating travel involving visiting former home (family visits) in both domestic and international settings;*
6. *Inbound versus outbound direction of trip making and the dynamics of such travel." (Arce and Pisarski, 2009)*

Also this thesis needs to cope with the above mentioned problems. In particular, regarding point 1 and 3.

Therefore, several assumptions were made in the thesis to avoid ambiguities. This thesis operates with the definitions of tourism and tourist as proposed by United Nations and World Tourism Organization (1994), so as to avoid confusion with traveler, vacationer or holidaymaker (Terrier, 2009). All these terms are used in the thesis interchangeably though all meaning a tourist. The main restriction this definition of tourist imposes, is that a person should be out of home (place of residence) for at least one night. It can be either a domestic (Austrian) or a foreign tourist. The person must not be specifically on vacation, business purposes or family visits are also allowed. It cannot be however a seasonal worker. Of interest are all trips and activities performed during the stay (leisure and non-leisure).

2.2 DATA COLLECTION METHODS

This section reviews the relevant literature and examines traditional as well as more recent data collection methods, keeping in mind that the thesis concentrates on the intra-destination mobility of tourists in rural and alpine regions, i.e. their activities and trips within mountain valleys and resorts.

The technological progress in recent years has provided academics with new opportunities for measuring mobility by utilizing passively collected big data. Apart from transport researchers also tourism researchers applied tracking technologies in a number of studies (Shoval et al., 2014; Shoval and Ahas, 2016). However, these deal with research questions relevant for tourism marketing, tourism demand or tourism geography and overlook the transportation-related aspects of tourist travel like traffic generated at destinations or transport mode choice.

Mobile positioning data have been widely utilized by tourism researchers in the last decade (Ahas et al., 2008; Zhao et al., 2018). Yet, they proved useful only in applications limited to long-distance travel demand and tourism statistics. In transportation, decisions strongly depend on characteristics of decision-makers (Lu and Pas, 1999). However, mobile positioning data, for technical and ethical reasons, is lacking this information. Only pure location data with time stamps is available, albeit in mountain regions the density of GSM transceiver stations is insufficient for high-resolution analysis at the destination level. In addition, in alpine regions, cross-border trips are very common, resulting in frequent changes of network provider. Thus, only parts of these trips will appear in the dataset obtained from a national provider.

GPS tracking can deliver very fine-grained data on tourist mobility allowing analyses of specific activities or monitoring visitors to facilities, parks and venues (Li et al., 2019). If complemented with additional questionnaires, GPS tracking can serve as a superior alternative to traditional travel surveys among tourists. Currently, mobile phones appear to be used more often in research than independent GPS trackers since smartphone apps allow for correcting and annotating trips by the user and answering supplementary questions (Prelipcean et al., 2018). Although the first studies reported on failed attempts of GPS tracking with mobile phones (McKercher and Lau, 2009), the success rate increased over the last few years. So far, the most complete and successful approach that combines an annotated travel diary and GPS tracking in a smartphone app for tourist tracking was developed by Hardy et al. (2017), who distributed 240 smartphones with a preinstalled tracking app among visitors to Tasmania. However, besides high costs of such studies, there are practical and organizational burdens. Tourists cannot be contacted before arrival to arrange handing over the GPS units. In the case of a smartphone app, a communication channel is necessary to make tourists aware of the app. Furthermore, battery consumption and data roaming in the case of foreign visitors have to be considered. Nonetheless, it is a promising approach and deserves further testing in the field.

Another alternative data source are social media services. Recent studies approximated tourist mobility patterns from geo-located *Twitter* data (Chua et al., 2016; Provenzano et al., 2018), *Flickr* photos (Önder et al., 2016; Yang et al., 2017) or *Foursquare* check-ins (Vu et al., 2018). However, in less populated areas, relevant Points-of-Interest are underrepresented and geo-tagged tweets and photos are scarce, which makes these methods applicable rather to city tourism (Sobolevsky et al., 2015) or estimates of inter-destination tourist flows (Barchiesi et al., 2015). Moreover, even though the data can deliver valuable information on tourist activity for the destination and park managers (Orsi and Geneletti, 2013), they are not of much use for transport planners since a full reconstruction of all trips made is impossible.

Nevertheless, despite the expansion of big data, traditional surveys appear to be still in use when investigating tourist populations. Big data on their own are not capable of substituting traditional methods as they do not provide sociodemographic information, cannot measure unobserved variables or deliver strong causal evidence (Chen et al., 2016; Mokhtarian, 2018). Unfortunately, as opposed to well-established surveys on daily travel behavior (Brög, 2009), there is no consensus on the design and methodology of such surveys in the tourism context that could lead to a replicable approach. Also, very few researchers provide details on the survey design and report on the fieldwork when applying travel diaries (Newmark, 2014; Thornton et al., 1997; Tschopp et al., 2010). Author's own experiences confirm many weaknesses of diary-based surveys of tourists that are also known from surveys of daily mobility, i.e. high costs, low response rate and high dropout rate. Besides, due to high spatiotemporal dynamics of tourists on site, the sampling frame is unknown and it is difficult to approach a representative sample when surveying outdoors. Surveying visitors at their accommodations allows for more control over sampling (e.g. indirect sampling through hotels) but requires a close cooperation with the accommodation providers, which is usually impossible without the support of local Destination Marketing Organizations. Even so, self-administered questionnaires distributed through tourism establishments prove very ineffective. It is therefore postulated that only fully-assisted interviews can guarantee good quality results. Moreover, although travel diary data is detailed enough to model destination and mode choice, it is usually insufficient to investigate route choice. Many of the above was already noticed by Thornton et al. back in 1997 and is still up-to-date:

"Time-space diaries offer advantages over the other techniques, particularly questionnaires generating lists of 'places visited'. Diaries offer a more comprehensive picture of tourist activities, including 'informal' ones such as relaxing. Anderson

argues: "The main quality of space - time diaries is perhaps that they record behaviour patterns which are not normally directly observable because of their spatial and temporal extent" (1971, page 359). However, diaries also present problems. Because diaries have been used for a wide variety of purposes they do not comprise a uniform field of study. Therefore, there is considerable variation in underlying methodologies, and important methodological and technical issues have not yet been settled satisfactorily. Although diaries may be rich in detail on the patterning of activities in space and time, there are still limitations on the amount of data that can be recorded. For example, the day is usually divided into recording blocks (to assist later analysis) but there is no clear guidance as to the appropriate length of these blocks. There is also an unresolved debate as to how to record the spatial coordinates of activities: whether in spatial zones, by precise named locations, or by grid references. There is, of course, a danger that the approach taken may impose an extraneous structure on the day or week that does not exist in reality. Furthermore, the considerable effort required on the part of respondents for the accurate recording of activities usually leads to low response rates. Similarly, the quality of data obtained varies according to the enthusiasm of individual respondents. In extreme cases, it is impossible to guarantee that uninterested respondents do not complete the diary in retrospect, thus making it a recall document. Bell also argues that diarists must be of a sufficient educational level to understand often complex instructions, let alone complete the diary (1987, page 82). Bias can also be seen to derive from the potential for accidental or willful misrepresentation of data within self-completed diaries. Oppenheim, for example, claimed respondents' particular interest in filling the diary will cause them to modify the very way that behaviour is recorded, either through 'dutiful action' (that is, activities undertaken in order to have something to record) or recording only those activities likely to give a favourable impression (1966, page 215). However, it should be added that many of these problems are common to other techniques, which also suffer from the further disadvantages of the spatial and temporal limitations of the data they obtain. Time - space diaries have been used in a number of social science disciplines and are relatively well developed in retailing studies [for example, see Wrigley and Guy (1983) for a review of this genre] compared with their relative neglect in tourism studies. There are, however, some exceptions, the most notable of which are Murphy and Rosenblood (1974), Gaviria (1975), Cooper (1978), Pearce (1981), Pearce (1988), Debbage (1991), and Dietvorst (1994)." (Thornton et al., 1997)

2.3 ACTIVITY-BASED TRAVEL MODELING

Following the industrial revolution and the emergence of private-use vehicles, the 20th century witnessed a rapid development of transport infrastructure. However, increasing construction costs, spatial limitations and, as a result, decreasing effectiveness of new investments in the last decades, have forced planners to switch from the supply-oriented approach, concentrated on extension of transport networks, to efficiently managing the growing demand for travel so that it suits the existing infrastructure (Bates, 2008; Pinjari and Bhat, 2011). Since 1970s, the modern transport planning focuses therefore no more on aggregate demand produced by undefined people masses but rather on actions of single individuals or households and hence is very behavior-oriented. Transport modeling techniques, which serve as a tool providing information for transport policy and demand management strategies, have undergone the same transformation, from the trip-based approach to the activity-based one. McNally (2000) and Pinjari and Bhat (2011) explain how and in what aspects these two methods differ from each other.

First, in the activity-based approach, the demand for travel derives from the individuals' needs to pursue activities, which is based on theoretically sound assumptions (Jones, 1979b). Secondly, travel is partitioned into tours, not trips. Tours is a chain of trips that starts and ends at the same location. It is a lifelike approach that can capture the interdependencies between subsequent trips (in terms of time, location or transport mode) and is more consistent with people's real behavior. Thirdly, activity-based models can replicate how the individual allocates his or her time, which is a constrained good, to activities and travel. Finally, activity-based models operate at the disaggregate level of single individuals and thus can realistically respond to sociodemographic or infrastructural changes at a very high level of detail, unachievable in trip-based models using average characteristics of arbitrarily created traffic analysis zones (TAZ). On the whole, the flexibility of activity-based modeling has made it possible to account for various dimensions of travel, e.g. interpersonal and intra-household interactions, social networks, time use or activity scheduling, resulting in a very powerful modeling instrument (Bhat and Koppelman, 1999).

Concurrent with the conceptual evolvement in the understanding of travel and with the switch from trip-oriented to activity-oriented approach, the mathematical apparatus available to researchers has undergone significant developments. The emergence of discrete choice modeling provided researchers with a versatile tool for reproducing travel behavior of individuals and operationalizing the activity-based approach at a high level of detail. These techniques are briefly described in section 2.4.

The most current state-of-the-art direction in research as well as in practice is to combine all the features mentioned above into one integrated model system that uses activities and daily schedules of individuals and households to derive tours and that models decisions with discrete choice methods and incorporates it all in a single (microsimulation) platform (Bowman and Ben-Akiva, 2001; Davidson et al., 2007; Miller et al., 2005). There is however still much to be done, especially in the days when the ICT technology blurs the distinction between travel and activity, flexible work arrangements allow for working from different places at different times and decisions are made under high uncertainty (Miller, 2020; Rasouli and Timmermans, 2014).

2.4 Discrete Choice Analysis

A distinctive feature of many decisions undertaken in travel and transport is that they are discrete. As opposed to continuous regression models answering the question of “how much”, the discrete choice models provide an answer to the question “which one” (Train, 2009). In other words, an individual chooses one specific alternative out of a finite set of alternatives. Examples could be the choice of groceries, mobile phone service providers, choice of university or number of cars in the household. In the transport context, typical discrete choices are the ones about transport mode (car/bus/train or private/public transport), trip destination (which shopping mall or restaurant) or about one of the possible routes leading to the destination.

Discrete Choice Analysis falls under a broad category of supervised machine learning techniques, which is currently a rapidly evolving area, constantly extended with new methods (Alpaydin, 2020). However, discrete choice itself is an already established modeling system and has been used in research since 1970s. The foundations of discrete choice analysis have been laid in mathematical psychology (Luce and Suppes, 1965) and consumer theory. Since then, the subject of discrete choice methods has been developing dynamically and expanding from econometrics and marketing to other areas like urban planning, transportation or policy making (Ben-Akiva and Lerman, 1985). The importance of discrete choice analysis has been acknowledged in 2000 by awarding Daniel McFadden *The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel*[1] for his contributions to discrete choice analysis. Currently, the most advanced research in discrete choice models is being conducted in the field of transportation.

The paramount assumption underlying the decision rules in discrete choice models of travel behavior is that the decision-makers always try to maximize the utility of their choices. This theory is called Random Utility Maximization (RUM) (Marschak, 1959; McFadden, 1977a). Outside the discrete choice framework also alternative mechanisms leading to a decision exist. These are not based on an optimality criterion but rather on heuristics and elimination rules.

2.4.1 *Random utility theory*

The random utility theory has been a fundamental concept underlying many econometrical models since 1960s as it possesses several convenient features. The RUM

[1] Which is often wrongly considered a Nobel Prize – according to NobelPrize.org (2020).

theory assumes the decision-maker behaves consistent with the concept of rational behavior, that is, he or she make consistent choices following logical rules that are in their best interests (Ben-Akiva and Lerman, 1985). At the same time, whilst the RUM theory assumes the decision-maker makes deterministic choice, the observer (analyst) is not capable of measuring the utilities perfectly and the model contains an error (is stochastic) (Anderson et al., 1992). So, the individual does choose the alternative with the highest utility but the utility is not known with absolute certainty and hence is random. Accordingly, the utility is comprised of the deterministic (observable) component V and random (unobservable) component ε denoted as follows:

$$U = V + \varepsilon \tag{2.1}$$

The deterministic part of the utility of is represented by a single objective function that reflects the attractiveness of the alternative. This function can take different forms but the linear-in-parameters additive formulation is the most common:

$$V_{in} = \beta^T x_{in} \tag{2.2}$$

where x_{in} is an explanatory variable (either attribute of the alternative i or characteristic of the decision-maker n) and β^T is a vector of coefficients.

To be able to solve the model and obtain the choice probabilities, an assumption about the distribution of the unknown error term is necessary. Different distributions lead to different choice models (described in the next section). A good example is the logit model for which the error term is assumed to be independently and identically Extreme Value distributed.

2.4.2 *Modeling approaches*

Up to now, many variations and flavors of the basic logit model have been developed, the most important of which are described below. Since the choice sets in transportation applications usually consist of more than two alternatives, the elementary binary models are not being considered in the thesis.

The Multinomial Logit Model (MNL) assumes that the random components of the utilities are independent, identically distributed and Gumbel distributed (Ben-Akiva and Lerman, 1985). An important property of MNL is the Independence from Irrelevant Alternatives (IIA), which means that the choice between any two alternatives cannot be affected by the existence of other alternatives. It has its consequences, which are well-documented (red/blue bus paradox) (McFadden, 1973).

The Nested Logit (NL) model allows to relax the IIA condition, which is the major shortcoming of the MNL model, and to model alternatives sharing some attributes within the so-called nests. For each nest a separate MNL model can be estimated, the inclusive value (logsum of estimated utilities) of the alternatives (lowest level) is then transferred to the utilities of the nests (upper level) and the model is estimated sequentially. This idea was first presented in the 1970s in works by Ben-Akiva (1973), McFadden (1977a) and McFadden (1981). Daly (1987) presented a convenient and efficient procedure of simultaneous estimation, which is implemented in most of modern software packages for discrete choice analysis.

The Cross-Nested Logit (CNL) belonging to the family of Generalized Extreme Value (GEV) models (McFadden, 1977a) was proposed by Vovsha (1997) as a generalization of the NL model. This flexible approach allows for correlations between alternatives within different nests as opposed to arbitrary set nest-wise similarities forced by the NL structure.

By combining different choice models, McFadden and Train (2000) proposed a new group of Mixed Models (MMNL) that allow to capture the taste heterogeneity among decision-makers and correlations between alternatives. Mixed Models can take very flexible functional forms and approximate any discrete choice model. However, they require to use the simulation methods for the estimation.

As for now, one of the most advanced development in the field of discrete choice are Hybrid Choice Models (HCM) (Ben-Akiva et al., 2002), which incorporate the effects of latent variables (e.g., attitudes, perceptions, social influences) into the discrete choice modeling framework. Hybrid choice models are currently being intensively researched in the transportation field (Abou-Zeid and Ben-Akiva, 2014; Vij and Walker, 2014, 2016).

Apart from the above mentioned, in the recent years a few alternative approaches have emerged that are based on different assumptions than the classic utility maximization principle. An example is the idea of Random Regret Minimization (RRM) rooted in the Regret Theory (Chorus, 2012).

2.4.3 *Discrete choice and tourist travel in large-scale transportation models*

It has been confirmed that the discrete choice models outstrip the gravity models in terms of accuracy, flexibility and robustness (Mishra et al., 2013), and that the activity-based models outperform the traditional four-step models and deliver more precise outcomes for the daily planning practice (Timmermans and Arentze, 2011). Accordingly, several implementations of discrete choice framework within the activity-based transportation models have been developed in the recent years (as mentioned in section 2.3). Besides the prominent European examples like the Swedish *SIMS* model (Algers et al., 1996), the *ALBATROSS* model for the Netherlands (Arentze et al., 2000) and the Belgian *FEATHERS* model (Bellemans et al., 2010), many implementations originate from the United States and Canada, for instance Portland (Bowman et al., 1999), Florida (Chow et al., 2005), Southern California (Bhat et al., 2013), Maryland (Maryland State Highway Administration, 2013), or Toronto and

Montreal (Miller et al., 2005; Yasmin et al., 2017). An example from Asia is Singapore, where discrete choice modeling has been applied for the workplace choice in the large-scale agent-based transportation model (Vitins et al., 2016).

Slowly, discrete choice models are being developed than can predict destination and mode choice for inter- and intrastate long-distance travel demand (both business and tourist/leisure), albeit they often suffer from problems related to data availability (Miller, 2004) or very coarse resolution (Rich and Mabit, 2012). There are several examples of successful implementations of such models in large scenarios, such as the Ohio statewide model (Erhardt et al., 2007), the model for the Canadian province of Ontario (Llorca et al., 2018) or the *Long-Distance Passenger Travel Demand Modeling Framework* (Outwater et al., 2015b; Outwater et al., 2015a) developed for the FHWA (US Federal Highway Administration). However, as far as the short-distance tourist travel at the destination is concerned, the author is not aware of any such implementations in large-scale transportation models.

If local tourist trips are modeled at all, it is done at the aggregate level, which has been criticized by Lew and McKercher (2006). The few examples of such models known to the author are: transportation model for the Austrian province of Salzburg (Hofer, 2015), transportation model of the *BVG Berliner Verkehrsbetriebe* (Berlin Transport Company) for Berlin in Germany (Franke, 2017) or the transportation model for the Swiss canton of Bern (Vrtic et al., 2010). A conceptual framework that integrates long- and short-haul travel demand into a single microscopic *MATSim* model (Horni et al., 2016) and allows for visitors' trips at the destination was recently proposed by Llorca et al. (2019) for the Munich metropolitan area in Germany. This is a promising design, however, not operational yet.

An integration of discrete choice models with an agent-based modeling framework appears currently to be the state-of-the-art approach amongst transport modeling researchers. In the US, implementations were done e.g. in Sacramento, where an activity-based disaggregate econometric model (*DaySim*) was developed to simulate residents' activity and travel schedules (Bradley et al., 2010). In Europe, an example is known from Copenhagen, where the same software platform was used to develop the activity-based discrete choice model system called *COMPAS* (Vuk et al., 2016). Both system built on the software platform *DaySim* and the work of Bowman (1998). Also Hörl et al. (2019) extended the *MATSim* microsimulation framework with a tour-based discrete mode choice model.

Also, tourism researchers highlight the potential of agent-based models in their field, but also stress their complexity and challenging communication of simulation results. A summary of latest applications of agent-based models within the tourism field has been done by Nicholls et al. (2016). They argue that ABM are better capable of accounting for the erratic character, instability and unstructured dynamics of tourism than the existing simplistic linear- and equilibrium-oriented modeling techniques. Applications to the alpine areas include for example models of winter tourism demand in the changing climate (snow) conditions (Balbi et al., 2013).

2.5 DESTINATION CHOICE

2.5.1 *Destination choice in daily travel*

Destination choice belongs to the set of three fundamental choice dimensions: destination, mode and route choice, which are probably one of the most researched topics in travel behavior science.

Daily travel is largely shaped by trips to primary activities, that is, work and education facilities, which are stable locations and do not change at short notice. They are analyzed over long periods, together with other long-term accompanying decisions like residential location choice, which has attracted considerable attention in the recent years (Pagliara et al., 2010b; Waddell et al., 2007). This is often combined with spatial aspects of mobility and interrelationships with land-use (Pozsgay and Bhat, 2001), finally resulting in complex land-use-transport interaction (LUTI) models (Acheampong and Silva, 2013; Katoshevski et al., 2013).

Destination choice by itself finds more direct application in modeling decisions concerning secondary activities i.e. shopping (Kristoffersson et al., 2018; Miller and O'Kelly, 1983) or recreational activities widely studied in environmental economics and nonmarket valuation (Champ et al., 2017; Mäler and Vincent, 2005; Train, 1998). Typically, these choices are driven by travel time and cost of travel to the destination and a set of attributes reflecting the attractiveness of the destination measured by e.g. retail area, entrance fee or number of opportunities.

As far as the non-work trips with many alternatives are concerned, the choice set formation process gains in significance. Usually in discrete choice models, it is assumed that the choice set is given and deterministically predictable (Ben-Akiva and Boccara, 1995). This assumption is true as long as the number of alternatives within the choice set is relatively small. However, unlike in mode choice, where the choice set is finite, small (usually not more than a few transport modes are available) and easy to determine (available modes for each individual are usually known), the set of available destinations is usually large and too complex to implement in an operational analytical model. Therefore, plausible choice sets of reasonable size are created for destination choice models by sampling the elemental destinations based on spatial similarities between them and aggregating them to traffic analysis zones (Kim and Lee, 2017), possibly accounting also for the dominance and perception attributes (Cascetta and Papola, 2009; Pagliara et al., 2010a). In other words, destination choice models can work at the level of regions, cities, traffic analysis zones or categories of destinations (e.g. restaurant, beach, school) but not precise locations.

The further work follows the two-stage modeling approach by Manski (1977) – having formed the choice set, a choice conditional on this generated choice set is made (Zheng and Guo, 2008).

An alternative approach is proposed by Horowitz and Louviere (1995) or Swait (2001), who argue that the choice set is rather another expression of preferences than a separate pre-choice step.

2.5.2 *Destination choice on vacation*

The choice of the vacation destination has always been of interest to researchers from tourism marketing and tourism management (Decrop, 2006; Sirakaya-Turk and Woodside, 2005). Learning and dissecting these decisions is crucial for tourism-dependent destinations to promote their assets, attract more guests, and as a result, generate more revenue.

Yet, the focus of these studies is long-distance travel and tourism demand, not necessarily tourist local mobility. According to Bieger and Laesser (2013), who analyzed the Swiss leisure market, the leisure mobility consists of three major components:

- Inter-destination mobility – travelling from home to a destination
- Intra-destination mobility – meaning trips made in order to perform activities within the destination area
- Leisure mobility at home – induced by sport or cultural activities at home

While the inter-destination travel patterns have been widely investigated in theoretical works (Rugg, 1973; Sirakaya et al., 1996; Woodside and Lysonski, 1989) and numerous case studies (Armstrong and Mok, 1995; Eymann and Ronning, 1997; LaMondia et al., 2010; van Nostrand et al., 2013), the research on the intra-destination movements, i.e. travel within the destination, is relatively limited. As McKercher and Zoltan (2014) argue, the reasons for that are threefold and pertain to the low accuracy of the geolocation data, insufficient resolution of travel-activity data collected from tourists, and lack of a theoretical framework. Only recently, there has been more attention paid to local travel behavior thanks to the use of GPS (Global Positioning System) traces from mobile devices (Shoval et al., 2014; Thimm and Seepold, 2016) and GIS (Geographic Information Systems) techniques (Lau and McKercher, 2006).

However, many of the existing studies are descriptive and focus on visualizing geographical and temporal dimensions of tourist movements and drawing conclusions on itinerary types and frequency of visits (McKercher et al., 2019; Wu and Carson, 2008). Lew and McKercher (2006), in the probably first theoretical work on tourist intra-destination travel, provide an extensive breakdown of factors[2] impacting intra-destination movements of tourists, ranging from tourist time budget to personal characteristics to place knowledge.

Works utilizing mathematical models are much less prevalent so far. However, the topic is slowly acquiring attention of researchers who start applying discrete choice models to quantify travel behavior of tourists and embed them into models. A relatively large study on tourist local movement (over 2000 face-to-face interviews in 29 tourism destinations) was conducted in three regions in Japan by Wu et al. (2011). Applying a latent class modeling framework, they revealed that, except travel time and distance, attractiveness of a destination (measured by number of attractions and number of visitors) is the main factor influencing destination choice, whereas sociodemographic variables (gender, age, marital status) are decisive for the travel party choice. Researchers have also started exploiting GPS data for model building. For instance, Hardy and Aryal (2020) employed neural networks to analyze GPS tracks of tourist movements in a national park in Australia. Based on survey data and GPS tracks, Li et al. (2019) built models of destination choice of tourist visitors to Gulangyu region in China. They observed that tourists who purchased a joint ticket that includes several attractions tend to travel to zones where these attractions are located. Tourists also avoid areas where they have already been to and areas with poor signage. As far as the intra-destination mobility within the Alpine regions is concerned, Zoltan and McKercher (2014) analyzed visitors' behavior in the Swiss canton of Ticino based on destination card consumption. Their findings reveal that tourist movement patterns are defined largely by the spatial dimension rather than through activity-based segmentation. Nevertheless, none of the papers mentioned differentiates between movements that are part of tourist activities (e.g. making a hiking trip) and movements to activities (e.g. driving to a zoo), which are of greater importance for transport planning since they generate road traffic and crowdedness in public transportation vehicles.

Compared to daily travel, the choice set of available destinations during a vacation stay can be a more complex issue. Unlike local residents, visitors do not have equal knowledge about the area and may or may not be aware of some alternatives (cf. the choice set formation process by Decrop (2010)) depending on whether they have already been to the area or not or whether they have informed themselves in advance about available options. Moreover, they usually have no fixed points regulating their mobility patterns (except the accommodation), while residents are constrained to the location where they work, or school where they drop their kids etc., which imposes limitations on their choice set. Due to the short nature of the stay, the visitors' choice set can be dynamic and change quickly over time (Crompton, 1992), making it even more difficult to recognize it in the models. It can be also be

[2] Many of these factors are used in the design of the survey instrument in section 3.3.

driven by habits, attachments or routine (Björk and Jansson, 2008), which contradicts the assumption of tourist's absolute rationality and optimization character of the decision process. For instance, the returning tourists might not consider new alternatives on-site (e.g., a restaurant) since they are used to the ones that they have been visiting for the last few years.

Besides tourism, there have also been applications of choice models to leisure trips of domestic populations. For instance, Simma et al. (2002) analyze the destination choice for leisure activities of Swiss residents within Switzerland. Bhat et al. (2016) apply the Multiple Discrete-Continuous Probit Model (MDCP) to study the leisure destination choice of domestic tourists in New Zealand. To the author's knowledge, by far the most comprehensive study dealing with leisure and tourism destination choice specifically in alpine regions was conducted for Switzerland by Tschopp et al. (2010). In their analyses of various tourism destinations, they utilize the Multinomial Logit and Nested Logit models. Although the objectives and spatial area of their work are similar to the ones defined in this thesis, they concentrate merely on the arrival/departure trips to/from the final destinations for both leisure and tourism purposes. Moreover, their destination choice model for holiday trips is limited only to the winter season (skiing activities) and to the trips of Swiss citizens. An example of a more locally and less state-wide focused study is the one by LaMondia and Bhat (2013), who applied the Multivariate Binary Probit Model to study the visitors' leisure travel behavior in Northwest Canada. Scarpa et al. (2008) analyzed the destination choice of members of the *Italian Alpine Club (CAI)* for one-day outdoor trips in the Alps and discovered that, except travel cost, also difficulty of hiking trails and number of mountain huts influence the decisions, while Scarpa and Thiene (2004) concentrated only on climbers and mountaineers and found travel cost, severity of the environment and number of alpine shelters to be influential factors.

2.6 MODE CHOICE

2.6.1 *Mode choice in daily travel*

Mode choice is the second of the three elementary choices in transportation. Literature on mode choice is vast and addresses the topic from a number of perspectives such as modeling methods or applications in cost-benefit analyses.

Thanks to a small number of alternatives in the choice set and conceptual simplicity, transport mode choice is a convenient field to develop and test new model types ranging from the simple Multinomial Logit to Nested, Cross-Nested, Mixed models with random coefficients and many others (cf. section 2.4). An interesting recent development are Discrete-Continuous models (Bhat, 2005) making it possible not only to model what alternative is chosen, but also how much the alternative is used given a certain money or time budget (cf. section 6.5). Finally, most current studies employ Latent Class and Hybrid models. These models often reveal that the mode choice is strongly affected by personal attitudes (Paulssen et al., 2014). It is therefore advisable to measure the psychological and sociological constructs in the survey (e.g., using the Likert-scale questions) and include them in the model through segmentations, latent classes and latent variables (Leong and Hensher, 2012).

In principle, the two basic factors always present in mode choice models are travel time and travel cost. They are usually very effective in explaining people's decisions even if not accompanied by other variables (Frank et al., 2007; Limtanakool et al., 2006). Other attributes are more mode-specific and pertain to level of service of a given mode like waiting time, delay and frequency for transit, but may also include attributes representing perceived comfort or safety (Daziano and Rizzi, 2015).

The literature dedicated to mode choice is split into two branches – one operating with revealed preference (RP) data and second one using stated preference (SP) data (Wardman, 1988). RP data provide information on what consumers actually do, which in transportation means that researchers observe factual choices of transport system users and collect data on their real market behavior. These data are considered very reliable in depicting current market equilibrium and personal constraints of decision-makers but are limited only to the existing alternatives and are often expensive to collect (Louviere et al., 2000). SP data on the other hand provide information on what consumers say they will do in hypothetical choice situations. Unlike RP data, SP data can inform about consumer preferences for new services or products with new features, however, at the cost of reliability and validity of responses. In recent years, also joint models using both RP and SP data have emerged, which attempt to combine the advantages of both data types (Cherchi and Ortúzar, 2002; Frejinger et al., 2006; Rashedi et al., 2017).

Substantial part of the research is policy-driven and delivers information on choice elasticities or Value of Travel Time Savings (VTTS) for various transport modes, which facilitates project appraisal and evaluation of policy and infrastructure measures (Graham and Glaister, 2004). This is where the mode choice models utilizing RP data are most useful since they reflect people's real choices in contrast to imaginable choices in the SP data, which still need calibration with RP data if are to be used for forecasting (Hensher and Li, 2010).

However, stated preference data prove more applicable to the experimental research purposes. The SP-based studies explore future mobility forms (Haboucha et al., 2017; Krueger et al., 2016; Peeta et al., 2008) or estimate the demand for yet non-existent or emerging modes (e.g. car-sharing, car-pooling, mobility-as-a-service) (Antoniou et al., 2019; Becker and Axhausen, 2017; Ciari and Axhausen, 2012; Ho et al., 2018; Wicki et al., 2019; Zhou and Kockelman, 2011). This is possible thanks to advance in methodologies, allowing efficient design of choice experiments, surveying larger populations and simulations for scenario predictions (Rose and Bliemer, 2009).

Mode choice models are also widely used for evaluation of transit pricing strategies (Sharaby and Shiftan, 2012) or introducing tolls and congestion pricing (Basso and Jara-Díaz, 2012; Washbrook et al., 2006).

2.6.2 *Mode choice on vacation*

Although the transport mode choice is relatively well represented in tourism literature, studies using discrete choice methods are very scarce. Much research with discrete choice has been done in the fields of tourism demand (Morley, 2012), significantly less in long-haul tourism destination choice (LaMondia et al., 2010) and very little in mode choice modeling (Thrane, 2015).

The transport mode choice is strongly dependent on the destination choice and hence they should be considered and modeled jointly, which has been repeatedly demanded in the literature (LaMondia et al., 2010; Masiero and Zoltan, 2013). What is more, the decision about the transport mode for vacation is not only driven by factors related to journey to the destination itself, but also factors concerning the on-site mobility. Visitors decide to travel to alpine regions by car for fear of insufficient mobility services at their destination and inflexibility of public transportation (Bursa and Mailer, 2018). In such a case, private car provides a high degree of independence and usually ensures the most effective utilization of time. Additionally, not every single tourist spot in rural regions is accessible by public transport, which discourages the exploration-focused tourists from relying only on public transport services on-site (Le-Klähn and Hall, 2013). Luggage transport is another factor deterring tourists from choosing a transport mode alternative to car (Böhler et al., 2006).

So, the decision about the transport mode choice for local trips within the vacation region depends strongly on the initial decision about the transport mode for long-distance trip to the region. However, there are also external conditions, e.g., the influence of weather (Becken and Wilson, 2013; Järv et al., 2007).

An extensive review of literature examining factors determining the mode choice in general is provided by De Witte et al. (2013), while van Middelkoop et al. (2016) and Thrane (2015) focus on mode choice for long-haul tourist trips. As far as tourists are concerned, a broad description of factors affecting their mode choice at the destinations is included in Le-Klähn and Hall (2013). They found that lack of information and personal preferences are the most common explanations for not using transit services in rural tourism sites. In urban areas on the other hand, tourists value the ease of use, efficiency and personal safety when choosing public transport and parking facilities when driving private car, as Thompson and Schofield

(2007) point out. Dickinson and Robbins (2008) also narrowed their research to rural destinations. Apart from identifying general convenience and need to carry equipment as main reasons for choosing private car, they also highlight a strong car attachment of some visitors who do not even consider alternatives no matter their availability, price or other attributes. Gutiérrez and Miravet (2016) analyzed the determinants of public transport use among tourists in a coastal region of Spain. However, their research is based only on dichotomous statements of visitors whether they used public transportation during their stay and no data on individual trips were collected. Moreover, their models ignore the attributes of the alternatives available at the destination. Gross and Grimm, in their review paper (2018), synthesized outcomes of many existing studies and found that above all the sociodemographic factors, transport mode chosen for trip to the destination, travel duration and expenses as well as type of vacation (organized or individual travel) play a role in transport mode choice at the destination.

Within the alpine setting, specific factors affecting the transport mode choice for travel to the destination and the mobility at the destination have been investigated by Seltenhammer et al. (2018) and Bieger and Laesser (2013), who revealed that the family/group size and transport of sport luggage (e.g., skiing equipment, mountain bike) is dominant in the decision process, particularly in the winter season. Masiero and Zoltan (2013) applied a Probit model for the mode choice of tourists in the Swiss canton of Ticino and observed, among other things, that domestic tourists and returning visitors (i.e. tourists who have been to the region before) are more likely to use public transportation, whereas older tourists and male tourists are more inclined to use private cars. The work by Pettebone et al. (2011) provides insights into mode choice at the destination from an American perspective. They found that visitors to the Rocky Mountain National Park are willing to switch from private car to shuttle bus if it enhances their chances of being in the park with fewer other people.

A potential effect of length of stay and (associated with it) satisfaction and well-being on mode choice is discussed in section 4.3.4 and footnote 10.

Nevertheless, none of the existing studies analyzed the importance of travel time and travel cost for the transport mode choice of tourists traveling within the destination in a quantitative way, which is a distinct gap in the research, making it impossible to apply a monetary measure to improvements or deteriorations in attributes of the available modes (e.g. a higher transit frequency or a longer travel time).

2.7 ROUTE CHOICE

Route choice is the third component of a minimum set of decisions that have to be made when planning a trip. It is built of two major elements: the generation of a choice set of alternative routes and the choice of a route from this choice set. Unlike the mode choice, where the set of alternatives is small and easily identifiable, and unlike the destination choice, where the set of alternatives is finite (though often large) and possible to enumerate, the set of alternatives in route choice can be very large and difficult to identify since the alternative routes share common links and overlap to some extent (Bovy, 2009). Information about the network as well as the manner of acquiring this information decides about the size of the choice set of alternatives that the decision-maker is aware of. Out of those, the decision maker might take into account only the selected ones, depending on specific preferences and trip constraints, which constitutes the consideration set. Correct replication of this process is a difficult task. Therefore much emphasis has been put in the last decades on developing realistic choice set generation methods (Prato, 2009).

Nevertheless, almost all studies on the route choice behavior concentrate on dense urban networks. This is understandable because these are the most challenging environments – urban networks are large, multimodal and the route choice plays a significant role in traffic management and the resulting level of service of network elements. The research on route choice in non-urban areas is very scarce. Tourism researchers address the topic from the perspective of destination management and roadside tourism facilities (Denstadli and Jacobsen, 2011), which is unusable for transport modeling purposes. However, they provide some interesting observations about how tourists differ in their route choice behavior from local residents, which should be considered when developing models of tourist route choice.

Lew and McKercher (2006) have raised the issue of tourists not possessing full knowledge about the transport system in the region they visit. They also highlight the different character of transport networks in mountainous regions from the ones in flat or urban areas, which makes the whole decision process about routing unlike to what is common in urban areas (shortest route, fastest route):

> *"A destination's topography will also influence the siting of facilities and the form of the transport network, which in turn, will affect tourist flows. Movements in mountainous destinations intersected by challenging passes will be different than in flat destinations. Linear, point-to-point touring on clearly defined routes is more likely to occur in mountainous or island areas, while the potential exists for more dispersed and alternative routing patterns in destinations located in flatlands." (Lew and McKercher, 2006)*

They also mention the factor of picturesqueness of routes that often prevails over travel time or distance when choosing a route to the destination or moving around within the destination. This is confirmed by Jacobsen (1996) who discovered that the views and landscape experience are cherished by motor tourists surveyed in Norway. The component of visual attractiveness of a route plays a particularly important role on optional (i.e. non-work) trips, which was already confirmed by Ben-Akiva et al. (1984), who found that the disutility of travel time on non-scenic roads is about five times the disutility of travel time on scenic roads. Problematic is however how to define picturesqueness and how to quantify the scenic attributes of a route. Alivand et al. (2015) developed a very promising approach capable of computing scenery-related attributes ranging from road curviness to the viewshed from the road elements using data from different sources and providers e.g. volunteered geographic information (VGI), digital terrain model (DTM), *TomTom*, *Panoramio* geotagged photos, *Google Earth*, census data etc. They found that an increased presence of water bodies, mountains, forests and parks along a route positively contributes to the probability of choosing it as a scenic route, whilst urban areas along the route decrease this probability.

The common use of the built-in and external GPS navigation devices among tourists should not be neglected. In the context of car use, it is supposed to result in tourists sometimes having even better knowledge about traffic conditions than local residents, who rely rather on their habits, common sense and heuristics. This, however, does not (yet) apply to the knowledge about parking facilities at the tourist attractions.

Yet, routing decisions are preliminary not going to be considered in the thesis as the alpine network systems provide limited routing alternatives and this topic is currently of secondary importance. It is however scheduled as a future research idea, especially the valuation of the visual component of the route choice is interesting (see Section 6.4).

2.8 Impact of weather

Typical activities performed by tourists in mountain regions, e.g. hiking, climbing, cycling or skiing, are obviously weather-dependent. One can argue that if the participation in activities is weather-dependent then the choice of transport mode used to reach the locations where these activities are practiced may be affected by weather too. It is therefore interesting to examine how and to what extent tourists at the destination locations adapt their travel-activity patterns to unfavorable weather conditions and whether they react in the same way as they do when they are at home. This section provides an overview of what is already known in terms of weather and climate effects on various facets of transportation and tourism.

In response to an increase in unexpected and severe weather events in the recent decades, scientists started exploring their influence on transport more intensively. Except a great deal of research on extreme weather, landslides, floods, unexpected snow and heat, all posing a danger to transport networks and causing disruptions in transit systems, there has also been some interest in weather influence at the level of individuals and their behavioral reaction to, not necessarily extreme weather, but above all to normal weather variability on a daily basis (a broad review of weather effects on all facets of transport can be found in Liu et al. (2017) or Böcker et al. (2013)).

There is abundant evidence that precipitation correlates positively with congestion and accident frequency (Andrey et al., 2003; Golob and Recker, 2003). It also negatively affects the performance of transportation networks and traffic flow and thus also travel time and travel time reliability (Maze et al., 2006), yielding larger effects of snowfall than of rainfall (Hranac et al., 2006). But as Koetse and Rietveld (2009) conclude in their review paper, the average effects of weather on traffic volume, daily travel and commute patterns are of low magnitude and compensate each other in a long-term (more leisure trips thanks to higher temperatures; less leisure trips due to longer heavy rains). There is however more clear evidence at the level of specific transport modes and instantaneous response of travelers to adverse weather. In particular, the use frequency of active modes – cycling and walking – decreases significantly in the presence of rain, very low or very high temperatures and strong wind (Sabir, 2011; Saneinejad et al., 2012). In the case of cycling, the effect is remarkably large for leisure trips, while bicycle commuters are more weather resistant (Heinen et al., 2010; Liu et al., 2015). Compared to cycling, walking starts being weather-sensitive in case of a very large temperature drop or very intensive rain. Research on weather effects on choice of private cars and public transportation provides weaker outcomes than for active modes. In urban environments, adverse weather interacts strongly with other attributes like traffic congestion, transit crowdedness and punctuality and the effects differ between cities, days of the week and population segments (Anta et al., 2016). In general, however, there is a distinct shift from walking and cycling to driving and transit in case of rain or snow (Sabir, 2011).

The influence of weather on tourism cannot be neglected since the whole industry relies to a great extent on “good weather” (Day et al., 2013). Heavy rains, heat waves and frequent storms of increasing severity can negatively affect local tourism markets. Also mountain regions have to face challenges and risks induced by climate change such as increasing snow uncertainty in winter and the resulting decrease in demand (Elsasser and Bürki, 2002; Gössling and Hall, 2006; Koenig and Abegg, 1997) or extended summer seasons resulting in intensive traffic on Alpine roads and mountain passes (Cavallaro et al., 2017). However, the evidence on if and how tourists’ weather experiences influence their behavior is complex, ambiguous and segment- and region-dependent (Gössling et al., 2012). Whilst generally weather is classified as one of the most powerful destination attributes and tourism motivators (Kozak, 2002), it must not always be decisive. As far as the planning stage is concerned, according to Pröbstl-Haider et al. (2015), tourists, when choosing a summer destination in the Alps, may not perceive weather as a determinative decision component since other factors (e.g. recreation attributes) often play a more important role. In terms of the effect during the stay, both Scott et al. (2008) and Steiger et al. (2016) found the absence of rain to be particularly important for visitors to mountain areas and their overall satisfaction, with a caveat that there are large differences between age groups, nationalities or first-time and returning tourists. However, satisfaction levels might not necessarily be reflected in the real behavior and the nature of the visit as well as the attraction mix must be considered. McKercher et al. (2014) analyzed the GPS tracks of visitors to Hong Kong and found that urban tourists are rather indifferent to weather, in particular if they are staying only for a short period or on a tight budget. A similar resilience to weather, increasing with the length of stay, was found among campers in Canada (Hewer et al., 2017). Also in the non-urban environment – as Becken and Wilson (2013) argue in their case study of New Zealand – tourists might have a great dose of understanding and acceptance to unfavorable weather, in particular if they are aware of and prepared for the unstable and variable weather on the islands of New Zealand (which is also the case of the Alps in Europe). They are not looking for the most optimal choice but rather proceed with the plan unless some threshold is exceeded and the weather turns very unappealing. However, whether the same holds in tourists' short-term transport mode choices or whether the effect of precipitation and temperature on choosing active transport modes is of the same magnitude as known from studies on daily mobility remains unexplored since there is so far no study concentrating on the influence of weather conditions on the on-site travel behavior at tourist destinations.

2.9 JOINT DECISIONS

It has been a standard approach in travel behavior modeling for many decades to posit an individual to be the representative agent in decision-making. However, the decisions about both solo and shared activities performed by group members are strongly influenced by other household or group members. An urgent attention to incorporate these interpersonal interactions explicitly in the models has been called by many scientists in the recent years, which finally resulted in special issues of *Transportation* (Bhat and Pendyala, 2005) and *Transportation Research Part B: Methodological* (Timmermans and Zhang, 2009) devoted solely to this topic. A broad literature review and a summary of most recent developments along with suggestions for future research directions in the field of joint decisions can be found in Ho and Mulley (2015). The importance of deepening the knowledge in this field in the context of travel behavior has been highlighted by Brewer and Hensher (2000) who stated that:

> *"Indeed the interdependencies between individuals in a household and even between individuals in a particular peer structure are examples of the potential failure of the interdependency imposed on nearly all discrete choice models in transportation [...]" (Brewer and Hensher, 2000)*

The term *joint decisions* in travel behavior is a broad concept. At one level, it covers the aspects of joint participation in activities, which is analyzed based on the data from travel-activity diaries (Ho and Mulley, 2015). At another level, it is about the structure of the joint decision-making process and interactions occurring during this process, which is usually studied within the setting of stated choice experiments (Ho and Mulley, 2015).

As far as the latter is concerned, researchers from many disciplines have focused on how the individual preferences affect the final decision of the group. In their extensive work, Corfman and Gupta (1993) provide a breakdown of theories and mathematical models dealing with group choice in various contexts (e.g., social psychology, marketing, game theory).

According to Ho and Mulley (2015) one could classify the surveying techniques into three categories:

- *Household Activity Travel Simulator (HATS)* proposed by Jones (1979a) employs a group analysis of one-day activity pattern and an evaluation of a modified activity pattern.
- *Hierarchical Information Integration (HII)* developed by Louviere (1984) and extended by Molin et al. (1999), where the group members categorize and integrate the attributes of alternatives into smaller constructs.
- *Interactive Agency Choice Experiment (IACE)* designed by Brewer and Hensher (2000), which consists in a sequential feedback and revisions between the agents making a choice.

However, as mentioned by Aribarg et al. (2010), the problem most often raised in the analysis of joint choices is the difficulty of data collection at the group level. Also Hensher et al. (2008) confirm that by saying:

"Despite the behavioral appeal of the IACE method, there has been very little ongoing effort to progress the method, although a great deal of interest in it. We suspect this is largely attributable to the cost of collecting such data (including the logistics challenge of source multiple agents who are willing to cooperate), as well as to the complexity of designing a survey instrument to capture the required information." (Hensher et al., 2008)

All three presented approaches require questioning the whole group at the same moment and thus present high organizational difficulties. However, an alternative methodology invented initially by Puckett and Hensher (2006) for freight transport modeling appears to be a trade-off solution in terms of the organizational costs and the information obtained. Their approach, referred to as *Minimum Information Group Inference (MIGI)*, provides information on the preference boundaries of each group member based on individual choice tasks simulating the negotiation process. The MIGI has been recently successfully applied to intra-household decision modeling by Beck and Rose (2017), who confirmed the correctness of this approach when the three previously mentioned group experiment methods are not feasible.

As far as the joint participation in activities and trips is concerned, the researchers concentrate above all on time allocation as well as constraints and attributes of the household that are affecting the final activity schedules. One of the first major contributions in this field was the one from Scott and Kanaroglou (2002), who found that including interactions between household heads in the models significantly increases model fit. Gliebe and Koppelman (2002) have analyzed joint activity patterns within households in a two decision maker case and proposed a new Parallel Choice Constrained Logit (PCCL) model (Gliebe and Koppelman, 2005). Zhang et al. (2005) have modeled the task and time allocation within households. Furthermore, the household decision-making (HDM) strategies have been of interest to Zhang et al. (2009), who modeled them using latent classes. Bradley and Vovsha (2005) recapitulate the research on joint choice of activity patterns:

> *"...independent individual models tend to produce unrealistic entire-household patterns (like cases where a preschool child stays at home while all adults go to work) while the model with intra-household interactions not only guarantees replication of the average observed individual patterns but also their proper linkage within each household." (Bradley and Vovsha, 2005)*

While the early studies were limited to the decisions within households, the more recent models reach beyond that and consider also wider social networks consisting of friends and further relatives (Arentze and Timmermans, 2008; Kowald and Axhausen, 2015; Páez et al., 2008). Arentze (2015) has analyzed the decision-making mechanisms in social networks with a focus on the negotiation processes.

The studies mentioned above concentrate on the interpersonal interactions between decision-makers and the effects on their daily tours performed at home locations (for various activities). However, it should be investigated how these interactions shape the decisions of groups spending time together on vacations away from home. It is supposed that travel decisions of groups staying together at the destination are shaped by interpersonal interactions, local setting and types of performed activities, which can be all different from those in daily life at home (characterized by e.g. dominance of full-time workers). Therefore, to account for joint decisions in leisure travel behavior during vacation is at least as important as in daily travel behavior, because families, groups of friends and groups traveling with tour operators comprise the majority of tourists visiting the Alps.

2.10 Undirected travel

Mokhtarian and Salomon (2001) and Mokhtarian et al. (2001) discuss the phenomenon of undirected travel as a *"case in which travel is not a byproduct of the activity but itself constitutes the activity"*. This concept might be very applicable in the tourism context when people opt for car to be able to drive the scenic roads and stop for taking photos or choose train to observe nature from its panoramic windows. That is, they treat the ride itself as part of the vacation experience, not just the unpleasant necessity of relocation from A to B, which is a valid concept in daily commute. Also Singleton (2020) investigated potential reasons for positive utility of travel and found well-being, positive travel experience and to some extent the possibility of travel-based multitasking be associated with a choice of commute mode. So far, there are no quantitative studies on these concepts in terms of tourist travel behavior. They would be however of potentially great value in terms of mode and route choice.

3 The survey work

Researchers conducting studies on daily travel behavior usually have good-quality datasets at their disposal (see for example Aschauer et al. (2018) and Sammer et al. (2011) for Austria, Axhausen et al. (2000) for Germany, Bundesamt für Statistik (BFS) (2017) for Switzerland, NatCen Social Research (2019) for the UK and Federal Highway Administration (2017) for the US). These studies concern local populations and serve as a basis for creating policies and procedures at the governmental or national level. Consequently, ministries and national agencies provide funding to ensure sufficient sample size and hence more representative results of higher quality.

This is not the case in tourist travel, which, despite being responsible for a substantial part of transport problems in countries with a developed tourism-industry (e.g. Austria, Italy, Switzerland), does not receive enough (monetary) attention from the policy-makers.

This study proposes a trade-off and, while relying on a limited budget, attempts to achieve an acceptable sample size. By asking the respondents to report on two days of their stay, fewer people must be questioned, which in the case of tourists, is very time- and money-consuming process. At the same time, by limiting the length of the diary to only two days, the response burden remains at a moderate level.

3.1 Travel pattern of a tourist

Deriving from the theory of activity-based modeling outlined in section 2.3, the conceptual representation of a full travel pattern of a tourist is given in Figure 3.1. In its simplest form (i.e. no "road-trip" with multiple destinations), it is comprised of in particular:

- A long-distance trip from home to the destination.
- At least one-night-long stay at the destination, during which activities are performed and tours are made.
- A long-distance return trip home.

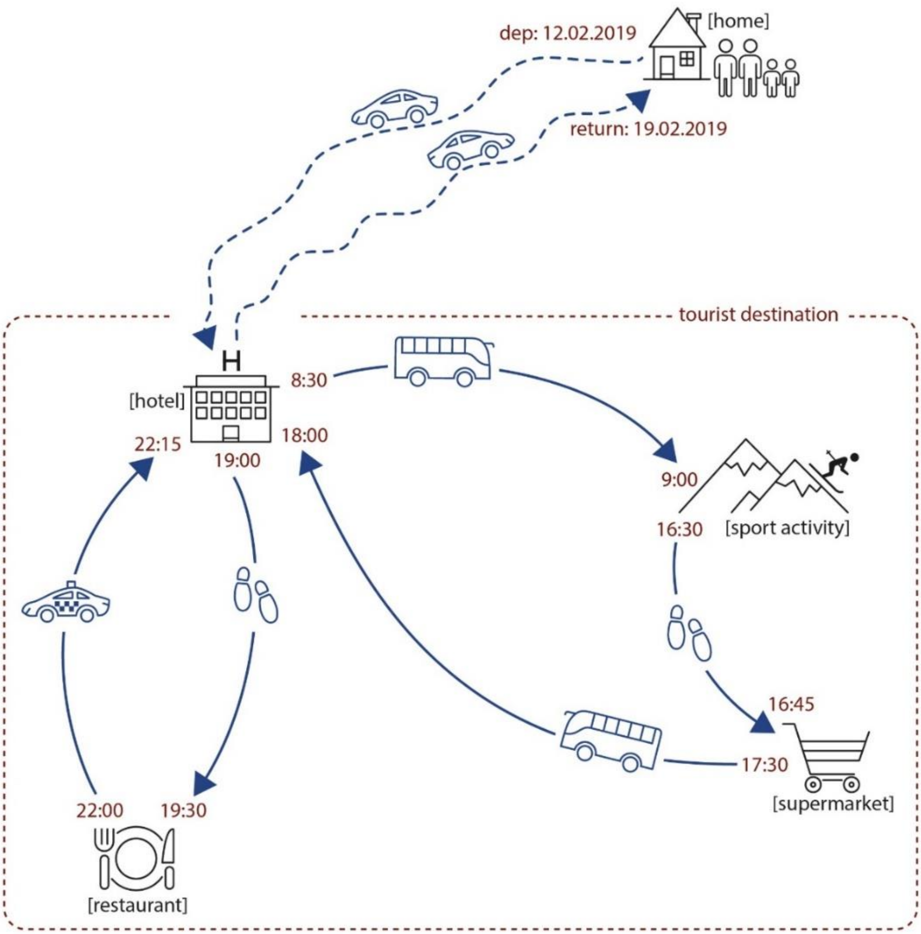


Figure 3.1 Example of a tourist daily schedule with long-distance trips to a destination and back home

The survey work operates on a selection of terms proposed by Axhausen (2008): trip, tour and activity. Since the data reported in travel diaries are defined at the precision level of trips, a trip is the smallest analytical unit used in the mode choice model. Stages were not distinguished in the data set.

The methodological framework assumed in the thesis relies on modeling tourist mode choice at the level of trips, which deviates from the concept illustrated in Figure 3.1. Although it is a considerable simplification, it is reasonable trade-off ensuring the feasibility of the thesis under limited time and human resources. Aggregating trips to tours and tours to schedules imposes higher data requirements (larger sample, higher quality control, comprehensive imputation methodology for missing trips) because no trips can be missing to compose a complete tour and because no tours can be missing to form a full daily schedule. Tours are defined as a chain of trips, which start and end at the accommodation. The mode variable for tours is created by aggregating the mode variable from the trip level using one the many possible arbitrary heuristics (Axhausen, 2008; Miller et al., 2005; Shiftan et al., 2003). It can either be the mode that was used for the longest distance or for the longest time during the tour or the mode that dictates the character of the movement (air plane being higher in the hierarchy than walking; feeder modes like walking being below transit, etc.). Even though the choice of the aggregation rule is crucial for the modeling results, it is often not reported by researchers (O'Fallon and Sullivan, 2005). Aggregation of trips to tours and tours to day plans lies outside the scope of the thesis.

3.2 SURVEY DESIGN

3.2.1 *Survey location*

The issue of tourist transport externalities in the Tyrol, Austria, was raised by Langer (1995) almost three decades ago and has only intensified since then. In response to his call for more scientific studies on the subject and better data collection methods, this research is based on data collected from visitors to three tourist regions (Figure 3.2 and Figure 3.3) in the province of Tyrol in Austria: the Ötztal, the Zillertal and the Hohe Salve, during the summer and winter seasons of 2018 and 2019. These are highly-frequented alpine destinations ranking top in the Alps (BAK Economics AG, 2019) in terms of overnight stays and tourist infrastructure (Table 3.1).

Table 3.1 Characteristics of the survey regions[a]

	Ötztal	Zillertal	Hohe Salve
Area [km^2]	881	1098	217
Residents	18,277	37,140	15,931
Accommodations	309	467	45
Beds[b]	27,865	51,457	5,826
Ski resorts	6	4	1
Ski slopes length [km]	326	535	258
Arrivals – Summer 2019	358,079	666,054	76,766
Overnights – Summer 2019	1,248,163	2,830,628	296,530
Arrivals – Winter 2018/19	618,600	882,405	66,459
Overnights – Winter 2018/19	2,903,563	4,584,125	312,437

[a]According to Landesstatistik Tirol
[b]Data from winter 2017/18.

Figure 3.2 Location of the study area on the map of Austria and its neighboring countries. Red-colored rectangle is presented in detail in Figure 3.3

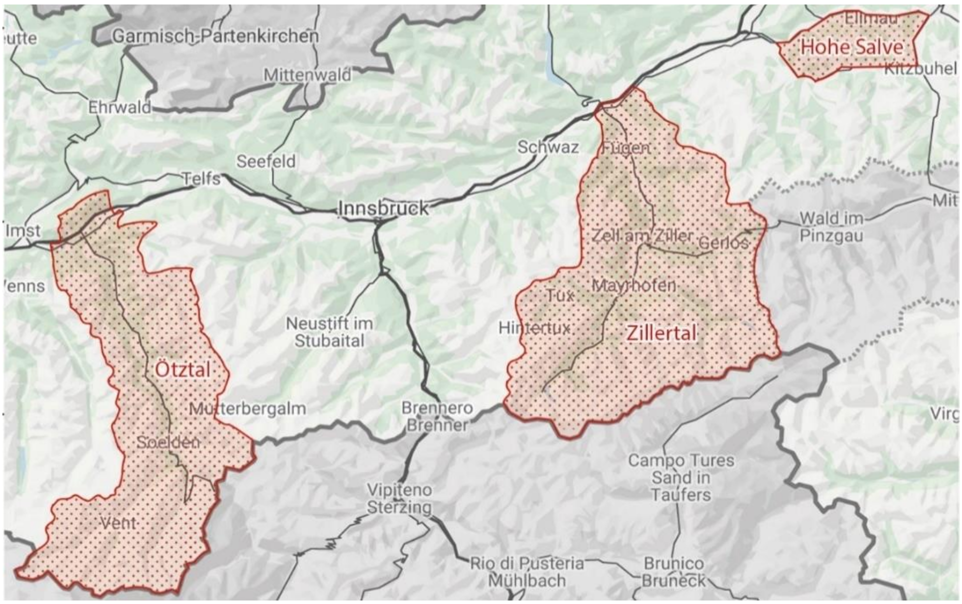


Figure 3.3 Location of the tourist regions Ötztal, Zillertal and Hohe Salve (red dotted areas) in the province of Tyrol (color map) in Austria

3.2.2 *Survey methods*

Despite the benefits and potentials of automated and semi-automated data collection methods based on GPS (as described in 2.2 and by Prelipcean et al. (2018)) and obvious drawbacks and difficulties resulting from using a memory-based approach, the survey was designed as a revealed preference (RP) single cross-sectional survey in two forms: as a PAPI (Paper-and-Pencil Interview) survey and CAPI (Computer Assisted Personal Interview) survey conducted with tablet computers.

The choice of these instruments is justified on the one hand by the characteristics of today's tourists, who prefer shorter but more frequent stays and booking on short notice, which results in organizational difficulty to contact them before the study, equip them with automated devices, instruct and advise during the study and collect the devices before they return home. On the other hand, in the case of semi-automated measurements with smartphones, the burden concerning the software deployment could not have been overcome in time for the study.

The survey was initially planned to be conducted exclusively using self-administered PAPI questionnaires distributed in accommodations in the three regions, following the principles proposed by Cambridge Systematics Inc. (1996). This approach would have facilitated the control over the sampling process. However, recruiting the hotels to participate in the survey turned out to be a major hurdle. The only successful way to approach the hotel owners about the project was through the local DMOs (Destination Marketing Organizations). The DMO employees knew which hoteliers in the area could be potentially willing to cooperate and were capable of convincing some of them to participate. The direct contact was ineffective and resulted in refusals justified with lack of time or human resources and concerns about guests being disturbed during their vacation time. Nevertheless, because the response rate proved extremely low (see section 3.4 for details), the survey method was changed to assisted PAPI and CAPI interviews conducted on-site in highly frequented locations spread over the valleys:

- Mountain huts in ski resorts, bars and restaurants
- Local hot-spots like amusement parks, wellness and spa centers, hot springs
- Recreation facilities like lakes, parks and playgrounds
- Sport facilities like mountain bike trails, hiking paths

This change resulted in a loss of control over the sampling – a pure convenience sampling was now used. It inevitably implies that the results from the sample cannot be easily generalizable to the whole study population (Lavrakas, 2008; Sirakaya-Turk et al., 2017).

A team of trained interviewers was conducting interviews in various tourist sites on selected days during the winter and summer peak season. Both fully and partially assisted interviewing methods were tested. In the latter method, the interviewers assisted more than one person at the same time and only stepped in into a fully assisted personal interview, when they noticed difficulties or someone giving responses of low quality.

In the on-site survey, incentives proved not to be very effective, which to some extent contradicts what is known from the literature (Massey et al., 2012; Simmons and Wilmot, 2004; Tooley, 1996). However, the studies on the incentives impact have concentrated only on household surveys so far. Both monetary (5 EUR banknotes) and non-monetary (university promotional items) incentives were tested. It was observed that although the incentives could convince the negatively oriented guests to fill out the questionnaire (which they presumably would not have done otherwise), the quality of their answers was low (empty fields, inadequate answers). On the other hand, among the positively oriented tourists, the motivation to fill out the questionnaire and the quality of their answers was not affected by the incentives, since they were willing to do it regardless of them.

As far as the quality of the answers is concerned, despite the attached instructions on completing the questionnaire as well as an example of a filled diary, respondents experienced problems with distinguishing between trips and activities. Due to a high response burden (over 30 questions and a diary for two days), the dropout while filling the questionnaire was not uncommon.

It is argued that only a fully assisted interview and filling the questionnaire in the constant presence of the interviewer can guarantee good-quality results. Tourists being approached in local tourist hot spots such as ski huts must fill the questionnaire in limited time (lunch break) and space (small tables) and in generally inconvenient conditions (children interrupting, wet clothes). This is a completely different environment compared to household surveys, where respondents can choose a suitable place, moment and take their time (e.g., to read the instructions). Additionally, various interaction techniques had to be used so as not to deter guests from filling the long questionnaire, such as approaching only selectively chosen tables or establishing contact with the children first, who then, if they find it entertaining, convince the parents to participate.

To the author's knowledge, this is one of the very few documented designs of questionnaires of tourist on-site mobility intending to collect data for Discrete Choice Analysis.

3.3 SURVEY INSTRUMENT

Three fundamental parts constitute the survey instrument:

- Personal questions
- Sojourn-related questions
- Activity diary

The following sections describe the content of the questionnaire and provide reasoning for choice of the questions. Attachments (sections A.1 and A.2) present the physical design of the paper questionnaires used in the PAPI survey and the CAPI forms implemented in *SoSci Survey* on-line system (Leiner, 2020).

3.3.1 *Personal questions*

According to Crawford et al. (1991) and Godbey et al. (2017), participation in leisure activities is subject to intrapersonal, interpersonal and structural constraints. Therefore, in section 1, data on factors constituting these constraints were collected using variables such as gender, age, nationality, education/employment status, age and number of children, health/fitness level and car availability.

The tourist regions of Ötztal, Zillertal and Hohe Salve, where the survey has been conducted, are very sport-profiled, both in winter and summer. While the information on sport activity of tourists during their stay in Tyrol is collected through the activity diary, it is also of interest to collect the data on guests' physical activity in general (while being at home). It is argued that the daily sport participation and frequency affect the sport-related behavior during vacation (De Knop, 2007).

3.3.2 *Sojourn-related questions*

Lew and McKercher (2006) have classified the factors influencing local travel behavior of tourists into three categories:

- The size and expenditure of tourist time budget
- Personal motivations, interests and travel group composition
- Tourist knowledge of the destination

In this section of the questionnaire, the respondents were asked basic questions about the length of their current vacation, exact place of stay, travel party composition and transport mode used for the trip to the destination.

According to LaMondia and Bhat (2013), tourists tend to have a main purpose characterizing the long-distance activity component of their holiday trip, which then drives them to choose a particular destination and particular activities. The topic of holiday and leisure motivations has been intensively studied by many researchers who developed different measurement scales and items (Beard and Ragheb, 1983; Crompton, 1979; Iso-Ahola, 1984; Ryan and Glendon, 1998). Bearing in mind the restricted space in the questionnaire, a question with eight predefined purpose categories has been developed.

According to Lehto et al. (2004), whether a tourist has visited a destination before or it is their first visit affects their knowledge about the destination (possible activities, local transportation, tourist attractions, etc.), which eventually influences their activity and travel choices on-site. The same applies to whether a destination is the main and only place of stay during vacation or is it one of many stops. A touring trip implies different on-site behavior than stationary vacation (Lew and McKercher, 2006). Questions regarding these two aspects have been incorporated in the survey.

The information search behavior is considered to be crucial for tourists' knowledge about the destination (Bieger and Laesser, 2016; Fodness and Murray, 1999; Gursoy and McCleary, 2004; Klassen, 2001). Therefore, two further questions on tourist's knowledge about the destination have been integrated in the questionnaire. Their purpose is to find out how, if at all, visitors inform themselves in advance about the journey to their destination and about the mobility on-site.

3.3.3 *Activity diary*

The bespoke travel-activity diary operates on a selection of terms proposed by Axhausen (2008), that is, trip, tour and activity. An activity-oriented approach was applied for the design of the diary, since it is the activities, not trips that are of greater importance and interest for people during vacation, and hence should prove more effective for the respondents to recall their movements. All travel data was collected at the resolution of trips. Stages were ignored in the survey.

In the activity diary, the respondents were asked to give information on all the activities that they performed out of their accommodation during two days of their stay. The diary included questions on the exact type and location of the activity, start/end time, as well as expenses, company and the influence of weather on the activity choice. Also the information about trips (transport mode, cost, company, impact of weather etc.) done between the activities was collected. The activities performed at the accommodation were not of interest as they do not induce any travel in the transport network.

The design of the diary draws from the existing well-established examples of household travel surveys (HTS) including the American *NHTS (National Household Travel Survey)* (Federal Highway Administration, 2017), the German *Mobidrive* (Axhausen et al., 2000) as well as the Austrian *Österreich Unterwegs* (Sammer et al., 2011) and *MAED (Mobility-Activity-Expenditure-Diary)* (Aschauer et al., 2018), all based on the trusted *New KONTIV Design* (Brög, 2009), and transposes them into the field of tourism. So as to keep the response burden in the PAPI survey low, the activity diary for two days along with personal, situational and preference questions was fit on a single A3 sheet (half-fold). The PAPI diary takes 50% of the questionnaire (two A4 pages) and provides space for 7 activities and 8 trips per day. In the case of the CAPI survey, the on-line questionnaire included exactly the same questions as the paper version. Automated rules controlled the data quality, correctness of variable types and detected missing answers. This, together with the positive effect of the interviewers conducting the CAPI survey, resulted in noticeably better quality of the collected data.

Opposite to typical HTS questionnaires, it was decided not to provide any predefined activity types in the questionnaire. While reliable and validated categories have been developed for daily activities (e.g., work, education, pick-up/drop-off, shopping, leisure), it is very difficult to create categories for all possible leisure activities (although there are some attempts, see Lanzendorf (2002)). Therefore, it is common to ask the respondent for their own detailed description of the performed activity (Axhausen, 2015) and classify it afterwards.

With regard to the influence of weather on the activity and mode choice, the respondents were asked to indicate whether they chose the activity/mode that they had planned to choose or whether they had to choose another ("plan B") activity/mode because of the (unfavorable) weather. This novel approach makes it possible to directly capture the impact of weather on every decision made during the reported day. In combination with historical weather measurement data for the survey dates, it is a very powerful dataset. In the few existing studies (Liu et al., 2016; Termida et al., 2016), only the information on subjective weather perception on a given day was collected.

3.3.4 *Joint travel*

The survey designed within this thesis has the aim to capture the differences between the individuals within a travel party and catch the process of making decisions about activities during their stay on site. For example, in their analysis of visitors' travel behavior in Northwest Territories in Canada, LaMondia and Bhat (2013), assumed that the responses of the individuals selected of each travel party were representative for all travelers in the party. Even accounting for the limitations of the data and the survey design, it is a brave assumption, which was criticized in the literature (Aribarg et al., 2010). It would have provided even more valuable insights for the research if more than one person from a party had filled the questionnaire.

In the current survey, each group member was asked to fill out his or her own separate travel diary. The activities and trips are then classified as individual or joint by comparing and matching each member's reported information such as origin and destination, starting and ending times, trip purposes, travel modes etc. as it was done for example by Gliebe and Koppelman (2005).

In order not to underestimate the number of joint activities and trips (as a wife and husband may report a trip slightly differently), the identification was done based on relaxed criteria (Kang and Scott, 2011). The algorithm allows for discrepancies up to 100m between the reported locations. It also distinguishes between activities and trips performed completely jointly (time difference in reported duration <1 hour) or partially jointly (time difference >1 hour).

3.4 Survey participation and response burden

The choice and wording of survey questions and the definition of the survey area were relatively comprehensive and manageable tasks, the eventual implementation of the survey in a tourist region was a much more complex undertaking. The most difficult issues concern the choice of the survey method, distribution method for PAPI questionnaires, arranging meetings with accommodation providers, convincing them to participate in the project, defining incentives and finding a way to approach the guests on-site and to overcome their participation and response burden. A summary of these efforts is provided in Table 3.2.

Table 3.2 Summary of the survey protocol depending on survey region, wave, method and language

Season	Region	Wave	Method	Incentives	Language	Interviewed	Distributed	Returned
Summer	Ötztal	July 16-19, 2019	CAPI	Promotional items	EN	15	-	-
					DE	139	-	-
		July 31 – Aug. 2, 2019	CAPI	Promotional items	EN	2	-	-
					DE	12	-	-
		July 31 – Aug. 3, 2019	CAPI	Promotional items	EN	4	-	-
					DE	26	-	-
		Aug. 20-23, 2019	CAPI	Promotional items	EN	17	-	-
					DE	109	-	-
	Zillertal	July 26-30, 2019	CAPI	Promotional items	EN	4	-	-
					DE	44	-	-
		Aug. 26 – Sept. 4, 2019	CAPI	Promotional items	EN	1	-	-
					DE	38	-	-
Winter	Ötztal	Dec. 2018 – Apr. 2019	PAPI self-adm.	No	EN	-	270	0
					DE	-	370	28
		Dec. 25-27, 2018	PAPI	Promotional items	EN	45	-	-
					DE	41	-	-
		Jan. 4-5, 2019	PAPI	5 EUR banknotes	EN	14	-	-
					DE	75	-	-
		Feb. 27 – Mar. 1, 2019	PAPI	Promotional items	EN	12	-	-
					DE	60	-	-
	Zillertal	Feb. 18-20, 2019	PAPI	Promotional items	EN	40	-	-
					DE	77	-	-
	Hohe Salve	Mar. 8, 2019	PAPI	Promotional items	EN	15	-	-
					DE	31	-	-
					Sum:	**821**	640	**28**

For the paper questionnaire with a travel-activity diary for two days the total response burden was calculated based on the methodology developed by Axhausen et al. (2015). For the minimum scenario of only one activity and two trips per day, the response burden is 381, whereas the maximum case of seven activities and eight trips (all boxes filled) results in a response burden of 1309. Employing their regression equation, one obtains a response rate range of 8.00% to 24.35% respectively.

Out of the 640 (270 in English, 370 in German language) questionnaires distributed in the hotels in the winter season, only 28 were returned, which results in the average response rate of 4.4%. It is below the lower bound of the range estimated using the method by Axhausen et al. (2015). Potential reasons for that are:

- Difficulties with acquiring enough hotels willing to cooperate in all three tourist regions.
- No control over how, when and whom the questionnaires were distributed after delivering them to the hotel.
- Possibly negative mediating role of the reception desk (not all questionnaires were distributed; guests were not encouraged enough to participate).
- Questionnaires were lost in several cases.

This result clearly highlights the distinctiveness of conducting travel surveys and collecting travel data from non-local visitors and from residential populations – in organizational, managerial and financial aspects.

In the face of the very low response rate, the remaining part of the PAPI survey was conducted in form of (semi-) assisted interviews where drop-outs were not noted any more. There were also refusals when interviewers approached potential respondents but interviewers were not obliged to report it.

In the case of the CAPI survey, which was done in the form of an interview as well, all started interviews were completed and denials were not reported.

3.5 COMPLEMENTARY DATASETS

The survey results comprise the primary data source used in the thesis. These data are complemented by additional secondary datasets consisting of:

- Historical weather data
- Geodata from *Google Maps* API
- Geodata from the regional transportation model
- Accommodation data from own booking systems of the tourist regions

Historical weather data are based on a meteorological network of the Central Institution for Meteorology and Geodynamics (*Zentralanstalt für Meteorologie und*

Geodynamik, ZAMG) in Austria. The data contains measurements of air temperature, precipitation, sky overcast, wind speed and snow depth, and was collected with one-hour resolution from following measurement stations located in the area of interest:

- Haiming, 669m a.s.l.
- Umhausen, 1035m a.s.l.
- Obergurgl, 1942m a.s.l.
- Mayrhofen, 640m a.s.l.
- Söll, 697m a.s.l.
- Innsbruck, 578m a.s.l.

Details on the range and pre-processing of *Google Maps* API data and data extracted from the transportation model are provided in section 4.1.2.
Information about the lodging comprises:

- object type (hotel, guesthouse, apartment, camping)
- standard (only for hotels, represented by number of stars)
- price per person per night (in EUR) in summer and winter season
- price per room/apartment per night (in EUR) in summer and winter season

3.6 Imputation of missing values

In order not to lose valuable observations where only few items were missing, it was necessary to impute the missing data. The multiple imputation method was chosen (van Buuren, 2018), as it delivers less biased results than the ad-hoc solutions (e.g. mean imputation) (Andridge and Little, 2010). The *missForest* package for R was used for this process (Stekhoven and Bühlmann, 2012). The package utilizes the random forest technique and can handle both continuous and categorical types of data.

Missing value imputation was used for the following sociodemographic variables (where all the variables acted also as predictors): income, age, gender, education, employment, residence country, nationality, car availability, car use frequency, driver's license possession, transport mode used for travel to the destination, main purpose of the stay, number of adults in household, number of children under 6, number of children aged 6 to 17, length of the stay, knowledge about the travel options, knowledge about the on-site mobility, sport frequency and time spent on sport activities. Furthermore, imputation with *missForest* was also used in case data were missing in the hotel-related variables. The results presented in the following sections are based on data after the imputation process.

3.7 DESCRIPTIVE ANALYSIS

This section reports descriptive results at the level of individuals (respondents). Information at the level of single observations (trips) might differ from those at the level of individuals since different data cleaning procedures were applied (see section 4.1.4).

3.7.1 *Exclusion of responses*

At the respondent level, following exclusion rules were employed:

- The only respondent from a group/family is under 18 years old (assumed not to be the decision-maker in a family/group).
- Respondent's place of stay is located outside the three tourist regions: Ötztal, Zillertal and Hohe Salve.
- The answer quality was unacceptable and no imputation could be applied (missing or contradicting answers, misunderstood questions). This pertains in particular to PAPI survey in winter with questionnaires distributed in hotels and to partially assisted interviews.

As a result, out of 849 questionnaires 224 were eliminated (predominantly winter questionnaires from Ötztal and Hohe Salve) and 625 remained (388 in summer and 237 in winter).

3.7.2 *Characteristics of the respondents*

3.7.2.1 *Sociodemographics*

Table 3.3 provides a statistical summary (group frequencies and mean values) of the respondents' sociodemographic characteristics from the summer and winter survey period.

Table 3.3 Sociodemographic description of the sample

Variable	Value	Summer		Winter	
		Number	%	Number	%
Age		Mean (SD): 47.7 (15.0)		Mean (SD): 39.3 (14.2)	
	6-17	4	1.0	7	3.0
	18-24	26	6.7	44	18.6
	25-40	98	25.3	69	29.1
	41-64	207	53.4	111	46.8
	65+	53	13.7	6	2.5

Continued on next page

Table 3.3 (continued from previous page)

Variable	Value	Summer		Winter	
		Number	%	Number	%
Gender	Female	210	54.1	109	46.0
	Male	176	45.9	128	54.0
Residence country	Germany	238	61.3	142	59.9
	Austria	82	21.1	12	5.1
	Netherlands	20	5.2	38	16.0
	Switzerland	11	2.8	6	2.5
	Italy	6	1.6	0	0.0
	France	5	1.3	1	0.4
	UK	5	1.3	21	8.9
	Other	21	5.4	17	7.2
Education	Primary level	25	6.4	5	2.1
	Secondary level (high school)	125	32.2	36	15.2
	A-levels / High school diploma	98	25.3	72	30.4
	University degree	140	36.1	124	52.3
Employment	Full-time employed	191	49.2	135	57.0
	Retired	72	18.6	7	3.0
	Part-time employed	54	13.9	13	5.5
	Pupil or student	27	7.0	43	18.1
	Doing housework, ...	21	5.4	8	3.4
	Self-employed / own business	21	5.4	28	11.8
	Unemployed / looking for a job	2	0.5	0	0.0
	Apprentice or trainee	0	0.0	3	1.3
Monthly net household income in EUR	< 1,000	20	5.2	26	11.0
	1,000-2,000	53	13.7	16	6.8
	2,001-3,000	106	27.3	26	11.0
	3,001-4,000	95	24.5	39	16.5
	4,001-5,000	35	9.0	41	17.3
	5,001-6,000	14	3.6	17	7.2
	6,001-7,000	22	5.7	22	9.3
	7,001-8,000	8	2.1	12	5.1
	8,001-9,000	4	1.0	14	5.9
	9,001-10,000	3	0.8	4	1.7
	10,001-12,000	3	0.8	3	1.3
	12,001-14,000	8	2.1	2	0.8
	14,001-16,000	3	0.8	2	0.8
	16,001-18,000	10	2.6	3	1.3
	18,001-20,000	1	0.3	1	0.4
	> 20,000	3	0.8	9	3.8
Household size		Mean (SD): 2.72 (1.4)		Mean (SD): 2.85 (1.28)	
	3	1	0.3	0	0.0
	4	59	15.2	39	16.5
	5	151	38.9	66	27.9
	6	57	14.7	49	20.7
	7	86	22.2	60	25.3
	8	27	7.0	21	8.9
	>8	7	1.9	2	0.8

Continued on next page

Table 3.3 (continued from previous page)

Variable	Value	Summer		Winter	
		Number	%	Number	%
Number of children under 6 in the household	1	334	86.1	0	0
	2	40	10.3	214	90.3
	3	13	3.4	15	6.3
	4	1	0.3	8	3.4
Number of children 6-17 in the household	1	274	70.6	152	64.1
	2	57	14.7	46	19.4
	3	47	12.1	28	11.8
	4	8	2.1	11	4.6
	5	2	0.5	0	0
Annual leave (days)		Mean (SD) : 17.6 (6.3)		Mean (SD) : 17.7 (6.9)	
Nights away in the last year	I did not go away	8	2.1	2	0.8
	1-5 nights	23	5.9	8	3.4
	6-10 nights	70	18.0	18	7.6
	11-20 nights	144	37.1	54	22.8
	21-30 nights	82	21.1	69	29.1
	More than 30 nights	61	15.7	86	36.3
Driver's license	No	20	5.2	23	9.7
	Yes	368	94.8	214	90.3
Car availability	Never	54	13.9	18	7.6
	Sometimes	44	11.3	28	11.8
	Always	290	74.7	191	80.6
Car use frequency	Less than once a month	26	6.7	8	3.4
	1-3 times a month	45	11.6	29	12.2
	1-3 days a week	92	23.7	42	17.7
	4-6 days a week	64	16.5	37	15.6
	Daily	161	41.5	121	51.1
Health status	Very bad	2	0.5	1	0.4
	Bad	5	1.3	0	0.0
	Fair	52	13.4	6	2.5
	Good	154	39.7	97	40.9
	Very good	175	45.1	133	56.1
Physical limitations	Severely limited	6	1.6	2	0.8
	Limited but not severely	87	22.4	18	7.6
	Not limited at all	295	76.0	217	91.6
Sport frequency (days in a week)	0	63	16.2	13	5.5
	1	76	19.6	34	14.4
	2	88	22.7	65	27.4
	3	59	15.2	53	22.4
	4	38	9.8	23	9.7
	5	35	9.0	26	11.0
	6	6	1.6	9	3.8
	7	23	5.9	14	5.9
Sport time (hours in a week)		Mean (SD) : 3.70 (3.6)		Mean (SD) : 4.60 (4.0)	

There are notable differences in both datasets. Winter tourists are substantially younger and better educated. They are also more professionally active and possess higher income. Their health is better, possibly because they are more physically active. Summer visitors on the other hand are older, less educated, often already retired or working part-time. They have less income is their disposal, lower car availability and use private cars less often than winter guests. In both season, visitors from Germany dominate. Noteworthy, they are followed by Austrian domestic tourists in summer, whilst in winter Dutch tourists are on the 2nd place.

Figure 3.4 illustrates correlations between selected sociodemographic variables. The categorical variables with a self-explanatory order of levels (education, employment, income, health) were transformed into numeric variables assuming the lowest level equals one and all higher levels are equidistant.

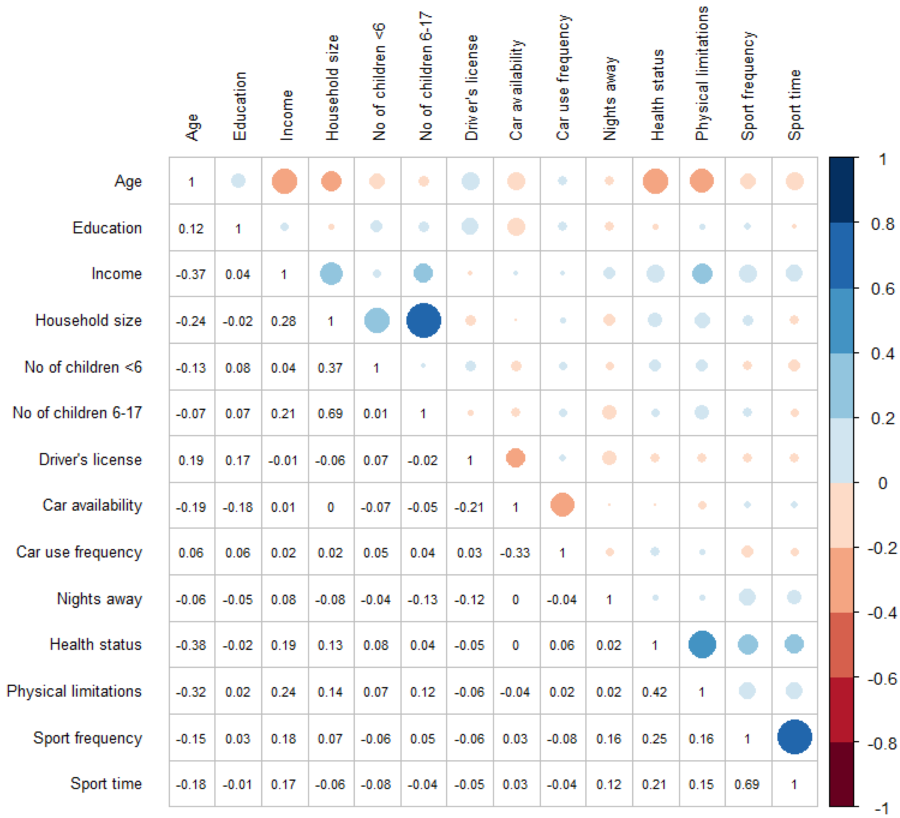


Figure 3.4 Correlations of the decision-makers' characteristics

3.7.2.2 *Sojourn*

Responses to questions related to the sojourn and long-distance trip to the destination (part 2 of the questionnaire) are summarized in Table 3.4.

Table 3.4 Description of the sojourn and the long-distance trip to the destination

Variable	Value	Summer		Winter	
		Number	%	Number	%
		Mean (SD): 8.70 (5.1)		Mean (SD): 6.25 (1.84)	
Length of stay	1-5	95	25.3	68	28.7
	6-10	178	45.9	165	69.6
	11-15	62	16.0	3	1.3
	>16	50	12.9	1	0.4
Company during the stay	Household size	Mean (SD): 2.44 (1.4)		Mean (SD): 2.77 (1.9)	
Alone	Yes	43	11.1	5	2.1
	No	345	88.9	232	97.9
With a spouse	Yes	271	69.9	127	53.6
	No	117	30.1	110	46.4
Children under 6	0	338	87.1	213	89.9
	1	37	9.5	13	5.5
	2	12	3.1	8	3.4
	>2	1	0.3	3	1.3
Children 6-17	0	280	72.2	154	65.0
	1	53	13.7	46	19.4
	2	43	11.1	26	11.0
	>2	12	3.1	11	4.6
Other household members	0	365	94.1	188	79.3
	1	12	3.1	11	4.6
	2	4	1.0	22	9.3
	>2	7	1.8	16	6.8
Other known persons	0	302	77.8	133	56.1
	1	29	7.5	23	9.7
	2	16	4.1	22	9.3
	>2	41	10.6	59	24.9
Type of holiday	Individual trip	327	84.5	197	85.3
	Organized travel	60	15.5	34	14.7
Number of previous visits	0	177	46.0	96	40.9
	1	50	13.0	28	11.9
	2	40	10.4	21	8.9
	3-5	51	13.3	36	15.3
	6-10	28	7.3	31	13.2
	>10	39	10.1	23	9.8
Main destination	Yes	330	85.7	227	97.4
	No, I am on a stopover here	55	14.3	6	2.6

Continued on next page

Table 3.4 (continued from previous page)

Variable	Value	Summer		Winter	
		Number	%	Number	%
Main purpose	Business	4	1.0	0	0.0
	Culture, heritage, sightseeing	16	4.1	0	0.0
	Health, wellness	47	12.1	6	2.5
	Rest, relaxation	115	29.6	26	11.0
	Shopping, fun, entertainment	2	0.5	5	2.1
	Social (time with family, friends)	60	15.5	13	5.5
	Sport, recreation	144	37.1	187	78.9
Main transport mode used for travel to the destination	Airplane	7	1.8	23	9.7
	Coach	18	4.6	10	4.2
	Motorcycle as a driver	2	0.5	0	0.0
	Private car as a driver	180	46.4	101	42.6
	Private car as a passenger	138	35.6	94	39.7
	Rented car, car-sharing as a driver	3	0.8	1	0.4
	Rented car, car-sharing as a passenger	3	0.8	1	0.4
	Train	37	9.5	7	3.0
Reason for choosing this mode[a]	No other mode was available	55	14.2	9	3.8
	Distance of the journey	50	12.9	72	30.6
	Fastest mode	51	13.1	79	33.6
	Cheapest mode	54	13.9	70	29.8
	Safest mode	7	1.8	16	6.8
	Most convenient mode[b]	236	60.8	120	51.1
	Most comfortable mode	59	15.2	56	23.8
	Personal mobility constraints	9	2.3	3	1.3
	Luggage transport	84	21.7	101	43.0
	Weather conditions	7	1.8	5	2.1
	Other	46	11.9	5	6.3
Information about travel options	Not informed at all	84	21.7	45	19.0
	Slightly informed	30	7.7	13	5.5
	Somewhat informed	46	11.9	43	18.1
	Well informed	128	33.0	83	35.0
	Very well informed	100	25.8	53	22.4
Source of this information[a]	On websites/mobile app of the region/...	92	23.7	81	34.8
	On websites/mobile app of the hotel	18	4.6	26	11.2
	On online/mobile map services...	97	25.0	56	24.0
	At the travel agency	9	2.3	10	4.3
	From travel guidebooks	8	2.1	2	0.9
	From friends and relatives	18	4.6	35	15.0
	Other	56	14.4	13	5.5
	I have not informed myself in advance	203	52.3	84	36.1
Information about on-site mobility	Not informed at all	97	25.0	22	9.3
	Slightly informed	46	11.9	19	8.0
	Somewhat informed	56	14.4	44	18.6
	Well informed	105	27.1	86	36.3
	Very well informed	84	21.7	66	27.9

Continued on next page

Table 3.4 (continued from previous page)

Variable	Value	Summer		Winter	
		Number	%	Number	%
Source of this information[a]	On websites/mobile app of the region/...	89	22.9	95	41.0
	On websites/mobile app of the hotel	34	8.8	46	19.8
	On websites/mobile apps of the local...	35	9.0	16	6.9
	On online/mobile map services...	37	9.5	30	12.9
	At the travel agency	7	1.8	5	2.2
	From travel guidebooks	16	4.1	4	1.7
	From friends and relatives	10	2.6	36	15.5
	Other	54	13.9	23	9.7
	I have not informed myself in advance	219	56.4	53	22.7

[a]Multiple choice question. Values indicate percent share of people who chose one of the answers.
[b]Convenient mode was defined in the questionnaire as direct, accessible and flexible, whereas comfort pertained to e.g. cleanliness, seats and ventilation. See the items used in question 28 in the questionnaire in the appendix.

Overall, summer stays are longer than winter stays. High standard deviation suggests wide spread of stay durations in summer. In winter, the length of stay oscillates around 6-7 overnights, which corresponds to a typical holiday week that starts and ends on a Saturday. A winter tourist is accompanied by more household members. Both summer and winter tourists prefer individually organized holidays, which comprise around 85% of all stays. In over 50% cases they have already been to Tyrol before. Winter stays are predominantly stationary, whereas in summer, a 15% share of respondents declare being on a road trip and moving to another place soon. An average winter tourist comes to almost 80% for sports and recreation, while a summer visitor is similarly attracted by sports (37%) and rest and relaxation (30%), followed by social and health purposes.

In terms of modal split for the trip from home to the destination, private car with around 80% share dominates in both seasons. This is followed by airplane in winter (mostly from the UK since there is a convenient direct connection from London to Innsbruck) and train in summer. The major reason for choosing a particular transport mode is convenience (most direct, accessible and flexible mode) in both seasons. In winter, luggage plays an important role, as do price, journey time and distance. In summer, factors other than convenience are far less important. Figure 3.5 illustrates the relationship between the chosen transport mode and the declared factors driving this decision. Visitors in both seasons declare to be generally well informed about the travel options. However, only winter tourists declare to be sufficiently informed about the transportation at the destination.

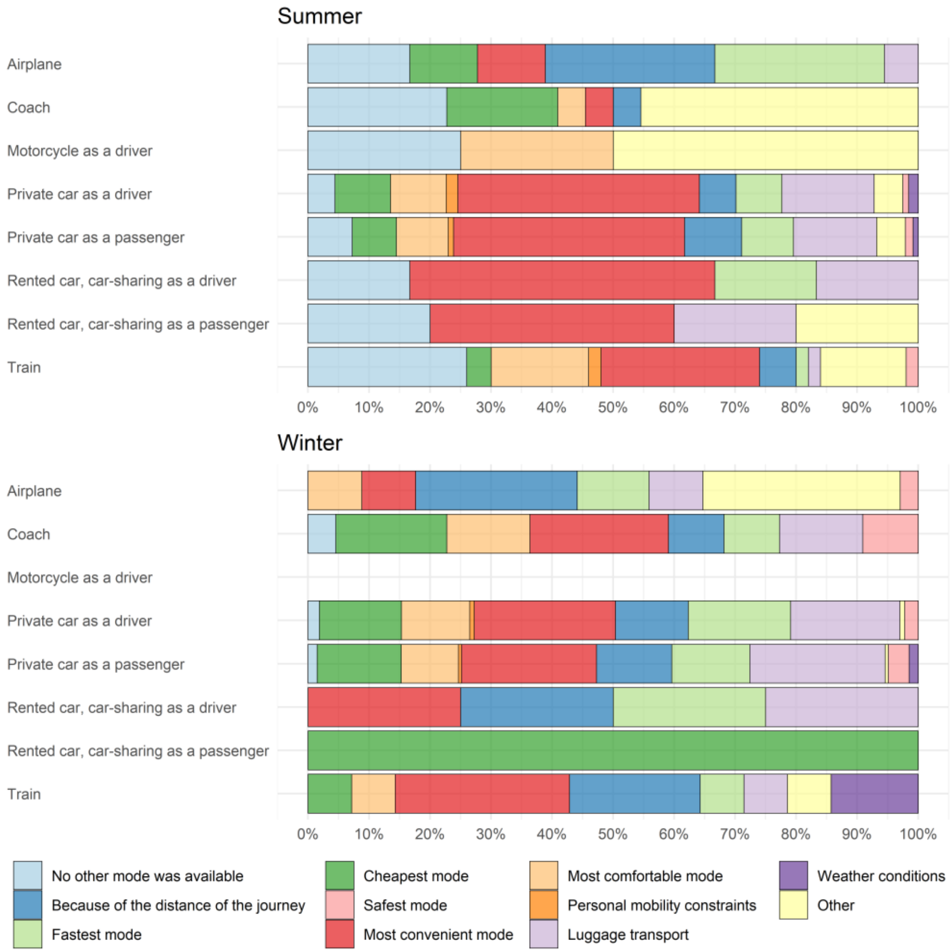


Figure 3.5 Reasons for choosing particular transport mode for travel to a tourist destination (multiple choice possible)

In terms of accommodation types, summer tourists definitely prefer hotels (65%) over guesthouses (19%) and other object types (Table 3.5). Winter tourists are more inclined to hotels (44%), but also choose guesthouses relatively often (35%). The mean prices (per person per night) are, even despite a higher share of guesthouse stays in the sample, about 15 EUR higher in winter than in summer, which clearly implies that winter is the more expensive season.

Table 3.5 Characteristics of the accommodations reported in the survey

Variable	Value	Summer		Winter	
		Number	%	Number	%
Type of accommodation	Apartment	42	10.8	49	20.7
	Camping	19	4.9	3	1.3
	Hotel	252	65.0	103	43.5
	Guesthouse	75	19.3	82	34.6
Standard (star rating)[a]	2	2	0.8	0	0
	3	50	19.8	15	14.6
	4	165	65.5	72	69.9
	4.5	35	13.9	13	12.6
	5	0	0	3	2.9
Price per person per night [EUR]		Mean (SD): 68.4 (32.9)		Mean (SD): 82.3 (39.3)	

[a]Only for hotels. Not available for apartments, campings and guesthouses.

3.7.2.3 *Activities*

Figure 3.6 presents locations of the accommodations where the respondents stayed.

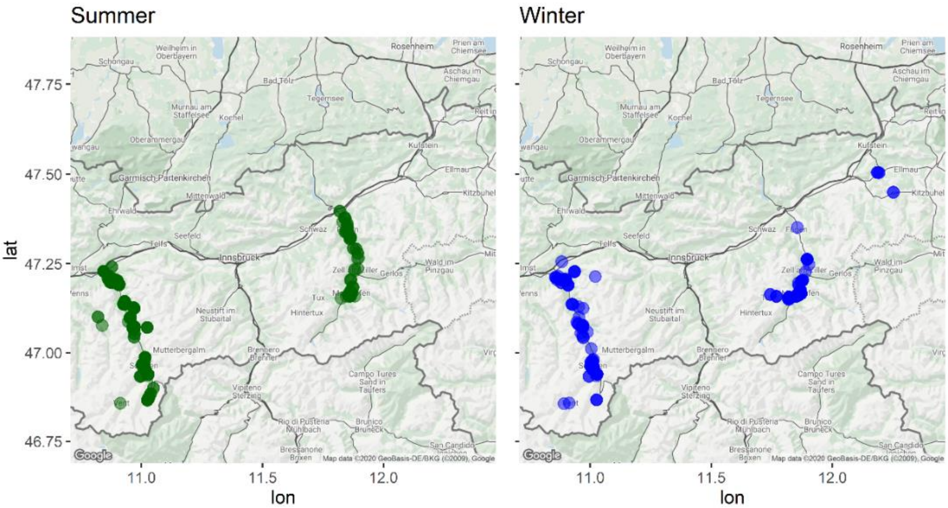


Figure 3.6 Locations of the accommodations reported in the survey

Figure 3.7 is an illustration of the activity locations (i.e. trip start points). The area overlaps to a large extent with Figure 3.6, i.e. activities are performed predominantly within the valley, in the vicinity of the place of stay. Tourists make excursions outside their region relatively rarely. The locations of activities are very concentrated in winter, being close to the main road axis and ski resorts, whereas in summer they are more uniformly distributed over the regions and more distant from the regions' center points. Visits to places outside the valleys, like picturesque lakes (Achensee) or cities with tourist attractions (Innsbruck, Schwaz, Kufstein) were reported more frequently in summer than in winter.

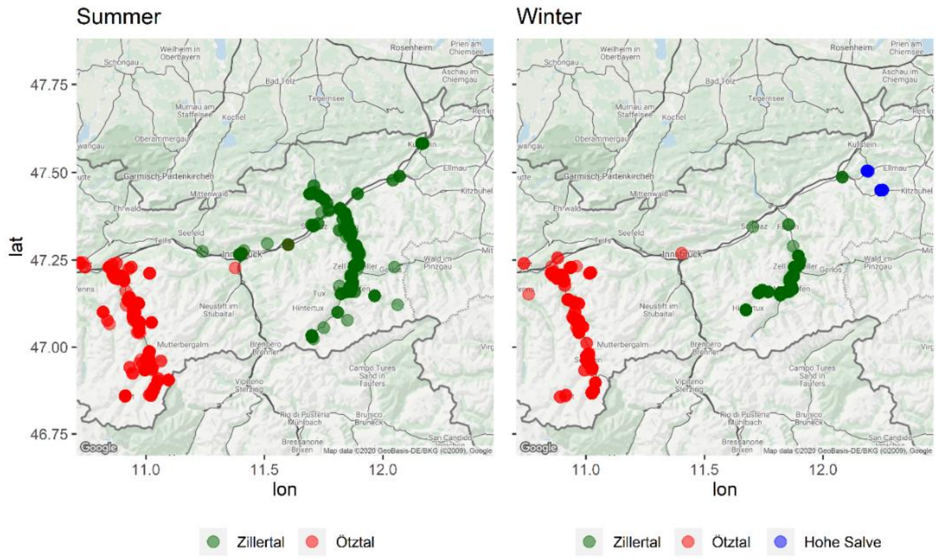


Figure 3.7 Location of the activities depending on survey location

3.7.2.4 *Trips and tours*

The general level of mobility of the tourists at the destination can be described in two ways, using the concept of trips and tours. The average number of trips per person per day in the sample is 2.5 (Table 3.6).

If compared to the values generated by the residents of Tyrol, tourists appear to be less mobile. The difference is much more visible if compared to mobility rates of residents living in intensive tourist municipalities, who generate 3.8 trips per day. Similarly, in comparison to mobility levels measured in countries where the visitors come from, the mobility levels during vacation are also trending lower (except for the UK[3]). It implies that people are generally less mobile during their out-of-home stays than when at home on a typical commute day. However, regional variations within these countries and methodological differences between the studies should be pointed out before generalizing the results.

[3] No data on trips per day available for the UK – only for England.

Table 3.6 Mobility rates of the surveyed sample of tourists and the corresponding rates in countries from which most guests in Tyrol originate. Values per day per person (mobile and not mobile persons together)

Study population	Daily distance [km]	Daily travel time [min]	No. of trips per day[a]
Tourists – total	23.2 (28.8 / 14.2)[b]	59 (72 / 39)[b]	2.5 (2.4 / 2.7)[b]
Tourists from AT	11.3	22	2.1
Tourists from DE	27.2	75	2.6
Tourists from NL	16.4	38	2.7
Tourists from CH	22.3	45	2.2
Tourists from UK	21.1	26	2.9
Residents in AT (2013/2014)[c]	36	68	2.6
Residents in AT, Tyrol (2013/2014)[c]	35	69	2.7
Residents in AT, Tyrol (2011)[d]	-	-	4.1
Residents in AT, Tyrol (tourism-intensive municipalities) (2011)[d]	-	-	3.8
Residents in DE (2018)[e]	39	80	3.1
Residents in NL (2013)[f]	35.6	65	3.1
Residents in CH (2017)[g]	36.8	90.4	3.4
Residents in England (2018)[h]	29	62	2.7

[a]Excluding cable car trips (see Table 4.1).
[b]Values for summer and winter respectively.
[c]Tomschy et al. (2016)
[d]Köll and Bader (2011)
[e]Bundesministerium für Verkehr und digitale Infrastruktur (2018)
[f]Hoogendoorn-Lanser et al. (2015)
[g]Bundesamt für Statistik (BFS) (2017)
[h]NatCen Social Research (2019)

In terms of distance travelled, tourist cover substantially fewer kilometers per day on vacation than on an average day at home. There are however large country-dependent differences, with Austrians traveling the shortest and Germans the longest distances. In terms of time spent on travel, both Austrian nationals as well as foreign tourists achieve significantly lower values during vacation than when at home. Only German visitors stand out and spend on average 75min per day compared to 80min in their daily behavior.

3.7.3 *Mode choice of the respondents*

In summer, the share of trips made by car in the sample hits the highest value of almost 50%, followed by walking with 40%, transit (9%) and cycling (1%). In winter, walking is the dominating mode reaching 47%, followed by driving and transit, with 36% and 17% respectively.

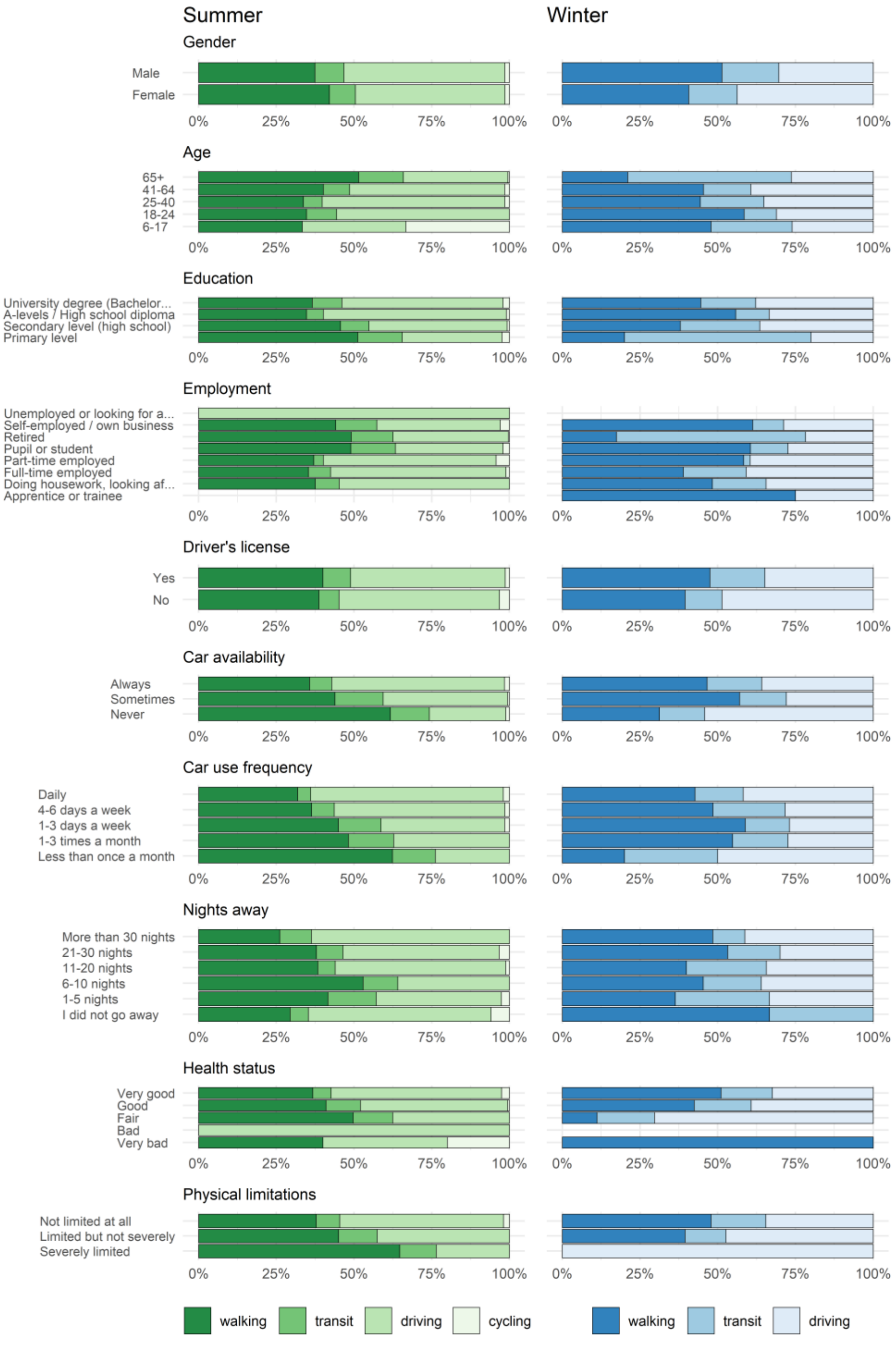


Figure 3.8 Chosen mode depending on the sociodemographic characteristics

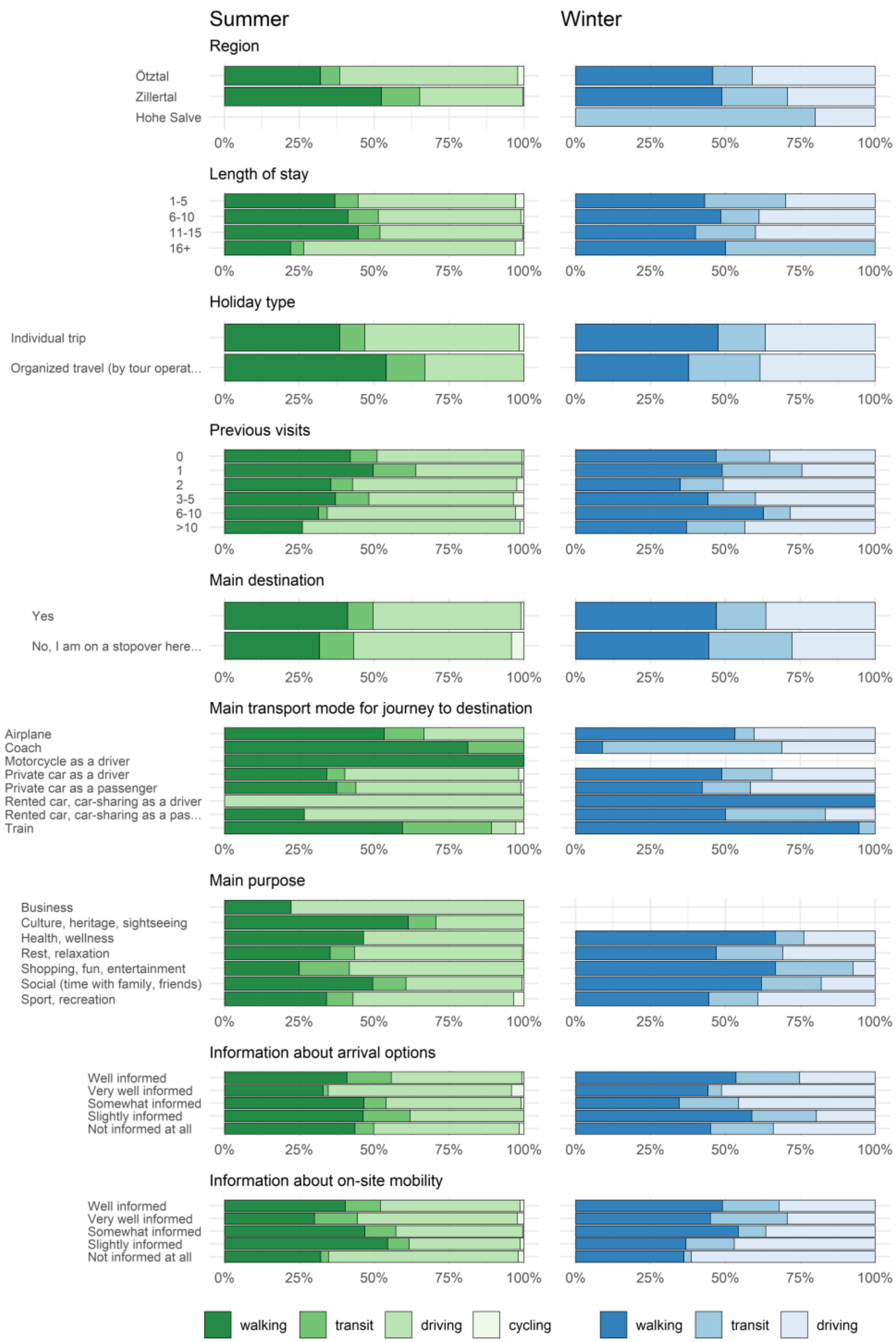


Figure 3.9 Chosen mode depending on the characteristics of the sojourn and travel to the destination

Figure 3.8 and Figure 3.9 provide informative insights about the relationship between the mode choice in summer and winter and the sociodemographic and sojourn-related variables. For instance, tourists over 65 years old are more often choosing transit than other age groups, in particular in winter. Frequent car users at home tend to choose car more often also on vacation in summer. Interestingly, good health and lack of physical disabilities result in more walking trips in winter, but less in summer.

As far as the characteristics of the stay are concerned, one can notice that guests in the Ötztal valley choose car more often than guests in the other two regions. This holds in both seasons. The Zillertal, on the other hand, has the highest percentage of transit users, which can be associated with a more extensive transit network, including a 32-kilometer-long narrow-gauge railway going through the valley. Having arrived by private car at the destination results in a high share of car trips on-site. In contrast, train and coach travelers tend to use transit relatively often on-site. Also, better knowledge about the destination has a favorable effect on choosing transit at the cost of car.

Figure 3.10 illustrates the temporal distribution of trips during a day (averaged) in summer and winter high season. Two distinct peaks are apparent for all three modes in winter, which clearly reflects how the mobility patterns of winter tourists are associated with the opening and closing hours of ski resorts. Driving in summer exhibits similar morning and evening peaks as it is in winter, whereas the temporal distribution of walking trips is more uniform over the course of a day. In summer, unlike in winter, the afternoon return trips on transit are spread over several hours and do not form a peak as it is in the morning.

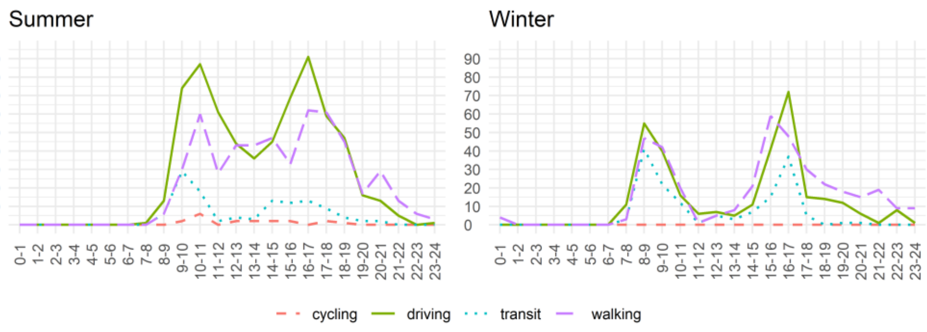


Figure 3.10 Number of trips made by a given mode depending on time of day

Figure 3.11 presents the modal split with respect to the trip purpose. A distinct pattern can be observed, in particular in summer, in mode choice preferences between travelling to social activities (e.g. going out, restaurant visit) and traveling to outdoor and sport activities. In the first case, walking is the dominant mode, whereas in the latter one, and generally with the increasing need to transport any kind of luggage or specific items (trekking poles, climbing or water sport equipment, etc.), the share of car trips escalates. An exception from that rule is skiing, where a relatively high share of transit trips can be explained by the high-quality ski-bus services offered in winter, tailored specifically to skiers' and snowboarders' needs.

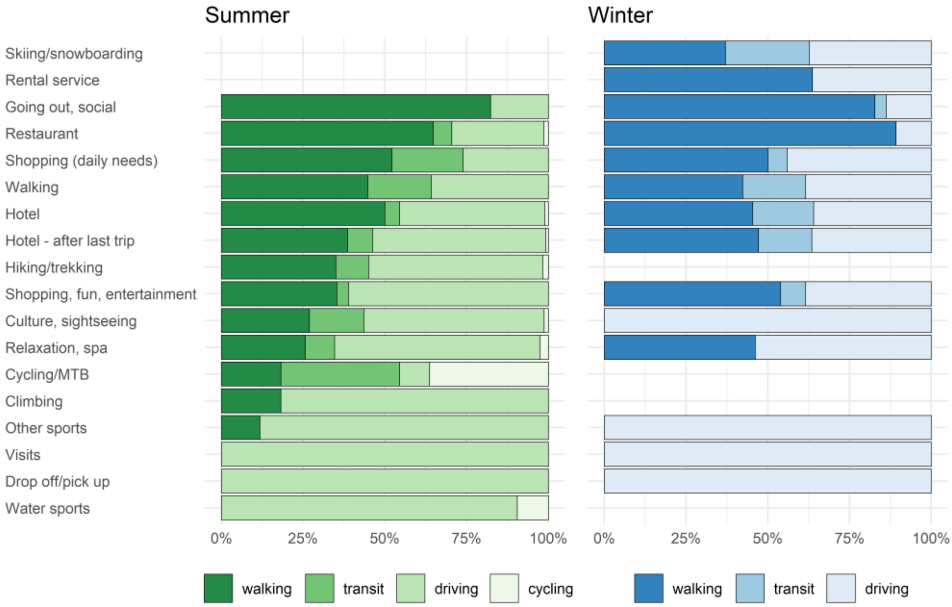


Figure 3.11 Chosen mode depending on current trip purpose

Figure 3.12 and Figure 3.13 illustrate how long the trips undertaken by tourists are with each of the modes (data at the level of single observations (trips), not respondents). Tourists in summer in general travel longer distances and spend more time traveling than in winter, no matter the mode they choose (see also Table 3.6).

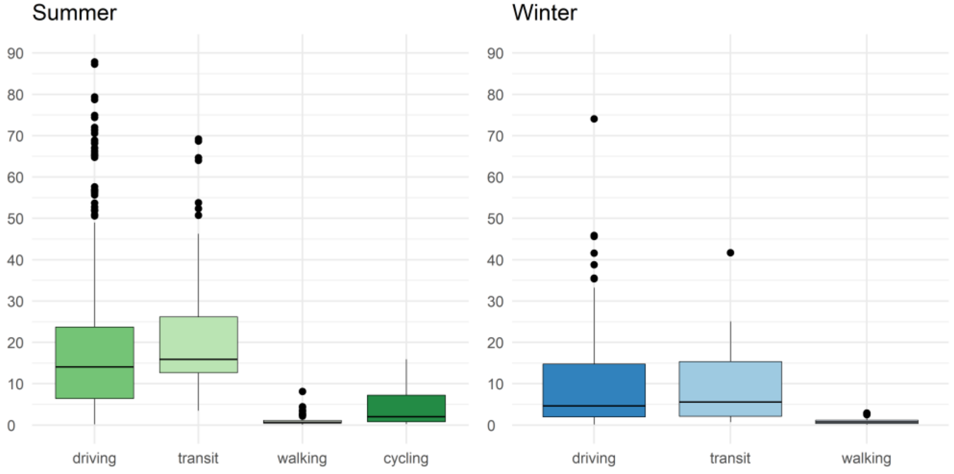


Figure 3.12 Length of trips [km] depending on chosen mode

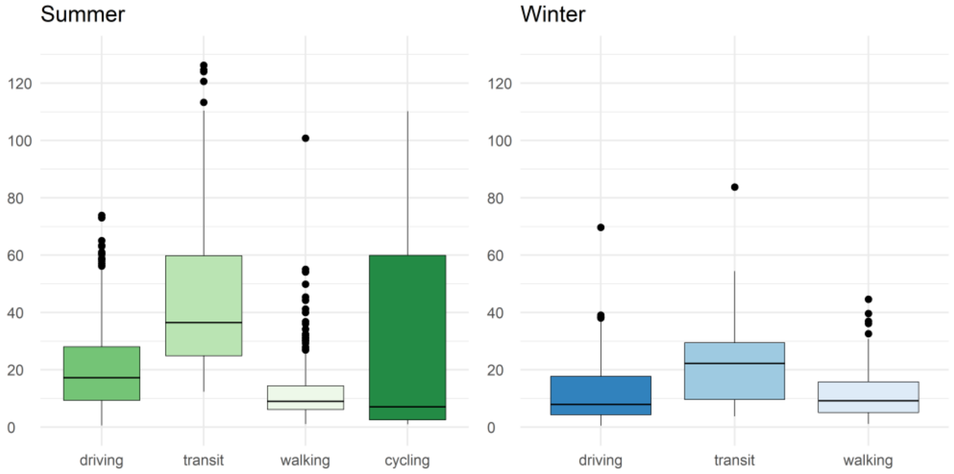


Figure 3.13 Duration of trips [min] depending on chosen mode

3.7.4 *Joint travel*

Joint travel accounts for a very high share of all trips in the sample. Out from 3120 trips, 3048 trips (98%) were made with some accompanying person (not necessarily a relative or household member), 2671 trips (86%) with at least one household member (which includes e.g. grandparents living with the family), whereas 2594 trips (83%) were made with closest family members, i.e. a spouse or children.

Figure 3.14 and Figure 3.15 illustrate the relationship between the chosen mode and the family composition on a trip and between the chosen mode and the number of accompanying household members. In principle, with the increasing party size, the preference for walking decreases and increases for driving instead.

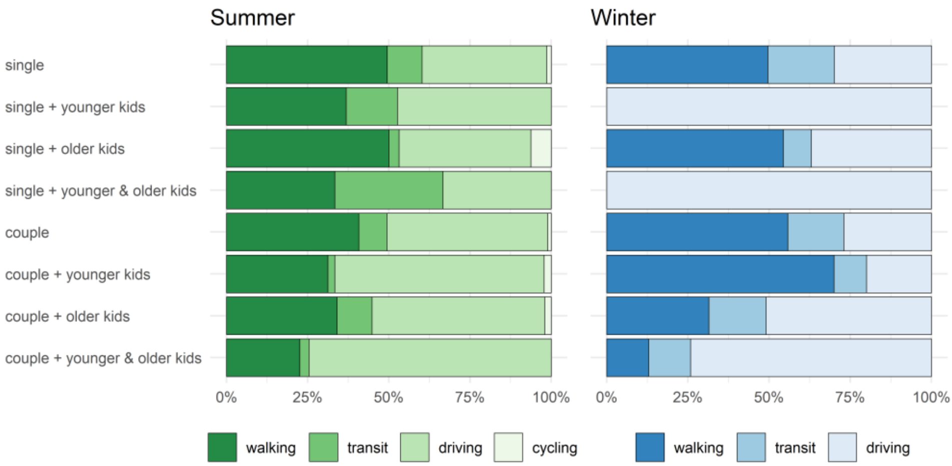


Figure 3.14 Chosen mode depending on family composition during the trip

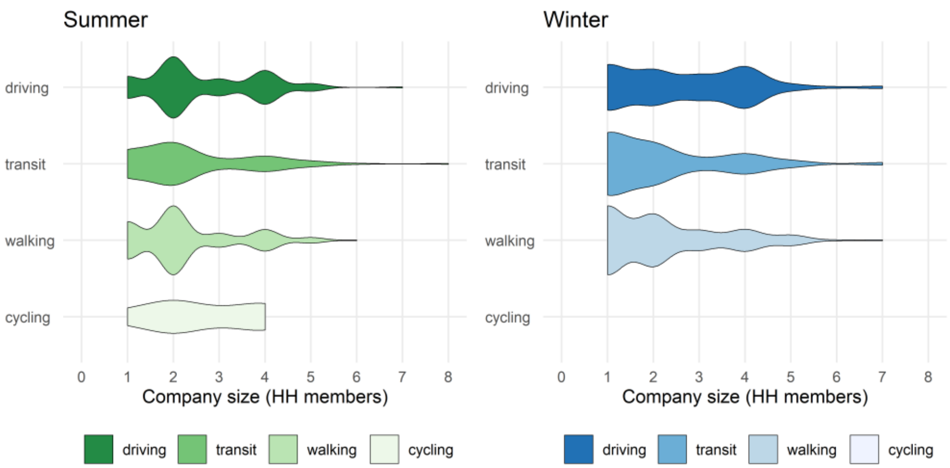


Figure 3.15 Chosen mode depending on company size (only household members)

Figure 3.16 illustrates the relationship between the distance of trips and the family composition. As long as traveling with children clearly affects the transport mode choice, it does not seem to influence the choice of destination much. Parents with and without children, solo and with spouse, undertake longer trips equally often. Apparently, parents do not avoid traveling with kids to distant locations within the vacation region. They adapt the mode choice in the first place but the final destination remains unaffected.[4]

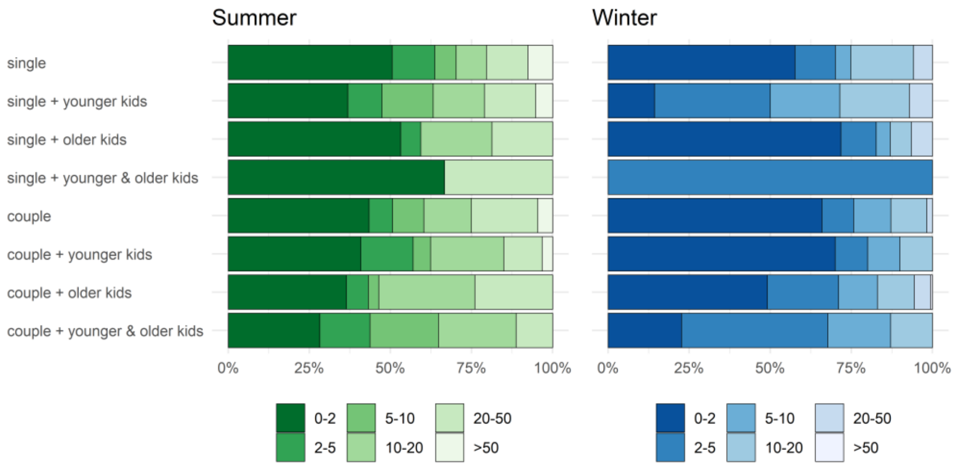


Figure 3.16 Distance travelled depending on family composition

3.7.5 *Impact of weather*

Respondents were asked to assess the impact of weather on their activity and transport mode choices. In 5.92% cases in summer and 1.52% cases in winter, they were forced to choose an alternative activity, whereas only in 0.98% cases in summer and 1.8% cases in winter, they had to resort to another means of transport due to unfavorable weather conditions. These statements show a very low impact of weather on tourists' choices and suggests that tourists determined to follow the vacation schedule (that they probably prepared beforehand) no matter the weather.

Combining the responses based on personal weather perception with real measurement data from weather stations located nearest to the starting points of the trips provides a similar picture (Table 3.7). In only up to 5% observations, when it was raining in summer, respondents declared to have chosen another transport mode than planned.

[4] It might however result from a limited number of alternatives for pursuing the planned activities, which forces families to travel far anyway (e.g. only one ski resort in the area).

Table 3.7 Impact of (perceived) weather on mode choice

Variable	Value	Summer		Winter	
		Precip. > 0	Precip. = 0	Precip. > 0	Precip. = 0
Impact of weather on mode choice	1st choice transport mode (as planned)	95.1%	99.6%	100.0%	98.0%
	2nd choice transport mode (plan B)	4.9%	0.4%	0.0%	2.0%

This finds confirmation in Figure 3.17 illustrating the mode choice depending on precipitation. Visitors seem to be very indifferent to precipitation in summer – in fact, they are even more likely to walk in the rain.

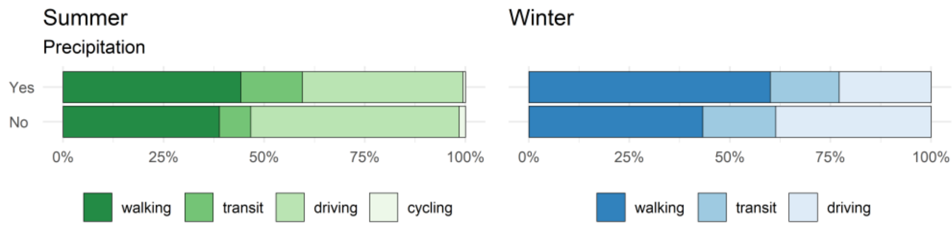


Figure 3.17 Mode choice of tourists depending on precipitation

Figure 3.18 illustrates how the distance of trips made in summer is affected by the presence of rain. It can be observed that for all modes except cycling, longer trips (above median) are still well represented, which might suggest that tourists adapt or give up the nearby activities, but would rather not give up the further ones (that cost more or were arranged more in advance).

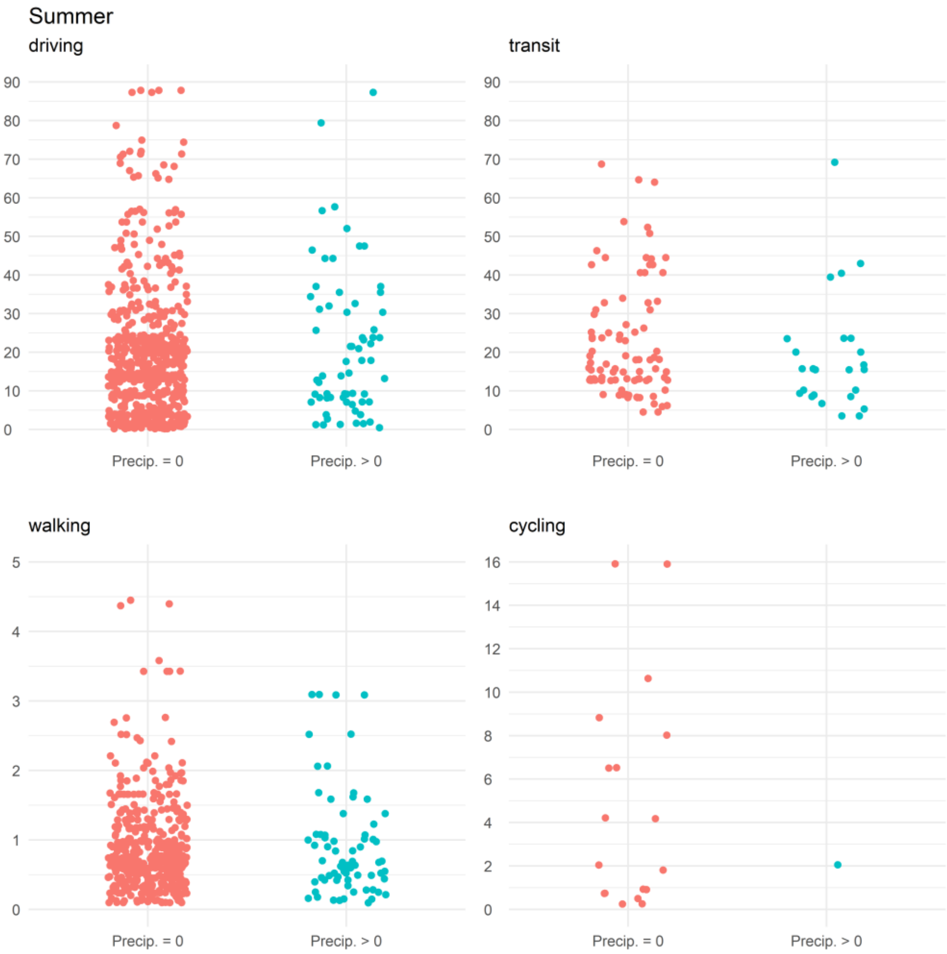


Figure 3.18 Trip distance for each mode in summer depending on precipitation

4 THE MODELING WORK

4.1 DATA PROCESSING

4.1.1 *Characteristics of the decision-makers and the sojourn*

An exploratory approach was chosen for the model building process. Based on the research on travel behavior and tourism, the survey work and common-sense-based presumptions, a set of variable candidates was preselected. Their explanatory power is investigated in section 4.3.

Sociodemographic variables:

- Age
- Gender
- Education
- Employment
- Household size
- Number of children under 6 in the household
- Number of children 6-17 in the household
- Monthly net household income in EUR
- Annual leave (in days)
- Nights away in the last year
- Driver's license
- Car availability
- Car use frequency
- Health status
- Physical limitations

- Sport frequency (days in a week)
- Sport time (hours in a week)

Sojourn- and travel-related variables:

- Length of stay
- Company size and composition during the stay
- Type of holiday
- Number of previous visits
- Main destination
- Main purpose
- Main transport mode used for travel to the destination
- Information level about travel options
- Information level about on-site mobility
- Type of accommodation
- Standard of hotel (* stars)
- Price per person per night [EUR]

Additional variables related to single observations (trips):

- Company size and composition during the trip
- Time of day
- Duration of the following activity
- Trip purpose
- Average duration of the activities of the respondent per day
- Average number of trips of the respondent per day
- Temperature in ºC (average from ±1 hour from the start time of the trip)
- Precipitation in mm (average from ±1 hour from the start time of the trip)
- Wind speed in km/h (average from ±1 hour from the start time of the trip)
- Sky overcast represented by sunshine hours (average from ±1 hour from the start time of the trip)

– Snow depth in cm (average from ±1 hour from the start time of the trip)

4.1.2 *Attributes of alternatives*

Attribute data for chosen and non-chosen alternatives were computed with the use of the API (Application Programming Interface) service of *Google Maps* and the transportation model of the federal province of Tyrol. While travel times and distances could be easily calculated for the alternatives: driving, cycling and walking, querying the data for transit proved cumbersome. *Google Maps* does have transit routing functionality, but not all transit schedules in the Tyrol are integrated in their service. For instance, the lines operated by *Verkehrsverbund Tirol*[5] are included, but the lines operated by *Ötztaler Verkehrsgesellschaft*[6] are not. Alternative open-source map projects such as *OpenStreetMap*[7] or *OpenRouteService*[8] do not provide routing with transit. Only the database of *Verkehrsauskunft Österreich*[9] covers all official public transport services in Austria, be it daily regional lines or seasonal services. However, it still does not account for local on-demand connections, ski-bus lines and shuttle services operated by hotels, which can make up for a substantial part of transit services in remote settlements. Besides, their API system is a paid service and there is no open-source solution to fetch the routing data from the API. Hence, it was not used in the thesis.

4.1.2.1 *Distance and travel time*

It was decided already at the survey design stage that the distances and travel times (in minutes) will have to be calculated based on external data rather than data obtained from the respondents. Data reported by the respondents are very prone to a bias, resulting from perception differences, over- and underestimation or rounding issues (Bovy and Stern, 1990; Chalasani et al., 2004). Asking these questions would have also substantially increased the response burden.

In the first place, start and end locations of trips (string addresses) were converted into geographic coordinates in WGS84 system using *Google Maps Geocoding* API controlled through R packages *ggmap* (Kahle and Wickham, 2013) and *googleway* (Cooley, 2018). The geocoded addresses were then used to calculate distances and travel times for modes driving, walking and cycling with the use of *Google Maps Distance Matrix* API. The driving travel times obtained through the *Google Maps* API are values from a loaded network, i.e. with the Google traffic information at the time of running the script. *Google Maps* does not offer the functionality to calculate

[5] https://www.vvt.at/
[6] https://www.oetztaler.at/
[7] https://www.openstreetmap.org/
[8] https://openrouteservice.org/
[9] https://www.verkehrsauskunft.at/

precise driving travel times for traffic conditions observed in the past (a time range is provided instead), nor does it allow to get transit travel times for departure times lying more than a few days in the past. Due to very incomplete transit data for the Tyrol in *Google Maps*, it was necessary to rely on more complete, yet old (dating back to 2010), travel time skim matrices from the regional VISUM transportation model. For transit, the access and egress walking distance and walking time were determined with the *Google Maps* API, benefiting from its algorithm being able to allow for the altitude difference, which is often considerable in the alpine topography. It is especially important for tourist trips since transit stops are usually located on the main road axis of the valley in its lowest point and hotels are spread on the slopes to the left and right of the valley's axis. In the case of transit trips to activities classified as "Cycling/MTB", we assumed the access and egress section from the start/end point to the bus stop was done by bicycle at an average speed of 20km/h.

4.1.2.2 *Travel cost*

Travel cost (in EUR) was calculated in different ways for different alternatives:

- Driving – driving distance multiplied by an average fuel consumption of 8l/100km and an average cost of fuel in Austria 1.30 EUR/l.
- Transit – for tourists staying in the valley and for trips starting and ending within the valley, following conditions apply depending on the region:
  - Ötztal – free unlimited access to transit in winter with the *ÖtztalGuest-Card* (issued free of charge by the accommodation provider) and in summer with the *ÖtztalPremiumCard* offered for free in 320 hotels (otherwise 60-105 EUR)
  - Zillertal – free unlimited transit services with the *ZillertalerSuperskipass* in winter and with the paid-for *ZillertalActivcard* in summer (cost 64-156 EUR).
  - Hohe Salve / Kitzbüheler Alpen - free transit services all year long
  - Otherwise, for people not entitled to free mobility or for trips exceeding the regions' boundaries, an average price of 0.26 EUR per km based on regional (VVT) single-ticket prices was calculated. The minimum fare was set on 1.30 EUR, which corresponds to the cheapest single ticket. The maximum fare was set on 17.50 EUR, which is the price for a day ticket valid for the entire province. It is assumed that parents cover the costs of transit tickets for their children, and in case both parents are traveling, the cost of tickets for the whole group is divided by two.
- Cycling and walking – travel cost is always 0.

Many other (sometimes very specific) exceptions must be considered when calculating the cost of car and transit trips. One could, for example, think of a group of tourists whose main means of transport for the journey from their home town to their destination was a coach. The group is traveling together to many activities during their stay (such as skiing) and the coach serves as kind of a free shuttle that does not require any instantaneous expenses (it is certainly included in the price of the holiday package by the tour operator). In case of such trips, the cost variable should be set to zero.

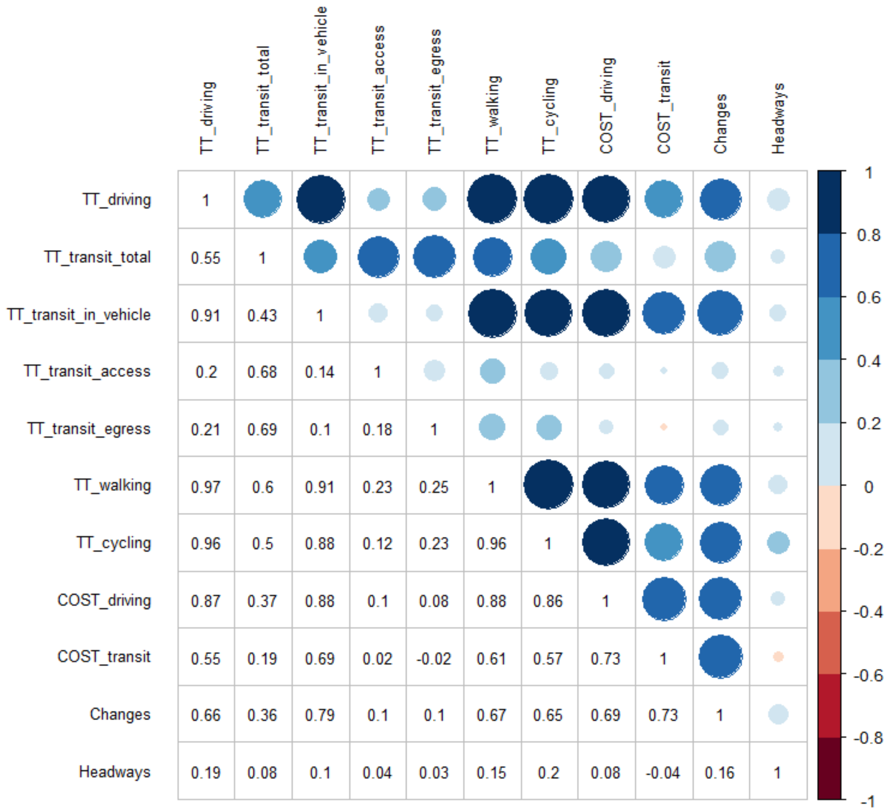


Figure 4.1 Correlations of the attributes of alternatives

4.1.3 *Individual choice set of available modes*

The transport modes used for trips reported in the diaries comprise nine alternatives. For modeling purposes, the modes were aggregated into four groups (Table 4.1). The reason being e.g. difficulties with determining the availability and the cost of modes of type “as a passenger” and of type “rented car”, marginal share of taxi rides etc.

Table 4.1 Choice alternatives – original alternatives reported in the survey and aggregated alternatives used in the models

Original alternative	Aggregated alternative
Motorcycle as a driver Motorcycle as a passenger Private car as a driver Private car as a passenger Rented car, car-sharing as a driver Rented car, car-sharing as a passenger Taxi, ride-sharing	Driving
Transit	Transit
Walking	Walking
Cycling	Cycling
Cable car	(alternative dropped as not relevant, collected only for the sake of diary completeness)

Furthermore, due to different mode availabilities, the choice set differs for every individual and every choice situation. It is very important, particularly when working with RP data, to apply strict reasoning to replicate the actual availabilities of alternatives at the moment of making a decision. This is often ignored or not reported by researchers, although there are some examples of well-documented availability calculations like Ton et al. (2019) or Gehrke and Clifton (2014).

In this thesis, following trip-chaining heuristics were applied to precisely identify the realistically available choice set:

- Availability of the driving alternative:
  - If a private or rented car was used for travel to the destination, it is assumed to be available during the whole stay. Otherwise, driving alternative is not available for traveling on-site.
  - Driving alternative is always available for the 1st trip from the accommodation on a given day. For subsequent trips, it is available only if it was used on a preceding trip or if the person returned to the accommodation between the trips.
  - Non-drivers must travel accompanied by persons possessing a driver’s license.

  - If the preceding trip was made by bicycle and did not end at the accommodation, one must return to it by bicycle as well. Hence, driving is not available.
  - Driving in not available for trips to/from activities “Hiking/trekking” and “Walking” if walking alternative was chosen. The reasoning in such cases is that these trips are regarded as part of the following/preceding activity and alternative modes are not considered.
  - The same pertains to trips to/from activities “Cycling/MTB” when cycling alternative was chosen as a transport mode.
  - Not available if *Google Maps* API did not return valid routing data.
- Availability of the transit alternative:
  - If either the access or egress distance to the next bus stop is >2km, transit is considered not available.
  - Not available at night between 12:01am and 6:59am.
  - Not available if the preceding trip was made by car or by bicycle and did not end at the accommodation, since one must return to it by car or by bicycle as well (although bicycle transport is possible on buses equipped with bicycle racks).
  - Not available if there is no information on travel time and distance in the transportation model or if it is very implausible (e.g. average speed >50km/h, distance > 2*distance from *Google Maps* API).
- Availability of the walking alternative:
  - Walking is initially always available.
  - Not available for trips that would have taken >120min on foot in summer and >60min on foot in winter.
  - Not available if the preceding trip was made by car or bicycle and did not end at the accommodation, since one must return to it by car or bicycle as well.
  - Not available if *Google Maps* API did not return valid routing data.
- Availability of the cycling alternative:
  - Initially always available given that guests can rent bicycles free of charge at majority of accommodations providers.
  - Available only in summer.
  - Not available for trips that would have taken >120min.

- Not available if the preceding trip was made by car and did not end in the hotel, since one must return to the hotel by car as well.
- Not available if *Google Maps* API did not return valid routing data.

There is very probably a certain amount of error in the data on transit routes as it was not possible to collect all information on existing transit options in each region. Apart from regular transit services, permanent and temporary ski-bus lines in winter as well as hiker's buses and hut taxies in summer, there are also non-regulated hotel shuttles and micro-mobility services organized on demand by municipalities and mountain lift operators. These are not covered in the dataset, which might result in biased model coefficients.

4.1.4 *Exclusion of observations*

Some observations had to be excluded from the data set if any of the following conditions applied:

- The only respondent from a group/family is below 18 (assumed not to be the decision maker in a group).
- Respondent's place of stay located outside of the regions: Ötztal, Zillertal and Hohe Salve.
- Start and end location of the trip are identical (trip length is zero).
- The reported trip was made by cable car.
- Trip length is under 100m – very short trips are potentially skewed by geolocation errors and often result in implausible *Google Maps* routing.
- Trip or activity starts or ends abroad, e.g. in South Tyrol in Italy (no transit routing data available for cross-border trips).
- Missing or wrong information for the attributes of alternatives (wrong geocoding, unavailable Google routing data, implausible data in the transportation model, etc.)
- The respondent reported trips from the arrival (first) or departure (last) day of their stay. These trips are assumed to be strongly influenced by the arrival/departure pattern, check-in/out at the hotel, unpacking, etc. and do not reflect the typical travel behavior of a person in a middle stage of their stay (a regularity noticed by McKercher and Lau (2008)).
- The content and quality of the travel-activity diary was insufficient to impute trip and activity characteristics (missing location, type, transport

mode, place of stay, etc.). This pertains in particular to the PAPI winter survey with questionnaires distributed in hotels and partially assisted interviews.

Furthermore, strolls and recreational walking and cycling, even if reported as a trip, were individually analyzed and if necessary reclassified into recreational activities and excluded from the dataset, as these are movements for which travel is a not a derived demand.

Eventually, out of 3120 observations, 884 had to be excluded from the data, that is, 2236 observations (71.67%) were retained for model building. Out of them, 1328 are from summer and 908 from winter.

4.2 MODEL SPECIFICATION AND ESTIMATION

In the first instance, base MNL models are specified and serve as point of reference for benchmarking more advanced approaches. Next, more complex structures are employed and compared with parsimonious specifications in terms of goodness of fit using the likelihood-ratio test.

The estimation results for all models are summarized in the sections below. The names of the models follow the natural numbering convention starting at zero or one for the base specifications and increasing with the increasing model complexity. Each model is prefixed with the abbreviation of the applied modeling approach used for the estimation (MNL, NL, CNL).

Modeling results are presented in Table 4.2 to Table 4.22. For each model, the following information and model diagnostics is provided:

- Model estimates with robust t-test ratios against 0 (or 1 in case of NL models), calculated with sandwich standard errors, and corresponding significance levels (0.01; 0.05; 0.1)
- Number of individuals
- Number of observations
- Number of estimated parameters
- Final log-likelihood at convergence
- Adjusted Rho-square
- AIC
- BIC
- P-value for the likelihood-ratio test under the hypothesis that the restricted model is true

All substantial or interesting differences between models are described in the text accompanying the tables. In particular, the seasonal differences between winter and summer are highlighted.

Data transformation and modeling tasks were done in the statistical software R 3.6.2 (R Core Team, 2019) employing the *Apollo* package for choice model estimation and application. *Apollo* is a *"a flexible, powerful and customisable freeware software package for choice model estimation and application"* developed at The Choice Modelling Centre of the University of Leeds (Hess and Palma, 2019). It enables estimation of various model specifications including models with random coefficients, discrete-continuous models, models with latent classes and many others. It also facilitates making model predictions and calculating various model indicators, including willingness-to-pay ratios using the Delta method (Daly et al., 2012). All models are estimated with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) routine.

4.3 Multinomial Logit models

Within this section, variables based on almost all questions described in section 3.2 were investigated in MNL models. To avoid the multicollinearity issues (Alin, 2010; Chatterjee and Hadi, 2006), all preselected variables were tested independently by adding to the base model containing only the fundamental predictors: travel time and travel cost. Only models with statistically significant variables are reported in this section. When specifying full models (MNL_3.1), efforts were made to identify highly correlated explanatory variables and exclude them from the specifications, since the model then starts to behave unpredictably, i.e. despite an increase in fit, the sign and magnitude of coefficients of the correlated variables fluctuates strongly. The fundamental predictors of travel time and travel cost were always preferred in case any additional variable correlated with them.

Among all tested variables, the following proved not significant both in summer and winter data: gender dummy interacting with travel time, age interacting with travel time, income interacting with travel cost, car use frequency (at home), holiday type (package/individual), length of stay and elapsed stay (main effects), physical disability, number of previous visits, number of vacation days, main purpose of holiday, main transport mode used for travel to the destination (though it determines the mode availabilities), sky overcast. Household size is significant, but the exact number of younger and older children and other family members has a greater effect and was used instead.

Models reported in this section:

- MNL_1.0 – travel time only
- MNL_1.1 (base) – travel time and travel cost with generic coefficient for all modes

- MNL_1.2 – travel time and travel cost with alternative-specific coefficients
- MNL_2.1 – access, egress and in-vehicle travel time for transit
- MNL_2.2-2.3 – base + quality variables for transit (transfers, headways)
- MNL_2.4 – base + interactions of travel time and cost with sociodemographics
- MNL_2.5 – base + hotel-related variables
- MNL_2.6 – base + company variables
- MNL_2.7 – base + peak-time variable
- MNL_2.8 – base + duration of the following activity
- MNL_2.9 – base + trip purpose
- MNL_2.10 – base + number of trips
- MNL_2.11 – base + average duration of activities
- MNL_2.12 – base + weather variables
- MNL_2.13 – base + information levels
- MNL_2.14 – base + sport frequency
- MNL_3.1 – full model with all significant variables

In general, the probability of a decision-maker n choosing alternative i from a choice set C_n is given by (Ben-Akiva and Lerman, 1985):

$$P(i|C_n) = Pr\left(U_{in} \geq U_{jn}, \forall j \in C_n\right) \quad (4.1)$$

where U_{in} is the utility of the alternative i and can be divided into two parts as fol

$$U_{in} = V_{in} + \varepsilon_{in} \quad (4.2)$$

with V_i denoting the deterministic component of the utility and ε_{in} representing the random component (error term).

Assuming independently and identically Gumbel distributed error terms, the probability can be then conveniently expressed as:

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \quad (4.3)$$

yielding the Multinomial Logit model (MNL).

The deterministic components of utilities used in the MNL models in this chapter are of additive and linear-in-parameters functional form.

The utility functions in the MNL_1.1 base model for summer are defined as follows:

$$V_{driving} = ASC_{driving} + \beta_{TT_{driving}} \cdot TT_{driving} + \beta_{COST_{driving}} \cdot COST_{driving} \quad (4.4)$$

$$V_{transit} = ASC_{transit} + \beta_{TT_{transit}} \cdot TT_{transit} + \beta_{COST_{transit}} \cdot COST_{transit} \quad (4.5)$$

$$V_{walking} = ASC_{walking} + \beta_{TT_{walking}} \cdot TT_{walking} \quad (4.6)$$

$$V_{cycling} = ASC_{cycling} + \beta_{TT_{cycling}} \cdot TT_{cycling} \quad (4.7)$$

The utility functions in the MNL_1.1 base model for winter are defined as follows:

$$V_{driving} = ASC_{driving} + \beta_{TT_{driving}} \cdot TT_{driving} + \beta_{COST_{driving}} \cdot COST_{driving} \quad (4.8)$$

$$V_{transit} = ASC_{transit} + \beta_{TT_{transit}} \cdot TT_{transit} \quad (4.9)$$

$$V_{walking} = ASC_{walking} + \beta_{TT_{walking}} \cdot TT_{walking} \quad (4.10)$$

Utilities of other model specifications (MNL_1.0, MNL_1.2-3.1) rely all on the base models MNL_1.1 and differ only in the additional variables.

4.3.1 *Models with travel time and travel cost*

A few versions of base MNL models were built, for both the summer and winter datasets. The models MNL_1.0 include only travel time, the models MNL_1.1 extend the specification by travel cost and model MNL_1.2 allows for alternative-specific cost coefficients (in summer). Table 4.2 presents model results and summary statistics.

With car alternative being the reference category, the values of alternative specific constants in summer models show that walking is the most preferred alternative, and transit and cycling are significantly disliked compared to car. In winter on the other hand, there is a high initial preference for walking, followed by transit and car. Estimates for travel time coefficients reveal a similar effect for all means of transport in models for both seasons, with the exception of transit in summer, where the effect is substantially lower than for other alternatives. Remarkable is that the difference in the magnitude of time and cost coefficients is larger in winter than in summer. That is, more price discount is needed to compensate for an increased travel time in winter than in summer. Or to put it another way, a decision-maker is generally willing to travel longer in winter than in summer to save 1 Euro, which implies a lower Value of Time in winter (except for transit in summer, where the ratio of coefficients is lower than in winter). Due to transit services offered free-of-charge in winter in all surveyed regions (for overnight guests), transit cost variable was omitted in the winter model. Including it, with almost no trips having cost >0, resulted in implausible coefficient values, quasi-separation and extreme standard errors (Albert and Anderson, 1984).

Table 4.2 MNL models with travel time and cost

Model name	MNL_1.0_ summer		**MNL_1.1_ summer (base)**		MNL_1.2_ summer		MNL_1.0_ winter		**MNL_1.1_ winter (base)**	
	Esti-mate	Rob.t-ratio(0)	Esti-mate	Rob.t-ratio(0)	Esti-mate	Rob.t-ratio(0)	Esti-mate	Rob.t-ratio(0)	Esti-mate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA	0	NA	0	NA	0	NA
$ASC_{walking}$	2.58***	7.95	2.669***	8.17	2.664***	8.2	1.704***	6.3	1.854***	6.52
$ASC_{transit}$	-1.775***	-5.1	-2.18***	-4.71	-2.158***	-4.55	0.217	0.7	0.537	1.45
$ASC_{cycling}$	-2.164***	-3.82	-1.994***	-3.68	-2.008***	-3.64				
$\beta_{TT_{driving}}$	-0.199***	-4.49	-0.131***	-2.79	-0.129***	-2.77	-0.232***	-4.1	-0.17***	-2.97
$\beta_{TT_{walking}}$	-0.158***	-9.58	-0.155***	-9.35	-0.154***	-9.4	-0.123***	-8.73	-0.124***	-8.54
$\beta_{TT_{transit}}$	-0.099***	-4.27	-0.069***	-2.55	-0.071***	-2.43	-0.131***	-4.6	-0.148***	-4.41
$\beta_{TT_{cycling}}$	-0.175***	-6.58	-0.172***	-6.67	-0.171***	-6.71				
β_{COST}			-0.769***	-4.41					-1.165**	-2.36
$\beta_{COST_{driving}}$					-0.852**	-2.43				
$\beta_{COST_{transit}}$					-0.716***	-4.29				
No. individ.	314		314		314		213		213	
No. obs.	1327		1327		1327		908		908	
Estimated param.	7		8		9		5		6	
LL(final)	-197.446		-192.497		-192.475		-281.904		-279.112	
Adj.Rho-square (0)	0.6162		0.6236		0.6218		0.1802		0.1853	
AIC	408.89		400.99		402.95		573.81		570.22	
BIC	445.23		442.52		449.67		597.86		599.09	
LR test p-value	-	-	comp. to MNL1.0	0.0017	comp. to MNL1.1	0.8332	-	-	comp. to MNL1.0	0.0181

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

The p-value of LR test for the MNL_1.2 specification is 0.8332. Consequently, the null hypothesis assuming the cost coefficient to be generic cannot be rejected. One should also point out a considerably higher value of the adjusted ρ^2 diagnostic in summer than in winter. However, if ρ^2 of 0.2 to 0.4 represents an excellent fit according to McFadden (1977b), then values of 0.180-0.185 in winter can be considered acceptably good.

4.3.2 *Models with access, egress and in-vehicle travel time for transit*

Splitting transit travel time into three components: access time, in-vehicle time and egress time unveils a higher effect of access and egress time compared to time spent in the vehicle. It is in line with findings known from studies on commute travel, where out-of-vehicle time does play a more important role that in-vehicle time. What is more, egress time appears to be even more important for tourists traveling by public transportation (see section 4.6 for a comment on that). However, these specifications do not perform better that the base MNL_1.1 and some coefficient values (access time in summer, travel cost in winter) are not significant (Table 4.3).

Table 4.3 MNL models with access, egress and in-vehicle time for transit

Model name	MNL_2.1_summer		MNL_2.1_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.683***	8.26	1.931***	6.47
$ASC_{transit}$	-1.821***	-3.97	0.878*	2.09
$ASC_{cycling}$	-1.956***	-3.57		
$\beta_{TT_{driving}}$	-0.113**	-2.41	-0.153***	-2.45
$\beta_{TT_{walking}}$	-0.151***	-9.22	-0.123***	-8.04
$\beta_{TT_{cycling}}$	-0.164***	-6.49		
$\beta_{TT_{transit\_access}}$	-0.07	-1.38	-0.193***	-3.72
$\beta_{TT_{transit\_invehicle}}$	-0.055**	-2.05	-0.122***	-3.05
$\beta_{TT_{transit\_egress}}$	-0.156***	-2.68	-0.257***	-3.07
β_{COST}	-0.704***	-4.88	-0.888*	-1.73
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	10		8	
LL(final)	-191.243		-276.6247	
Adj.Rho-square (0)	0.6222		0.1867	
AIC	402.49		569.25	
BIC	454.39		607.74	
LR test p-value	comp. to MNL_1.1	0.2854	comp. to MNL_1.1	0.0831

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.3 *Models with service quality variables for transit*

Table 4.4 and Table 4.5 present coefficient estimates for models with variables describing the quality of transit service – number of transfers on a trip and headway (in minutes) between the successive vehicles.

Table 4.4 MNL models with number of transfers on transit trips

Model name	MNL_2.2_summer		MNL_2.2_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.66***	8.11	1.898***	6.5
$ASC_{transit}$	-2.224***	-4.71	0.392	0.98
$ASC_{cycling}$	-2.015***	-3.7		
$\beta_{TT_{driving}}$	-0.138***	-2.94	-0.089	-1.3
$\beta_{TT_{walking}}$	-0.156***	-9.42	-0.113***	-7.9
$\beta_{TT_{transit}}$	-0.07***	-2.59	-0.109***	-2.97
$\beta_{TT_{cycling}}$	-0.173***	-6.72		
β_{COST}	-0.734***	-3.8	-1.688***	-2.48
$\beta_{TRANSFERS}$	-0.425	-0.42	-4.279***	-3.91
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	9		7	
LL(final)	-192.415		-274.9116	
Adj.Rho-square (0)	0.6219		0.1945	
AIC	402.83		563.82	
BIC	449.55		597.5	
LR test p-value	comp. to MNL_1.1	0.6856	comp. to MNL_1.1	0.0038

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

Adding the transfers variable to models results in a low and insignificant effect in summer and very large negative and significant effect in winter. It might be explained by the fact that in summer tourists travel on transit to very diverse destinations, where line changes are unavoidable due to the complexity of the connections, whilst in winter trips are simpler and more direct, and transfers on such trips have a very negative impact.

Table 4.5 MNL models with headways between transit vehicles

Model name	MNL_2.3_summer		MNL_2.3_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.633***	8.04	1.865***	6.53
$ASC_{transit}$	-2.031***	-3.91	0.464	1.26
$ASC_{cycling}$	-2.066***	-3.74		
$\beta_{TT_{driving}}$	-0.153***	-3.02	-0.165***	-2.92
$\beta_{TT_{walking}}$	-0.157***	-9.41	-0.124***	-8.6
$\beta_{TT_{transit}}$	-0.078***	-2.73	-0.146***	-4.5
$\beta_{TT_{cycling}}$	-0.175***	-6.81		
β_{COST}	-0.733***	-4.4	-1.169***	-2.38
$\beta_{HEADWAYS}$	-0.002	-0.73	0.001	0.56
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	9		7	
LL(final)	-192.2342		-278.9608	
Adj.Rho-square (0)	0.6222		0.1829	
AIC	402.47		571.92	
BIC	449.18		605.6	
LR test p-value	comp. to MNL_1.1	0.4686	comp. to MNL_1.1	0.5826

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

Frequency of bus connection seems not to play a role for tourists either in summer or in winter. The implausibly low significance levels and positive value of $\beta_{HEADWAYS}$ in winter might be attributed to the low quality of timetable data in the transportation model of Tyrol.

4.3.4 *Models with interactions of travel time and cost with sociodemographic- and sojourn-related variables*

Table 4.6 presents results of a model where the travel time and travel cost variables interact with sociodemographic characteristics of the respondents (age and income) and the sojourn attributes (length of stay).

Table 4.6 MNL models with interactions of travel time and cost with sociodemographic- and sojourn-related variables

Model name	MNL_2.4_summer		MNL_2.4_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.685***	8.18	1.954***	6.44
$ASC_{transit}$	-2.191***	-4.74	0.631*	1.65
$ASC_{cycling}$	-1.938***	-3.59		
$\beta_{TT_{driving}}$	-0.159***	-3.27	-0.591***	-2.94
$\beta_{TT_{walking}}$	-0.187***	-7.72	-0.225***	-4.42
$\beta_{TT_{transit}}$	-0.102***	-3.18	-0.396***	-3.58
$\beta_{TT_{cycling}}$	-0.213***	-6.33		
β_{COST}	-0.862***	-4.56	-2.26***	-3.04
$\beta_{TT_{sensitivity\_lengthofstay}}$	0.004**	2.32		
$\beta_{COST_{shift\_highincome}}$			1.109***	2.51
$\beta_{TT_{sensitivity\_age\_driving}}$			0.425***	2.45
$\beta_{TT_{sensitivity\_age\_walking}}$			0.094**	2.17
$\beta_{TT_{sensitivity\_age\_transit}}$			0.232***	2.46
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	9		10	
LL(final)	-190.9874		-270.6486	
Adj.Rho-square (0)	0.6246		0.1981	
AIC	399.97		561.3	
BIC	446.69		609.41	
LR test p-value	comp. to MNL_1.1	0.0016	comp. to MNL_1.1	0.002

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

In summer, one can observe a positive sensitivity of travel time coefficients with respect to the length of stay (in full days). The coefficient $\beta_{TT_{sensitivity\_lengthofstay}}$ is generic for all modes and significant at 5% level. For short stays, the effect is rather weak compared to other estimates. It can however make a substantial difference for stays longer than one week. In addition to the direct effect of the (fixed) length of stay, also the effect of the (varying) moment of the stay, represented by the elapsed fraction of stay $\frac{elapsed\ days\ of\ stay}{days\ of\ stay}$, was investigated. This was driven by two hypotheses. The first one posits that with the vacation days going by, people are becoming more relaxed[10], and hence, might potentially react less negatively to travel time. Their positive attitude might also follow a non-linear curve, as proposed by Lin et al. (2014), reaching its peak around the middle of the stay. The second one assumes the opposite – that they are becoming more stressed and impatient[11] and hence are reacting more negatively, which would be in line with the findings of Nawijn et al. (2013). However, no such effect in response to travel time was observed. So, interestingly, this positive time sensitivity does not change during the stay but is constant and works from the day one. Therefore, it should not be associated with a change in one's perception of travel time during the stay, yet it rather reflects an initial attitude developed before the arrival depending on how long the stay is scheduled for. No significant influence of age, gender or income on the perception of travel time were found in the summer data.

An interesting finding is the positive age sensitivity of travel time coefficients in MNL_2.4 for winter. With the increasing age, the response to longer travel time becomes less negative. That is, older people "take their time" more than younger counterparts.

As far is income is concerned, it does significantly affect the perception of travel cost among winter visitors. The cost coefficient becomes less negative (shifted by 1.109) for people belonging to the high-income group, which is rather unusual in daily commute travel, where larger income results in higher valuation of travel time and hence more negative reaction to longer travel time than among less wealthy individuals. High income was defined in the dataset as above the 2nd quantile, i.e. starting from 4.001 EUR. No such high-income shift is visible in the summer data.

4.3.5 *Models with hotel-related variables*

It was hypothesized that the characteristics of the accommodation chosen for the stay at the destination might correlate with the transport mode chosen for the on-site mobility. Accommodation providers can offer different quality of parking facilities, electric car charging stations, better or worse accessibility by public transportation or provide hotel-owned cars and bicycles for their guests, therefore possibly influencing their subsequent travel behavior. Four variables were investigated: object type, standard (only for hotels, represented by number of stars), price per person per night and price per room/apartment per night. Only price of the accommodation (in EUR) per person per night proved significant for some alternatives. As it

[10] The phenomenon of positive vacation effects on travelers' happiness and well-being is widely researched and its existence is confirmed (see for example Gilbert and Abdullah (2004) and Sirgy et al. (2011)). There is however no consensus on its dynamics over the course of the vacation stay. Nor there is any work so far that studied this phenomenon in the context of perception of travel time or travel cost.

[11] They might have not managed to see everything they planned and are trying catch it up before they leave. They might also be getting more stressed by the perspective of going back to work soon.

turns out (Table 4.7), staying in a pricier accommodation results in significantly lower odds of using bicycle compared to car in summer. However, the effect is small. In winter, on the other hand, hotel prices correlate positively (at 10% level) with more frequent transit choices, which could be associated with the fact that hotels located more centrally, and thus closer to bus and ski bus routes, tend to have higher night rates.

Table 4.7 MNL models with hotel-related variables

Model name	MNL_2.5_summer		MNL_2.5_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.387***	6.04	2.367***	3.68
$ASC_{transit}$	-2.047***	-2.94	-0.416	-0.64
$ASC_{cycling}$	-0.131	-0.14		
$\beta_{TT_{driving}}$	-0.132***	-2.74	-0.18***	-3.02
$\beta_{TT_{walking}}$	-0.155***	-9.42	-0.13***	-8.02
$\beta_{TT_{transit}}$	-0.072***	-2.58	-0.147***	-4.21
$\beta_{TT_{cycling}}$	-0.174***	-6.82		
β_{COST}	-0.802***	-4.36	-1.043**	-2
$\beta_{HOTEL\_PRICE_{driving}}$	0	NA	0	NA
$\beta_{HOTEL\_PRICE_{walking}}$	-0.011	-1.57	-0.005	-0.8
$\beta_{HOTEL\_PRICE_{transit}}$	-0.001	-0.17	0.011*	1.68
$\beta_{HOTEL\_PRICE_{cycling}}$	-0.033**	-2.23		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	11		8	
LL(final)	-189.4026		-270.1016	
Adj.Rho-square (0)	0.6238		0.2053	
AIC	400.81		556.2	
BIC	457.9		594.69	
LR test p-value	comp. to MNL_1.1	0.1028	comp. to MNL_1.1	0.0001

Significance levels (robust): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

4.3.6 *Models with company variables*

The influence of company size and structure was analyzed in terms of persons accompanying the respondent on a given trip. The structure and size of the company (in general) staying together during vacation as well as the structure and size of the respondent's household was also examined and no significant effects were noticed.

The model results are shown in Table 4.8. The summer model confirms what has always been claimed by hoteliers and destination managers. Namely that the presence of children under six years old, who obviously must be escorted by parents in their travel, strongly discourages them from choosing transit, walking or cycling. However, the presence of children between six and seventeen years old increases the utility of the transit and cycling alternatives. It is a reasonable outcome as the older children do not require any bulky items to be transported on the bus (e.g. baby carriage), and can already ride their own bicycle. The company of other household members appears to increase the odds of choosing walking and decrease the odds of choosing transit in summer.

Not only the influence of other household members is not visible in the winter model, but also children do not affect the mode choice of parents as clearly as they do in summer. The influence of children under six is less negative, and significant only for walking at $p < 0.1$, whereas the influence of older children is not significant at all. Consequently, the model does not perform much better than the base model, scoring only $p = 0.0621$ in the likelihood ratio test.

Table 4.8 MNL models with company variables

Model name	MNL_2.6_summer		MNL_2.6_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.057***	7.57	2.072***	6.57
$ASC_{transit}$	-2.445***	-3.88	0.668*	1.7
$ASC_{cycling}$	-2.195***	-3.42		
$\beta_{TT_{driving}}$	-0.148***	-2.89	-0.167***	-2.85
$\beta_{TT_{walking}}$	-0.175***	-8.76	-0.119***	-8.36
$\beta_{TT_{transit}}$	-0.078***	-2.72	-0.144***	-4.32
$\beta_{TT_{cycling}}$	-0.189***	-6.58		
β_{COST}	-0.804***	-3.69	-1.053**	-2.2
$\beta_{COMPANY\_CHILDREN\_6_{driving}}$	0	NA	0	NA
$\beta_{COMPANY\_CHILDREN\_6_{walking}}$	-0.953*	-1.82	-0.955*	-1.88
$\beta_{COMPANY\_CHILDREN\_6_{transit}}$	-1.584**	-1.94	-0.564	-0.86
$\beta_{COMPANY\_CHILDREN\_6_{cycling}}$	-1.338**	-2.11		
$\beta_{COMPANY\_CHILDREN\_6\_17_{driving}}$	0	NA	0	NA
$\beta_{COMPANY\_CHILDREN\_6\_17_{walking}}$	-0.144	-0.68	-0.384	-1.41
$\beta_{COMPANY\_CHILDREN\_6\_17_{transit}}$	0.705***	2.77	-0.157	-0.71
$\beta_{COMPANY\_CHILDREN\_6\_17_{cycling}}$	0.628*	1.8		

Continued on next page

Table 4.8 (continued from previous page)

Model name	MNL_2.6_summer		MNL_2.6_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$\beta_{COMPANY\_OTHER\_HH_{walking}}$	0.619**	2.39		
$\beta_{COMPANY\_OTHER\_HH_{transit}}$	-3.03***	-4.9		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	16		10	
LL(final)	-178.0694		-274.6324	
Adj.Rho-square (0)	0.6357		0.1867	
AIC	388.14		569.26	
BIC	471.19		617.38	
LR test p-value	comp. to MNL_1.1	0.0003	comp. to MNL_1.1	0.0621

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.7 *Models with peak-time variables*

The peak-time variable has five levels defined as follows:

- Morning peak: 7:00am-10:59am
- Noon off-peak: 11:00am-2:00pm
- Afternoon peak: 2:00pm-6:29pm
- Evening off-peak: 6:30pm-11:59pm
- Night: 12:01am-6:59am

Having transformed first four levels into dummy variables, only morning peak hours turned out to have a significant effect in the models. Both in summer and in winter, the transit alternative exhibits significant preference over car for trips between 7 and 11 am. Cycling and walking are significantly disfavored in the morning.

Table 4.9 MNL models with peak-time variables

Model name	MNL_2.7_summer		MNL_2.7_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.202***	7.75	2.171***	6.26
$ASC_{transit}$	-3.604***	-6.24	0.238	0.57

Continued on next page

Table 4.9 (continued from previous page)

Model name	MNL_2.7_summer		MNL_2.7_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{cycling}$	-1.062*	-1.75		
$\beta_{TT_{driving}}$	-0.069	-1.51	-0.157***	-2.62
$\beta_{TT_{walking}}$	-0.16***	-9.5	-0.131***	-9.04
$\beta_{TT_{transit}}$	-0.051**	-2.06	-0.157***	-4.57
$\beta_{TT_{cycling}}$	-0.166***	-6.01		
β_{COST}	-0.934***	-3.14	-1.431***	-2.67
$\beta_{PEAK\_MORNING_{driving}}$	0	NA	0	NA
$\beta_{PEAK\_MORNING_{walking}}$	-0.726*	-1.68	-0.399	-1.23
$\beta_{PEAK\_MORNING_{transit}}$	2.384***	4.25	0.727**	2.06
$\beta_{PEAK\_MORNING_{cycling}}$	-1.927**	-2.25		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	11		8	
LL(final)	-177.2864		-272.9281	
Adj.Rho-square (0)	0.6465		0.1973	
AIC	376.57		561.86	
BIC	433.67		600.35	
LR test p-value	comp. to MNL_1.1	0.0000	comp. to MNL_1.1	0.0021

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.8 *Models with duration of the following activity*

As the results in Table 4.10 show, the longer the activity duration (in minutes), the more probable is the choice of transit and less probable the choice of walking and cycling (compared to car) in summer. This can be associated with specific types of activities that take longer (like hiking or trekking), which is investigated in section 4.3.9. No such trend can be observed in winter.

Table 4.10 MNL models with duration of the following activity

Model name	MNL_2.8_summer		MNL_2.8_winter	
	Estimate[a]	Rob.t-ratio(0)	Estimate[a]	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.379***	6.5	2.15***	5.79

Continued on next page

Table 4.10 (continued from previous page)

Model name	MNL_2.8_summer		MNL_2.8_winter	
	Estimate[a]	Rob.t-ratio(0)	Estimate[a]	Rob.t-ratio(0)
$ASC_{transit}$	-3.042***	-6.61	0.48	1.13
$ASC_{cycling}$	-0.239	-0.29		
$\beta_{TT_{driving}}$	-0.098**	-2.02	-0.167***	-2.8
$\beta_{TT_{walking}}$	-0.159***	-9.23	-0.126***	-8.74
$\beta_{TT_{transit}}$	-0.067***	-2.6	-0.151***	-4.46
$\beta_{TT_{cycling}}$	-0.187***	-6.6		
β_{COST}	-0.871***	-2.49	-1.225**	-2.33
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{driving}}$	0	NA	0	NA
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{walking}}$	-0.003*	-1.83	-0.001	-1.27
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{transit}}$	0.005***	3.71	0.001	0.55
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{cycling}}$	-0.009**	-2.28		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	11		8	
LL(final)	-180.0524		-276.8726	
Adj.Rho-square (0)	0.6413		0.186	
AIC	382.1		569.75	
BIC	439.2		608.24	
LR test p-value	comp. to MNL_1.1	0.0000	comp. to MNL_1.1	0.1065

Significance levels (robust): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

[a]Activity duration variables are expressed in minutes. Hence, low coefficient values.

4.3.9 *Models with trip purpose*

Sport activities, defined in summer as climbing, cycling/MTB, hiking/trekking, walking, water sport or other sports, correlate negatively with choosing walking or cycling and positively with choosing transit over car (albeit significant only at 10% level). In winter on the other hand, next activity being sport, defined in winter only as skiing/snowboarding, has a large positive and highly significant effect on the utility of transit.

A very different pattern can be seen in trips to social activities understood as going out and visits to restaurants. Both in winter and in summer walking is clearly preferred over car for trips with social purpose. This is reasonable as people try avoiding using car when they might potentially drink alcohol. At the same time, transit has a significantly lower utility for such trips than car, which should be a clear message for the local transit operators, that the evening transit offer is unattractive for potential customers. Possible reasons could be low bus frequency in the evening and last services departing too early.

Table 4.11 MNL models with trip purpose

Model name	MNL_2.9_summer		MNL_2.9_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.043***	7.68	1.28***	2.92
$ASC_{transit}$	-2.421***	-4.53	-0.559	-1.2
$ASC_{cycling}$	-1.591**	-2.07		
$\beta_{TT_{driving}}$	-0.099**	-2.18	-0.128**	-1.97
$\beta_{TT_{walking}}$	-0.157***	-8.86	-0.127***	-8.44
$\beta_{TT_{transit}}$	-0.054**	-2.07	-0.151***	-4.17
$\beta_{TT_{cycling}}$	-0.163***	-6.41		
β_{COST}	-0.769***	-4.1	-1.767***	-2.62
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{driving}}$	0	NA	0	NA
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{walking}}$	-2.12***	-4.21	0.529	1.27
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{transit}}$	0.679*	1.79	1.524***	3.67
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{cycling}}$	-2.012**	-2.02		
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{driving}}$	0	NA	0	NA
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{walking}}$	1.452**	2.04	2.407***	3
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{transit}}$	-3.444***	-3.94	-6.615***	-6.67
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{cycling}}$	0.864	0.95		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	14		10	
LL(final)	-171.9392		-263.9735	
Adj.Rho-square (0)	0.6509		0.2171	
AIC	371.88		547.95	
BIC	444.55		596.06	
LR test p-value	comp. to MNL_1.1	0.0000	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.10 *Models with number of trips*

Number of different trips done on a single day can be seen as a proxy for being an active or a less active person. People making many trips, undertake many activities too. Hence, they consider car more attractive than transit (effect not significant in summer) but above all, they most probably choose walking and cycling, as it gives them the highest level of flexibility.

Table 4.12 MNL models with number of trips

Model name	MNL_2.10_summer		MNL_2.10_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	1.078*	1.75	-0.624	-1.06
$ASC_{transit}$	-1.381	-1.34	1.171*	1.91
$ASC_{cycling}$	-4.445***	-4.52		
$\beta_{TT_{driving}}$	-0.129***	-2.64	-0.201***	-2.99
$\beta_{TT_{walking}}$	-0.152***	-9.66	-0.132***	-8.69
$\beta_{TT_{transit}}$	-0.069***	-2.53	-0.149***	-3.93
$\beta_{TT_{cycling}}$	-0.164***	-6.8		
β_{COST}	-0.762***	-4.1	-1.099**	-2.09
$\beta_{NUMBER\_OF\_TRIPS_{driving}}$	0	NA	0	NA
$\beta_{NUMBER\_OF\_TRIPS_{walking}}$	0.457***	3	0.8***	3.92
$\beta_{NUMBER\_OF\_TRIPS_{transit}}$	-0.266	-0.91	-0.304*	-1.8
$\beta_{NUMBER\_OF\_TRIPS_{cycling}}$	0.759***	3.18		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	11		8	
LL(final)	-184.7642		-251.0166	
Adj.Rho-square (0)	0.6325		0.2599	
AIC	391.53		518.03	
BIC	448.63		556.52	
LR test p-value	comp. to MNL_1.1	0.0015	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.11 *Models with average duration of activities*

As the variables average duration of activities (in minutes) and the average number of different activities performed during a day exhibit a very strong negative correlation, the coefficients in model MNL_2.11 have opposite signs to the coefficients in model MNL_2.10. Tourist preferring activities that take many hours are significantly more inclined to use transit than any other mode since it is suits well their travel patterns that are simple and homogenous (mostly one trip in the morning from the hotel to the activity start location and one trip back in the afternoon).

Table 4.13 MNL models with average duration of activities

Model name	MNL_2.11_summer		MNL_2.11_winter	
	Estimate[a]	Rob.t-ratio(0)	Estimate[a]	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.389***	6.49	3.007***	5.59
$ASC_{transit}$	-3.314***	-6.65	-0.527	-1.04
$ASC_{cycling}$	-0.749	-0.9		
$\beta_{TT_{driving}}$	-0.103**	-1.96	-0.176***	-2.84
$\beta_{TT_{walking}}$	-0.155***	-9.15	-0.132***	-8.78
$\beta_{TT_{transit}}$	-0.063**	-2.31	-0.143***	-4.22
$\beta_{TT_{cycling}}$	-0.177***	-6.53		
β_{COST}	-0.803**	-2.4	-1.111**	-2.21
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{driving}}$	0	NA	0	NA
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{walking}}$	-0.004*	-1.77	-0.004***	-2.87
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{transit}}$	0.006***	3.59	0.003**	2.28
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{cycling}}$	-0.006*	-1.85		
Number of individuals	314		213	
Number of observations	1327		908	
Estimated parameters	11		8	
LL(final)	-182.7527		-263.9516	
Adj.Rho-square (0)	0.6363		0.2229	
AIC	387.51		543.9	
BIC	444.6		582.39	
LR test p-value	comp. to MNL_1.1	0.0002	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

[a]Activity duration variables are expressed in minutes. Hence, low coefficient values.

4.3.12 *Models with weather-related variables*

Since weather is assumed to be a particularly influential factor for tourist mode choice decisions, a number of different combinations of weather-related variables was thoroughly tested, which eventually led to the specification presented in Table 4.14. The model accounts for the effect of temperature, precipitation and wind on choosing weather-exposed means of travel, i.e. walking and cycling. All variables enter the utilities in linear form. Interactions capturing the differences in perception of weather depending on travel distance proved insignificant and were not included in the final specification.

Table 4.14 MNL models with weather-related variables

Model name	MNL_2.12_summer		MNL_2.12_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.805***	8.31	1.72***	5.72
$ASC_{transit}$	-2.17***	-4.71	0.478	1.27
$ASC_{cycling}$	-3.138***	-4.33		
$\beta_{TT_{driving}}$	-0.125***	-2.67	-0.177***	-3.04
$\beta_{TT_{walking}}$	-0.169***	-9.17	-0.122***	-8.16
$\beta_{TT_{transit}}$	-0.067***	-2.43	-0.147***	-4.32
$\beta_{TT_{cycling}}$	-0.179***	-6.48		
β_{COST}	-0.799***	-3.96	-1.097**	-2.23
$\beta_{PRECIPITATION_{walking}}$	0.831***	4.61	-1.061**	-2.41
$\beta_{WIND_{cycling}}$	0.228***	3.13		
Number of individuals	314		200	
Number of observations	1313		833	
Estimated parameters	10		7	
LL(final)	-183.2578		-260.248	
Adj.Rho-square (0)	0.6355		0.1688	
AIC	386.52		534.5	
BIC	438.32		567.57	
LR test p-value	comp. to MNL_1.1	0.0001	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

Interestingly, the model for summer returns relatively unusual results regarding temperature, precipitation and wind. Temperature has no effect on either choosing walking or cycling. But unexpectedly, precipitation in summer has a very positive effect on choosing walking (visible also in Figure 3.17 in section 3.7.5). This seemingly counterintuitive positive correlation (but reported already in literature, see for example Saneinejad et al. (2012)) can be explained by the fact that in bad weather people often cancel outdoor activities, where they would have travelled by car or transit, in favor of indoor activities or short strolls in the neighborhood. Besides, precipitation in summer does not have to mean a long-lasting cold front. Some visitors might associate it only with a short-term shower rain and go outdoors anyway either hoping for weather improvement or knowing from the forecast that the weather will improve. For other visitors, walking in the rain in moderate temperature might be fully acceptable, especially if they come from northern-European countries. It was not possible to estimate the precipitation effect on cycling because of insufficient observations and quasi-complete separation. Wind appears not to influence the choice of walking in a significant way. It does however influence the choice of cycling and the effect is positive, which means that people are more willing to choose cycling in windy weather. This surprising finding may be attributed to the fact that windy weather in summer is usually accompanied by dry, warm and sunny conditions caused by the *"Föhn"* wind, typical of the alpine climate (Elvidge and Renfrew, 2016; Quaile, 2001). Yet, whether these peculiar weather effects are only sample or region specific remains questionable. This outcome could be validated with models operating on precipitation data aggregated over longer periods than ± 1 hour.

In winter on the other hand, the impact of weather on mode choice behavior is limited and less complex. It is in accordance with the presumptions that winter activities and trips, while being more homogenous, are less sensitive to weather. Only precipitation was found significant for the choice of walking. The effect is strongly negative as expected since precipitation in winter in Alpine valleys results in very unfavorable conditions for walking with slippery sidewalks and low visibility.

4.3.13 *Models with tourists' information levels*

As argued in chapter 2 and postulated by Lew and McKercher (2006) and Lehto et al. (2004), tourists' prior knowledge about the destination might affect their mode choice on-site. As Table 4.15 shows, this is in particular true if the person informed himself or herself about the mobility options at the destination. These respondents are significantly more likely to use transit over car in both seasons and more likely to walk than to drive in winter. Interestingly, the more someone is informed about the journey from home to the destination (available modes, possible routes, journey time, etc.), the significantly less likely they are to walk or use transit at the destination in winter, compared to car.

Table 4.15 MNL models with tourists' information levels about trip to destination and mobility on-site

Model name	MNL_2.13_summer		MNL_2.13_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.182***	4.47	2.021**	2.39
$ASC_{transit}$	-3.995***	-4.41	-1.124	-1.14
$ASC_{cycling}$	-3.102*	-1.74		
$\beta_{TT_{driving}}$	-0.101**	-2.01	-0.151**	-1.99
$\beta_{TT_{walking}}$	-0.15***	-9.96	-0.124***	-7.77

Continued on next page

Table 4.15 (continued from previous page)

Model name	MNL_2.13_summer		MNL_2.13_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$\beta_{TT_{transit}}$	-0.056**	-1.98	-0.151***	-4
$\beta_{TT_{cycling}}$	-0.175***	-7.11		
β_{COST}	-0.878***	-3.73	-1.239**	-1.98
$\beta_{INFORMED\_ARRIVAL_{driving}}$	0	NA	0	NA
$\beta_{INFORMED\_ARRIVAL_{walking}}$	0.007	0.04	-0.423**	-2.25
$\beta_{INFORMED\_ARRIVAL_{transit}}$	0.067	0.44	-0.776***	-4.54
$\beta_{INFORMED\_ARRIVAL_{cycling}}$	0.381	1.17		
$\beta_{INFORMED\_ONSITE_{driving}}$	0	NA	0	NA
$\beta_{INFORMED\_ONSITE_{walking}}$	-0.144	-0.85	0.404**	1.98
$\beta_{INFORMED\_ONSITE_{transit}}$	0.501***	2.78	1.122***	4.24
$\beta_{INFORMED\_ONSITE_{cycling}}$	0.014	0.06		
Number of individuals	284		210	
Number of observations	1214		899	
Estimated parameters	14		10	
LL(final)	-170.0756		-241.2378	
Adj.Rho-square (0)	0.6197		0.2703	
AIC	368.15		502.48	
BIC	439.57		550.49	
LR test p-value	comp. to MNL_1.1	0.0000	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

In models MNL_2.13, the information level variables were created by transforming respondents' answers from a five-item Likert-scale to a numeric scale, i.e. they assume equal distance between each of the five possible answers.

4.3.14 *Models with sport frequency*

The presumption that the level of fitness, defined by the frequency of practicing sport activities when at home, can be in favor of choosing cycling compared to other modes appears to be true, according to model results in Table 4.16. An additional linear interaction term was introduced to capture the sensitivity of the sport frequency effect on distance of the cycling trip (normalized by dividing through mean cycling distance in the sample). It is however hardly significant at 10% level.

A similar effect can be observed for walking in winter, this time however, no sensitivity to distance was noticed.

Table 4.16 MNL models with sport frequency

Model name	MNL_2.14_summer		MNL_2.14_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	2.693***	8.13	1.046***	2.62
$ASC_{transit}$	-2.126***	-4.56	0.484	1.32
$ASC_{cycling}$	-2.728***	-3.9		
$\beta_{TT_{driving}}$	-0.134***	-2.82	-0.173***	-2.99
$\beta_{TT_{walking}}$	-0.152***	-9.3	-0.129***	-8.23
$\beta_{TT_{transit}}$	-0.071***	-2.56	-0.147***	-4.35
$\beta_{TT_{cycling}}$	-0.135***	-4.81		
β_{COST}	-0.747***	-4.29	-1.134**	-2.31
$\beta_{SPORT\_FREQUENCY_{cycling}}$	0.417***	2.49		
$\beta_{SPORT\_FREQUENCY_{sensitivity\_distance\_cycling}}$	-1.256*	-1.63		
$\beta_{SPORT\_FREQUENCY_{walk}}$			0.273***	2.5
Number of individuals	309		213	
Number of observations	1309		908	
Estimated parameters	10		7	
LL(final)	-188.0644		-271.4419	
Adj.Rho-square (0)	0.6201		0.2044	
AIC	396.13		556.88	
BIC	447.9		590.56	
LR test p-value	comp. to MNL_1.1	0.0119	comp. to MNL_1.1	0.0001

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.3.15 *Full models*

The MNL_3.1 models incorporate variables found significant in previous sequential tests into one single model (Table 4.17). However, the model operating on all variables suffered from high multicollinearity between the model predictors (see Figure 3.4 and Figure 4.1 for the correlation plots), in particular in the attributes of alternatives, which is typical of revealed preference data.

Table 4.17 Full MNL models for summer and winter

Model name	MNL_3.1_summer		MNL_3.1_winter	
	Estimate	Rob.t-ratio(0)	Estimate	Rob.t-ratio(0)
$ASC_{driving}$	0	NA	0	NA
$ASC_{walking}$	3.503***	8	2.62***	3.89
$ASC_{transit}$	-2.222***	-3.43	-2.085**	-2.14
$ASC_{cycling}$	-4.209***	-4.24		
$\beta_{TT_{driving}}$	-0.123***	-2.47	-0.159**	-2.06
$\beta_{TT_{walking}}$	-0.175***	-8.39	-0.144***	-7.59
$\beta_{TT_{transit}}$	-0.065**	-2.29	-0.167***	-3.9
$\beta_{TT_{cycling}}$	-0.163***	-5.21		
β_{COST}	-0.752***	-3.54	-1.536**	-2.15
$\beta_{COMPANY\_CHILDREN\_6_{driving}}$	1.011**	2.36		
$\beta_{COMPANY\_CHILDREN\_6\_17_{transit}}$	0.571**	2.4		
$\beta_{COMPANY\_OTHERHH_{walking}}$	0.864***	3.75		
$\beta_{COMPANY\_OTHERHH_{transit}}$	-2.758***	-4.29		
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{walking}}$	-1.969***	-3.74		
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{transit}}$	-4.881***	-4.93		
$\beta_{PRECIPITATION_{walking}}$	0.709***	3.1	-1.697***	-4.71
$\beta_{WIND_{cycling}}$	0.278***	3.71		
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{transit}}$			1.699***	4.36
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{walking}}$			2.924***	3.13
$\beta_{INFORMED\_ARRIVAL_{driving}}$			0.507***	3.88
$\beta_{INFORMED\_ONSITE_{transit}}$			0.785***	3.86
$\beta_{SPORT\_FREQUENCY_{walking}}$			0.29***	2.47
Number of individuals	314		197	
Number of observations	1313		824	
Estimated parameters	16		12	
LL(final)	-160.18		-207.002	
Adj.Rho-square (0)	0.6677		0.3067	
AIC	352.36		438	
BIC	435.24		494.57	
LR test p-value	comp. to MNL_1.1	0.0000	comp. to MNL_1.1	0.0000

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

For variable selection the backward elimination procedure was chosen (Mantel, 1970). Variables exhibiting high correlation with the elementary variables, travel time and travel cost, were sequentially removed from the model until only the stable and statistically significant explanatory variables remained. Moreover, only predictors backed by sound theoretical presumptions were considered for the model. The artificially generated variables, like number of trips or average duration of activities, are potentially endogenous and were excluded in the first place. It should be highlighted that there is no consensus on the recommended variable selection technique within and across many scientific disciplines utilizing multivariable regression models (Harrell, 2015; Heinze and Dunkler, 2017). In transportation, it is a common practice to specify mode choice models using only travel time and travel cost (or their transformations and interactions with sociodemographic variables) and other variables are rarely used. In the context of transport mode choice of tourists at the destination, adding further variables, which factor in the effects of travel company, trip purpose and weather in summer as well as trip purpose, information about the destination, fitness level and weather in winter, results in a highly significant increase in model fit. It is thus recommended to use models of a structure as in Table 4.17 or similar.

Table 4.18 and Table 4.19 do not present any additional findings but compile results of all model specifications for summer and winter accordingly. One can observe the stability of time and cost coefficients regardless of the additional explanatory variables used.

Table 4.18 Comparison of all MNL models for summer.

Models for summer	1.0	1.1	1.2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	3.1
$ASC_{driving}$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$ASC_{walking}$	2.58***	2.669***	2.664***	2.683***	2.66***	2.633***	2.685***	3.387***	3.057***	3.202***	3.379***	3.043***	1.078*	3.389***	2.805***	3.182***	2.693***	3.503***
$ASC_{transit}$	-1.775***	-2.18***	-2.158***	-1.821***	-2.224***	-2.031***	-2.191***	-2.047***	-2.445***	-3.604***	-3.042***	-2.421***	-1.381	-3.314***	-2.17***	-3.995***	-2.126***	-2.222***
$ASC_{cycling}$	-2.164***	-1.994***	-2.008***	-1.956***	-2.015***	-2.066***	-1.938***	-0.131	-2.195***	-1.062*	-0.239	-1.591**	-4.445***	-0.749	-3.138***	-3.102*	-2.728***	-4.209***
$\beta_{TT_{driving}}$	-0.199***	-0.131***	-0.129***	-0.113**	-0.138***	-0.153***	-0.159***	-0.132***	-0.148***	-0.069	-0.098**	-0.099**	-0.129***	-0.103**	-0.125***	-0.101**	-0.134***	-0.123***
$\beta_{TT_{walking}}$	-0.158***	-0.155***	-0.154***	-0.151***	-0.156***	-0.157***	-0.187***	-0.155***	-0.175***	-0.16***	-0.159***	-0.157***	-0.152***	-0.155***	-0.169***	-0.15***	-0.152***	-0.175***
$\beta_{TT_{transit}}$	-0.099***	-0.069***	-0.071***	-	-0.07***	-0.078***	-0.102***	-0.072***	-0.078***	-0.051**	-0.067***	-0.054**	-0.069***	-0.063**	-0.067***	-0.056**	-0.071***	-0.065**
$\beta_{TT_{cycling}}$	-0.175***	-0.172***	-0.171***	-0.164***	-0.173***	-0.175***	-0.213***	-0.174***	-0.189***	-0.166***	-0.187***	-0.163***	-0.164***	-0.177***	-0.179***	-0.175***	-0.135***	-0.163***
β_{COST}	-	-0.769***	-	-0.704***	-0.734***	-0.733***	-0.862***	-0.802***	-0.804***	-0.934***	-0.871***	-0.769***	-0.762***	-0.803**	-0.799***	-0.878***	-0.747***	-0.752***
$\beta_{COST_{driving}}$	-	-	-0.852**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{COST_{transit}}$	-	-	-0.716***	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{transit\_access}}$	-	-	-	-0.07	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{transit\_invehicle}}$	-	-	-	-0.055**	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{transit\_egress}}$	-	-	-	-0.156***	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TRANSFERS}$	-	-	-	-	-0.425	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{HEADWAYS}$	-	-	-	-	-	-0.002	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{sensitivity\_lengthofstay}}$	-	-	-	-	-	-	0.004**	-	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{driving}}$	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{walking}}$	-	-	-	-	-	-	-	-0.011	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{transit}}$	-	-	-	-	-	-	-	-0.001	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{cycling}}$	-	-	-	-	-	-	-	-0.033**	-	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{driving}}$	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	1.011**
$\beta_{COMPANY\_CHILDREN\_6_{walking}}$	-	-	-	-	-	-	-	-	-0.953*	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{transit}}$	-	-	-	-	-	-	-	-	-1.584**	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{cycling}}$	-	-	-	-	-	-	-	-	-1.338**	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{driving}}$	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{walking}}$	-	-	-	-	-	-	-	-	-0.144	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{transit}}$	-	-	-	-	-	-	-	-	0.705***	-	-	-	-	-	-	-	-	0.571**
$\beta_{COMPANY\_CHILDREN\_6\_17_{cycling}}$	-	-	-	-	-	-	-	-	0.628*	-	-	-	-	-	-	-	-	-

Continued on next page

Table 4.18 (continued from previous page)

Models for summer	1.0	1.1	1.2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	3.1
$\beta_{PEAK\_MORNING_{driving}}$	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{walking}}$	-	-	-	-	-	-	-	-	-	-0.726*	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{transit}}$	-	-	-	-	-	-	-	-	-	2.384***	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{cycling}}$	-	-	-	-	-	-	-	-	-	-1.927**	-	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{driving}}$	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{walking}}$	-	-	-	-	-	-	-	-	-	-	-0.003*	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{transit}}$	-	-	-	-	-	-	-	-	-	-	0.005***	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-0.009**	-	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-2.12***	-	-	-	-	-	-1.969***
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	0.679*	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-2.012**	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	1.452**	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-3.444***	-	-	-	-	-	-4.881***
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	0.864	-	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	0.457***	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-0.266	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	0.759***	-	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.004*	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	0.006***	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.006*	-	-	-	-
$\beta_{PRECIPITATION_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.831***	-	-	0.709***
$\beta_{WIND_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.228***	-	-	0.278***

Continued on next page

Table 4.18 (continued from previous page)

Models for summer	1.0	1.1	1.2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	3.1
$\beta_{INFORMED\_ARRIVAL_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-
$\beta_{INFORMED\_ARRIVAL_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.007	-	-
$\beta_{INFORMED\_ARRIVAL_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.067	-	-
$\beta_{INFORMED\_ARRIVAL_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.381	-	-
$\beta_{INFORMED\_ONSITE_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-
$\beta_{INFORMED\_ONSITE_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.144	-	-
$\beta_{INFORMED\_ONSITE_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.501***	-	-
$\beta_{INFORMED\_ONSITE_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.014	-	-
$\beta_{SPORT\_FREQUENCY_{cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.417***	-
$\beta_{SPORT\_FREQUENCY_{sensitivity\_distance\_cycling}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-1.256*	-
Number of individuals	314	314	314	314	314	314	314	314	314	314	314	314	314	314	314	284	309	314
Number of observations	1327	1327	1327	1327	1327	1327	1327	1327	1327	1327	1327	1327	1327	1327	1313	1214	1309	1313
Estimated parameters	7	8	9	10	9	9	9	11	16	11	11	14	11	11	10	14	10	16
LL(final)	-197.45	-192.50	-192.47	-191.24	-192.42	-192.23	-190.99	-189.40	-178.07	-177.29	-180.05	-171.94	-184.76	-182.75	-183.26	-170.08	-188.06	-160.18
Adj.Rho-square (0)	0.6162	0.6236	0.6218	0.6222	0.6219	0.6222	0.6246	0.6238	0.6357	0.6465	0.6413	0.6509	0.6325	0.6363	0.6355	0.6197	0.6201	0.6677
AIC	408.89	400.99	402.95	402.49	402.83	402.47	399.97	400.81	388.14	376.57	382.1	371.88	391.53	387.51	386.52	368.15	396.13	352.36
BIC	445.23	442.52	449.67	454.39	449.55	449.18	446.69	457.9	471.19	433.67	439.2	444.55	448.63	444.6	438.32	439.57	447.9	435.24

Significance levels (robust): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

Table 4.19 Comparison of all MNL models for winter.

Models for winter	1.0	1.1	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	3.1
$ASC_{driving}$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$ASC_{walking}$	1.704***	1.854***	1.931***	1.898***	1.865***	1.954***	2.367***	2.072***	2.171***	2.15***	1.28***	-0.624	3.007***	1.72***	2.021**	1.046***	2.62***
$ASC_{transit}$	0.217	0.537	0.878*	0.392	0.464	0.631*	-0.416	0.668*	0.238	0.48	-0.559	1.171*	-0.527	0.478	-1.124	0.484	-2.085**
$\beta_{TT_{driving}}$	-0.232***	-0.17***	-0.153***	-0.089	-0.165***	-0.591***	-0.18***	-0.167***	-0.157***	-0.167***	-0.128**	-0.201***	-0.176***	-0.177***	-0.151**	-0.173***	-0.159**
$\beta_{TT_{walking}}$	-0.123***	-0.124***	-0.123***	-0.113***	-0.124***	-0.225***	-0.13***	-0.119***	-0.131***	-0.126***	-0.127***	-0.132***	-0.132***	-0.122***	-0.124***	-0.129***	-0.144***
$\beta_{TT_{transit}}$	-0.131***	-0.148***	-	-0.109***	-0.146***	-0.396***	-0.147***	-0.144***	-0.157***	-0.151***	-0.151***	-0.149***	-0.143***	-0.147***	-0.151***	-0.147***	-0.167***
β_{COST}	-	-1.165**	-0.888*	-1.688***	-1.169**	-2.26***	-1.043**	-1.053**	-1.431***	-1.225**	-1.767***	-1.099**	-1.111**	-1.097**	-1.239**	-1.134**	-1.536**
$\beta_{TT_{transit\_access}}$	-	-	-0.193***	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{transit\_invehicle}}$	-	-	-0.122***	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{transit\_egress}}$	-	-	-0.257***	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TRANSFERS}$	-	-	-	-4.279***	-	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{HEADWAYS}$	-	-	-	-	0.001	-	-	-	-	-	-	-	-	-	-	-	-
$\beta_{COST_{shift\_highincome}}$	-	-	-	-	-	1.109***	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{sensitivity\_age\_driving}}$	-	-	-	-	-	0.425***	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{sensitivity\_age\_walking}}$	-	-	-	-	-	0.094**	-	-	-	-	-	-	-	-	-	-	-
$\beta_{TT_{sensitivity\_age\_transit}}$	-	-	-	-	-	0.232***	-	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{driving}}$	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{walking}}$	-	-	-	-	-	-	-0.005	-	-	-	-	-	-	-	-	-	-
$\beta_{HOTEL\_PRICE_{transit}}$	-	-	-	-	-	-	0.011*	-	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{driving}}$	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{walking}}$	-	-	-	-	-	-	-	-0.955*	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6_{transit}}$	-	-	-	-	-	-	-	-0.564	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{driving}}$	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{walking}}$	-	-	-	-	-	-	-	-0.384	-	-	-	-	-	-	-	-	-
$\beta_{COMPANY\_CHILDREN\_6\_17_{transit}}$	-	-	-	-	-	-	-	-0.157	-	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{driving}}$	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{walking}}$	-	-	-	-	-	-	-	-	-0.399	-	-	-	-	-	-	-	-
$\beta_{PEAK\_MORNING_{transit}}$	-	-	-	-	-	-	-	-	0.727**	-	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{driving}}$	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{walking}}$	-	-	-	-	-	-	-	-	-	-0.001	-	-	-	-	-	-	-
$\beta_{DURATION\_FOLLOWING\_ACTIVITY_{transit}}$	-	-	-	-	-	-	-	-	-	0.001	-	-	-	-	-	-	-

Continued on next page

Table 4.19 (continued from previous page)

Models for winter	1.0	1.1	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12	2.13	2.14	3.1
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{driving}}$	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{walking}}$	-	-	-	-	-	-	-	-	-	-	0.529	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SPORT_{transit}}$	-	-	-	-	-	-	-	-	-	-	1.524***	-	-	-	-	-	1.699***
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{driving}}$	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{walking}}$	-	-	-	-	-	-	-	-	-	-	2.407***	-	-	-	-	-	2.924***
$\beta_{CLASS\_FOLLOWING\_ACTIVITY\_SOCIAL_{transit}}$	-	-	-	-	-	-	-	-	-	-	-6.615***	-	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	0.8***	-	-	-	-	-
$\beta_{NUMBER\_OF\_TRIPS_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-0.304*	-	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-0.004***	-	-	-	-
$\beta_{AVG\_DURATION\_OF\_ACTIVITIES_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	0.003**	-	-	-	-
$\beta_{PRECIPITATION_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-1.061**	-	-	-1.697***
$\beta_{INFORMED\_ARRIVAL_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	0.507***
$\beta_{INFORMED\_ARRIVAL_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.423**	-	-
$\beta_{INFORMED\_ARRIVAL_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.776***	-	-
$\beta_{INFORMED\_ONSITE_{driving}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-
$\beta_{INFORMED\_ONSITE_{walking}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.404**	-	-
$\beta_{INFORMED\_ONSITE_{transit}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.122***	-	0.785***
$\beta_{SPORT\_FREQUENCY_{walk}}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.273***	0.29***
Number of individuals	213	213	213	213	213	213	213	213	213	213	213	213	213	200	210	213	197
Number of observations	908	908	908	908	908	908	908	908	908	908	908	908	908	833	899	908	824
Estimated parameters	5	6	8	7	7	10	8	10	8	8	10	8	8	7	10	7	12
LL(final)	-281.90	-279.11	-276.62	-274.91	-278.96	-270.65	-270.10	-274.63	-272.93	-276.87	-263.97	-251.02	-263.95	-260.25	-241.24	-271.44	-207.00
Adj.Rho-square (0)	0.1802	0.1853	0.1867	0.1945	0.1829	0.1981	0.2053	0.1867	0.1973	0.186	0.2171	0.2599	0.2229	0.1688	0.2703	0.2044	0.3067
AIC	573.81	570.22	569.25	563.82	571.92	561.3	556.2	569.26	561.86	569.75	547.95	518.03	543.9	534.5	502.48	556.88	438
BIC	597.86	599.09	607.74	597.5	605.6	609.41	594.69	617.38	600.35	608.24	596.06	556.52	582.39	567.57	550.49	590.56	494.57

Significance levels (robust): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

4.4 NESTED LOGIT MODELS

Nested Logit models try to account for the similarity between alternatives by assuming that alternatives grouped into a nest share a part of the error term, which is defined by the nesting structure. For instance, alternatives walking and cycling could be grouped in a common nest, under the assumption that they share some common characteristics as both are non-motorized transport modes. This is then accounted for in the NL models by separating the error terms into two components: the nest-specific error term identical for all alternatives and the alternative specific error term. Thanks to this common error component and the resulting covariance between the (overall) error terms of the alternatives in the nest, the NL models can explain correlations between the alternatives grouped in the nests, which MNL models are not capable of (see also the very well-known example of red and blue bus paradox).

For a Nested Logit model (McFadden, 1977a), following the notation in Train (2009), if the alternatives are partitioned in K non-overlapping nests B, the choice probability of an alternative $i \neq j$ belonging to the nest B_k where $k \neq l$, is given by:

$$P_n(i) = \frac{e^{\frac{V_{in}}{\lambda_k}} \left(\sum_{j \in B_k} e^{\frac{V_{nj}}{\lambda_k}} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} e^{\frac{V_{nj}}{\lambda_l}} \right)^{\lambda_l}} \tag{4.11}$$

where λ_k is called an inclusive value or a logsum parameter and measures the substitution rate among the alternatives in nest k. It is generally constrained between 0 and 1, where values close to 0 indicate high substitution (low independence) between the alternatives and values close to 1 low substitution (high independence), in which case the NL model reduces to standard logit model.

Utility functions in the Nested Logit model NL_1.1_summer are exactly the same as those for the base MNL model MNL_1.1_summer presented in Eq. 4.4 to 4.7. Accordingly, utility function for the model NL_1.2_winter are identical to those for MNL_1.1_winter given by Eq. 4.8 to 4.10.

Several nesting structures were tested for both summer and winter datasets. Eventually, it was found that in summer, nesting the transit and walking together reveals a significant substitution between these alternatives. Figure 4.2 shows the nesting structure of model NL_1.1_summer. The reasoning behind this structure is that both transit and walking share the strenuousness and impracticality when traveling with luggage and items necessary to perform summer activities. The logsum (nesting) parameter is $\lambda_{luggage} = 0.0286$, which implies very high similarity of the alternatives within the nest.

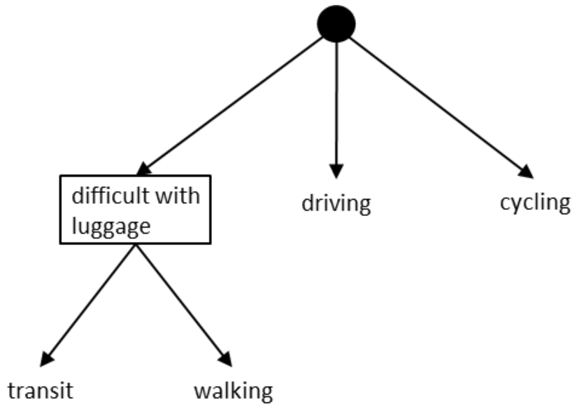


Figure 4.2 Structure of the NL model for summer

For this model, bootstrap estimation was employed (Efron and Tibshirani, 1986). Table 4.20 presents the model estimates. The t-tests were performed based on standard errors obtained from 500 new samples generated by sampling from the original dataset. The model performs significantly better (LR test yields $p = 0.0002$) than the corresponding MNL model that assumes independence of the random errors in the utilities.

Table 4.20 NL model for summer

Model name	NL_1.1_summer		
	Estimate	Bootstrap. t-ratio(0)	Bootstrap. t-ratio(1)
$ASC_{driving}$	0	NA	
$ASC_{walking}$	2.506***	5.15	
$ASC_{transit}$	-1.693***	-2.68	
$ASC_{cycling}$	-2.032**	-2.52	
$\beta_{TT_{driving}}$	-0.106**	-2.16	
$\beta_{TT_{walking}}$	-0.141***	-4.8	
$\beta_{TT_{transit}}$	-0.064**	-2.4	
$\beta_{TT_{cycling}}$	-0.153	-1.4	
β_{COST}	-0.688**	-2.13	
$\lambda_{luggage}$	0.029***		-25.80

Continued on next page

Table 4.20 (continued from previous page)

Model name	NL_1.1_summer	
Number of individuals	314	
Number of observations	1327	
Estimated parameters	9	
LL(final)	-185.476	
Adj.Rho-square (0)	0.6349	
AIC	388.95	
BIC	435.67	
Number of bootstrap repetitions	500	
LR test p-value	comp. to MNL_1.1	0.0002

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

In winter on the other hand, this nesting structure proved ineffective and resulted in logsum parameter > 1, implying more similarity between alternatives outside the nest than inside. Another structure was specified (Figure 4.3), which nests driving and walking alternatives together. The rationale for this structure is that both alternatives are private and individual means of transport, unlike transit.

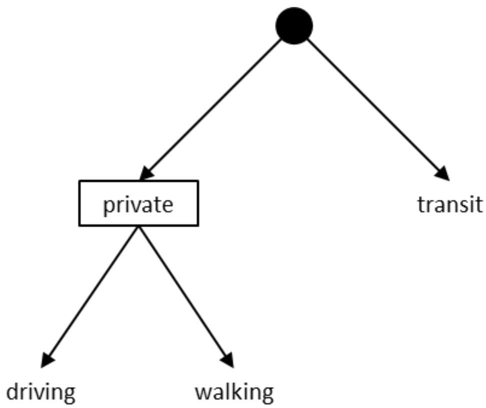


Figure 4.3 Structure of the NL model for winter

The NL model for winter (Table 4.21) performs only marginally better than the corresponding base MNL model, yielding $p = 0.0823$ in the LR test. Also the logsum parameter for the “private” nest is significant only at 10% level. These measures, along with a relatively high value for the logsum parameter $\lambda_{private} = 0.6186$, imply only moderate similarity between the walking and driving alternatives in winter.

Table 4.21 NL model for winter

Model name	NL_1.2_winter		
	Estimate	Rob.t-ratio(0)	Rob.t-ratio(1)
$ASC_{driving}$	0	NA	
$ASC_{walking}$	1.237***	2.73	
$ASC_{transit}$	0.190	0.51	
$\beta_{TT_{driving}}$	-0.185***	-3.39	
$\beta_{TT_{walking}}$	-0.099***	-4.78	
$\beta_{TT_{transit}}$	-0.137***	-4.56	
β_{COST}	-0.931**	-2.00	
$\lambda_{private}$	0.619*		-1.74
Number of individuals	213		
Number of observations	908		
Estimated parameters	7		
LL(final)	-277.603		
Adj.Rho-square (0)	0.187		
AIC	569.21		
BIC	602.88		
LR test p-value	comp. to MNL_1.1	0.0823	

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

4.5 CROSS-NESTED LOGIT MODELS

For the Cross-Nested Logit (Vovsha, 1997) the notation by Wen and Koppelman (2001) is used. With K potentially overlapping nests B, the nesting parameter λ_k and the allocation parameter α_{jk} determining the degree to which the alternative j belongs to a nest k, the probability of individual n choosing alternative $i \neq j,\ i$ is given by:

$$P_n(i) = \frac{\sum_k (\alpha_{ik} e^{V_{ni}})^{\frac{1}{\lambda_k}} \left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{\frac{1}{\lambda_k}} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{\frac{1}{\lambda_l}} \right)^{\lambda_l}} \tag{4.12}$$

Utility functions used in the Cross-Nested Logit model CNL_1.2_winter are exactly identical to those for MNL_1.1_winter given by Eq. 4.8 to 4.10.

The value of logsum parameter for private nest in the NL model for winter may suggest that only some part of the variance can be explained better by nesting car with walking, which implies that the NL model with this particular nesting structure may not fit the data well. In a further step, a Cross-Nested Logit model for the winter dataset was prepared, resembling the nested model NL_1.2, with car and walk modes nested together but additionally allowing for the membership of the car alternative in its own nest, was tested. Standard errors of coefficients were calculated by drawing 2000 bootstrap samples from the original dataset. Several specifications of a CNL model were tested also for the summer data and none performed better than the base Multinomial Logit model MNL_1.1 or Nested Logit model NL_1.1 in a likelihood-ratio test.

The structure of the model CNL_1.2_winter is illustrated in Figure 4.4. Table 4.22 presents the model statistics.

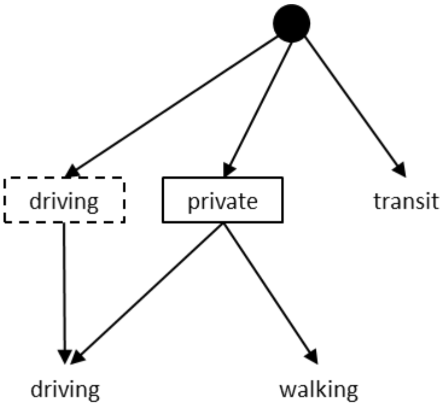


Figure 4.4 Structure of the CNL model for winter

Table 4.22 CNL model for winter

Model name	CNL_1.2_winter		
	Estimate	Bootstrap. t-ratio(0)	Bootstrap. t-ratio(1)
$ASC_{driving}$	0	NA	
$ASC_{walking}$	0.953**	2.40	
$ASC_{transit}$	0.031	0.08	
$\beta_{TT_{driving}}$	-0.185**	-2.53	
$\beta_{TT_{walking}}$	-0.092***	-4.59	
$\beta_{TT_{transit}}$	-0.131***	-3.59	
β_{COST}	-0.847	-1.55	

Continued on next page

Table 4.22 (continued from previous page)

Model name	CNL_1.2_winter		
	Estimate	Bootstrap. t-ratio(0)	Bootstrap. t-ratio(1)
$\lambda_{private}$	0.002***		-9.65
$\alpha_{0,driving,driving}$	0		NA
$\alpha_{0,driving,private}$	-0.143		-0.72
Number of individuals	213		
Number of observations	908		
Estimated parameters	8		
LL(final)	-270.329		
Adj.Rho-square (0)	0.2047		
AIC	556.66		
BIC	595.15		
Number of bootstrap repetitions	500		
LR test p-value	comp. to NL_1.2	0.0001	
LR test p-value	comp. to MNL_1.1	0.0002	

Significance levels (robust): *** : p < 0.01, ** : p < 0.05, * : p < 0.1

Table 4.23 presents the final structure of the model. The allocation parameters alpha, after the logistic transformation are given by:

$$\alpha_{driving,private} = \frac{e^{\alpha_{0,driving,private}}}{e^{\alpha_{driving,private}} + e^{\alpha_{driving,driving}}} \tag{4.13}$$

$$\alpha_{driving,driving} = 1 - \alpha_{driving,private} \tag{4.14}$$

Their values imply that the driving alternative is allocated in almost 54% in root and 46% in the private nest. Walking and transit belong to one nest only. The model performs significantly better than the base MNL and NL models.

Table 4.23 Structural parameters of the CNL model

Nests	Alternatives			
	driving	walking	transit	λ
driving	0.5358	0	0	1
private	0.4642	1	0	0.002
transit	0	0	1	1

It must be mentioned that neither the NL nor the CNL models make any assumptions about the decision sequence through their nesting structures (Train et al., 1987). Nests used in the models NL_1.1_summer, NL_1.2_winter and CNL_1.2_winter serve only as a structural concept allowing the modeler better explain the variance in the data.

4.6 INDICATORS FOR POLICY MEASURES

4.6.1 *Elasticity to changes in attributes of alternatives*

Measures of elasticity are broadly used for policy analyses in transportation, in particular to study potential effects of changes in fuel costs, toll or level of service in the network (such as travel time or frequency of transit services) (Pratt et al., 2000). Elasticity measures the responsiveness of one (dependent) variable with respect to a change in another (explanatory) variable and is typically defined as a ratio as illustrated by the general formula (Sydsæter and Hammond, 2016):

$$E_x^y = \frac{\frac{\partial y}{y}}{\frac{\partial x}{x}} \tag{4.15}$$

Several forms of elasticity measures can be distinguished. Point elasticity is defined as a response to an infinitesimally small change of the policy variable whereas arc elasticity captures the response to a change between two values of the policy variable (e.g. a 10% change). For point elasticities, one needs the functional relationship between the numerator and the denominator to make the derivation – which is known in discrete choice models. However, transport policy practitioners often use arc elasticity instead as it approximates point elasticity very well for small changes in model predictors and can be easily computed from empirical data.

One can consider various demand elasticities in transportation, such as car usage or passenger kilometers, where the response is measured on a continuous dependent variable describing the level of consumption of a certain good. In the context of mode choice, where the dependent variable is discrete, we are talking about the elasticity of probability of choosing a particular alternative given a change in a variable entering the utility function of that alternative.

Elasticity for an alternative can be formulated with respect to a change in an attribute of this particular alternative, which is called direct elasticity. Or it can be formulated with respect to a change in an attribute of a competing alternative, which is then called cross elasticity (Bhat and Koppelman, 2006).

Elasticity > 0 (positive) means that an increase in attribute causes an increase in demand (e.g. higher transit frequency results in more passenger kilometers), whilst elasticity < 0 (negative) means that an increase in attribute causes a decrease in demand (e.g. higher fares results in less passenger kilometers). Elasticity $-1 < E < 1$ is called inelastic, which means that the demand response is less than proportional to the attribute change (e.g. fuel price increase only results in small decrease of vehicle kilometers). Elasticity $E = 1$ denotes proportional change in the demand given a change in the attribute. Elasticity $E < -1$ *or* $E > 1$ is called elastic, which means that the demand response is more than proportional to the attribute change.

The general form of a disaggregate direct point elasticity of the probability of individual n choosing the alternative i with respect to a change in the value of an attribute k of this alternative denoted by x_{ink} is given by (Ben-Akiva and Lerman, 1985):

$$E_{x_{ink}}^{P_n(i)} = \frac{\partial P_n(i)}{\partial x_{ink}} \frac{x_{ink}}{P_n(i)} = \frac{\partial \ln P_n(i)}{\partial \ln x_{ink}} \tag{4.16}$$

Which for a logit model with linear-in-parameters utilities reduces to:

$$E_{x_{ink}}^{P_n(i)} = (1 - P_n(i)) x_{ink} \beta_k \tag{4.17}$$

The aggregate elasticity is an average of disaggregate elasticities, weighted by choice probabilities:

$$E_{x_{ink}}^{\bar{P}(i)} = \frac{\sum_{n=1}^{N} P_n(i) E_{x_{ink}}^{P_n(i)}}{\sum_{n=1}^{N} P_n(i)} \tag{4.18}$$

which for linear-in-parameter specification takes form:

$$E_{x_{ink}}^{\bar{P}(i)} = \frac{\beta_k}{N \cdot \bar{P}(i)} \sum_{n=1}^{N} P_n(i)(1 - P_n(i)) x_{ink} \beta_k \tag{4.19}$$

Analogously, disaggregate cross point elasticity is represented by:

$$E_{x_{jnk}}^{P_n(i)} = \frac{\partial P_n(i)}{\partial x_{jnk}} \frac{x_{jnk}}{P_n(i)} = \frac{\partial \ln P_n(i)}{\partial \ln x_{jnk}} \tag{4.20}$$

which for logit reduces to:

$$E_{x_{jnk}}^{P_n(i)} = -P_n(j) x_{jnk} \beta_k \tag{4.21}$$

And aggregate cross point elasticities is given by:

$$E_{x_{jnk}}^{\bar{P}(i)} = \frac{\beta_k}{N \cdot \bar{P}(i)} \sum_{n=1}^{N} -P_n(i)P_n(j)x_{ink}\beta_k \tag{4.22}$$

Using similar notation, the disaggregate direct and cross arc elasticities are given by:

$$E_{x_{ink}}^{P_n(i)} = \frac{\Delta P_n(i)}{\Delta x_{ink}} \frac{x_{ink}}{P_n(i)} = \frac{\Delta \ln P_n(i)}{\Delta \ln x_{ink}} \tag{4.23}$$

And:

$$E_{x_{jnk}}^{P_n(i)} = \frac{\Delta P_n(i)}{\Delta x_{jnk}} \frac{x_{jnk}}{P_n(i)} = \frac{\Delta \ln P_n(i)}{\Delta \ln x_{jnk}} \tag{4.24}$$

In the aggregate counterparts of the above formulas, probability is replaced by the aggregate share of the alternative in the population.

An advantage of models based on revealed preference data over those based on stated preference data is that they allow calculating elasticity values based on people actual true choices. These are more credible than the SP-based values (unless scaled with RP data). The measures investigated in this thesis are aggregate elasticities of choice probabilities of different modes. In terms of the influencing attribute, both cost and time elasticities were calculated. In terms of the response direction, both direct and cross elasticities were calculated. In terms of method of computation, both point and arc elasticities were calculated.

Table 4.24 and Table 4.25 contain results based on the base MNL models: MNL_1.1_summer and MNL_1.1_winter.

Table 4.24 Point cost elasticities for summer and winter – direct and cross

	Summer		Winter	
Mode affected	Mode altered			
	Car	Transit	Car	Transit[a]
Car	**-0.03**	0.002	**-0.08**	-
Transit	0.026	**-0.01**	0.07	-
Walking	0.002	0.000	0.01	-
Cycling	0.001	0.004	-	-

Direct elasticities in boldface. Cross elasticities in regular font.
[a]Transit is free of charge in winter.

Table 4.25 Point time elasticities for summer and winter – direct and cross

	Summer				Winter			
Mode affected	Mode altered							
	Car	Transit	Walking	Cycling	Car	Transit	Walking	Cycling
Car	**-0.10**	0.49	0.09	0.24	**-0.23**	0.67	0.15	-
Transit	0.09	**-0.53**	0.03	0.18	0.18	**-0.94**	0.15	-
Walking	0.01	0.03	**-0.17**	0.64	0.06	0.27	**-0.29**	-
Cycling	0.003	0.01	0.05	**-1.07**	-	-	-	-

Direct elasticities in boldface. Cross elasticities in regular font.

The author is not aware of any other work that reported elasticities of mode choice probabilities for non-local travelers, against which he could compare the results. Nevertheless, it is worth comparing the elasticity values obtained from current dataset for both summer and winter season with values reported in studies on daily mobility of local residents in countries in Europe and North America. Only short-run elasticities (analyzing the response within up to two years after the change) were considered in comparison given the very short tourist stays at the destination.

The aggregate cost elasticities for car presented in Table 4.24 can be juxtaposed with fuel price elasticities often reported in literature since travel cost of car is defined in this thesis as a function of distance, fuel consumption and fuel price. Table 4.26 provides a breakdown of cost and time elasticities from international studies.

The research on transport elasticities is very fragmentary and country-dependent. Direct elasticities for transit as well as cross elasticities in general are unknown, except for the UK. However, even with the incomplete data, it clearly stands out that the cost elasticities of tourist travelers differ substantially from their counterparts reported in Table 4.26. The cost elasticity of -0.03 in summer and -0.08 in winter for tourist car trips is very low compared to the European average of -0.16, not to mention Austrian values of around -0.40. Only the Canadian results are of the same magnitude. In terms of direct transit fare elasticity, the discrepancy is even larger – for example, the elasticity for rural leisure trips in the UK is -0.55. The cross elasticities are also at least an order of magnitude lower than the corresponding values calculated for the UK residents.

Car travel time elasticities on the other hand are larger and, particularly in winter (-0.23), come close to the values reported in the Netherlands (-0.20) and Switzerland (-0.40). For transit, they largely exceed (-0.53 in summer, -0.94 in winter) the UK values (-0.16/-0.37). Interestingly, tourist cross elasticities with respect to travel time are very different from the UK values – much lower for transit demand (0.09/0.18 comp. to 0.63) and much higher for car demand (0.49/0.67 comp. to 0.04). Although these comparisons are based on incomplete data from different countries collected with different methodologies and should by no means be used to assess the plausibility of the results for tourist in Austria, they give an overview of the magnitude of the effects.

Table 4.26 International comparison of direct and cross elasticities with respect to cost and time

	Country						
	EU	AT	CH	UK	NL	CA	US
	(Jong and Gunn, 2001; TRACE Consortium, 1999)	(Graham and Glaister, 2002)	(Axhausen and Fröhlich, 2012)	(Wardman, 2012, 2014; Wardman et al., 2018)[a]	(Jong and Gunn, 2001; TRACE Consortium, 1999)	(Litman, 2013)	(Litman, 2013)
Car – fuel price	**-0.16**	**-0.34 to -0.42**	**-0.15**	**-0.08**[b] **-0.12**[c]	**-0.19**	**-0.046 to -0.091**	**-0.16 (2007)** **-0.29 (2011)**
Car – travel time	**-0.60**		**-0.40**	**-0.04**[d] **-0.07**[e]	**-0.20**		
Transit – fare				**-0.45**[f] **-0.55**[g]			
Transit – travel time				**-0.16**[d] **-0.37**[e]			
Transit – fuel price	0.33		0.15	0.19	0.17		
Transit – car travel time	0.27		0.50	0.63	0.95		
Car – transit fare				0.08			
Car – transit travel time				0.04			

Direct elasticities in boldface. Cross elasticities in regular font.
[a]All values implied by a meta-model.
[b]Urban leisure trips.
[c]Inter-urban leisure trips.
[d]Distance up to 10 miles.
[e]Distance above 10 miles.
[f]Urban (non-London) leisure trips.
[g]Rural leisure trips.

In general, travel cost elasticities of tourists, both direct and cross, are considerably lower than any typical values reported in literature. Tourists' reaction to fare and fuel price changes is marginal – that is, they are very inelastic. A 1% increase in ticket price, *ceteris paribus*, results only in 0.01% decrease in probability of choosing transit and 0.002% increase in choosing car instead. This is a particularly valuable finding for tourist regions offering free public transportation for guests. Guests would not be deterred from using transit, should the ticket prices increase. It casts doubt upon the economical sense of providing free transit services at the destination. Especially, if visitors pay higher tourist tax and/or higher accommodation prices because of that. However, the values are calculated with a dataset where the majority of transit trips was completely free of charge. The estimates might have looked differently if the respondents had paid the normal ticket prices. Unfortunately, it is not unambiguous how exactly these costs are covered in every tourist region since each of them provides different packages under different conditions.

Tourists are more elastic to changes in travel time. For instance, a 1% increase in transit travel time can results in 0.49% increase in demand for car, whilst the same deterioration in car travel time induces only 0.09% more demand for transit. It provides evidence for transit operators and tourist municipalities that it is not low fares but high level of service (even at higher cost) in public transportation that is essential to prevent visitors from switching to private cars. This corresponds well with the evidence in literature that people respond more to service improvements than they do to fare discounts (Cervero, 1990).

Apart from point elasticities, also arc elasticities were calculated (Table 4.27 and Table 4.28) – under a scenario of a 10% increase in cost and time attribute for car and transit alternatives – and they reveal similar effects as point elasticities. Arc elasticities assuming a change in travel time for walking and cycling were not calculated as it is hardly feasible to contribute to such a change through either policy measures or even infrastructural investments (in alpine terrain).

Table 4.27 Arc cost elasticities – direct and cross

	Summer		Winter	
Mode affected	Mode altered			
	Car	Transit	Car	Transit[a]
Car	**-0.03**	0.00	**-0.09**	-
Transit	0.15	**-0.01**	0.16	-
Walking	0.00	0.00	0.01	-
Cycling	0.02	0.04	-	-

Direct elasticities in boldface. Cross elasticities in regular font.

[a]Transit is free of charge in winter.

Table 4.28 Arc time elasticities – direct and cross

	Summer		Winter	
Mode affected	Mode altered			
	Car	Transit	Car	Transit
Car	**-0.11**	0.08	**-0.25**	0.31
Transit	0.53	**-0.54**	0.39	**-0.98**
Walking	0.02	0.01	0.05	0.10
Cycling	0.11	0.10	-	-

Direct elasticities in boldface. Cross elasticities in regular font.

4.6.2 *Value of Travel Time Savings (VTTS)*

Apart from elasticities, another indicator conventionally used in transportation is the Value of Travel Time Savings (VTTS). It is defined as the price one would be ready to pay to save travel time. VTTS serves as a fundamental concept in travel demand modeling and is crucial for cost analysis, policy evaluation and project appraisal (Hensher, 2001). Willingness to pay indicators can be estimated not only for pure travel time, but also for transit headways or in-vehicle and out-of-vehicle time separately. In general, VVTS is given by a simple ratio of model coefficients (Eq. 4.25), provided a linear-in-parameter specification. The standard errors can be calculated by employing the Delta method (Daly et al., 2012).

$$VTTS = \frac{\beta_{travel\ time}}{\beta_{cost}} \tag{4.25}$$

There is a broad literature on VTTS, both on its applications in transportation as well as on the methodological aspects. According to Small (2012), who summarizes findings from many review studies, the VTTS varies significantly depending on trip purpose – from low values for leisure travel to high values for business trips. It also varies depending on one's income and reaches higher values for population segments with higher wages. Finally, the results differ depending on what time element is valuated, with higher values for waiting time, for access time to transit or for driving in congested traffic.

Given the complexity of the VTTS concept depending on travel purpose, distance etc., one can hypothesize that the also the VTTS in a tourist context might differ from the VTTS in daily travel. Under this premise, the rest of this chapter provides VTTS calculations for both winter and summer models and collates the results with typical values reported in the international literature.

Table 4.29 compiles the VTTS results obtained from base models and base models with transit travel time split into three components: in-vehicle time, access time and egress time.

Table 4.29 Value of Travel Time Savings (VTTS) [EUR/h]

	Summer		Winter	
	MNL_1.1	MNL_2.1	MNL_1.1	MNL_2.1
Car	10.23	9.64	8.76	10.34
Transit	5.40		7.61	
Transit in-vehicle		4.71		8.24
Transit access		5.98		13.05
Transit egress		13.27		17.36

Tourists at the destination are generally valuing their travel time in car higher than in transit, which is in line with what is reported in studies on daily mobility. In current sample, this trend is particularly strong in summer, when the value of one-hour time saving for a car trip is worth around 10 EUR, almost twice as much as for transit. In winter, the difference is less distinct. The segmentation of transit travel time into in-vehicle, access and egress time reveals an interesting picture. Not only is the value of access time to transit services higher than the in-vehicle time, but the egress time is considerably higher than access time. Tourists, specifically in summer, are willing to pay far more for a shorter last-mile section than for a shorter first-mile section. It might be attributed to them becoming more impatient while traveling to the destination or being afraid of getting lost and wasting time on the last stage just before reaching the destination. The outcomes are plausible and fit well into the typical VTTS values reported in many empirical studies, where out-of-vehicle time (OVT) is usually valued between 1.5 and 2.5 times in-vehicle time (IVT) (Fosgerau et al., 2007; Wardman, 2001, 2004).

It is interesting to compare the VTTS of tourists in Austria with the corresponding VTTS of Austrian residents and residents in the neighboring countries and countries where the most of visitors to Tyrol originate from (Landesstatistik Tirol, 2021). The values in Table 4.30 derive from national official values as reported by Wardman et al. (2016) (who provide so far the most comprehensive meta-review of VTTS in Europe), Department for Transport (2015), Kouwenhoven et al. (2014), Axhausen et al. (2014), Hess et al. (2008), Jokubauskaitė et al. (2019) and Schmid et al. (2019). Reporter are VTTS for commute and other (leisure) urban trips by car, train and bus (or bundled together). VTTS values for business trips are omitted as typically much higher and not of interest for the comparison with tourist VTTS.

Table 4.30 International comparison of Value of Travel Time Savings (VTTS) [EUR/h][a]

Mode	Purpose	Country								
		AT	CH	DE[b]	UK[c]	NL	BL[d]	IT[d]	CZ[d]	PL[d]
Car	Commute	12.60	21.05	4.20		9.25	7.54	6.33	4.94	3.84
	Other	10.10/13.40[e]	21.05[f]	3.49[f]		7.50	6.64	7.92	4.35	3.39
PT[g]	Commute	8.30	11.46	3.89		7.75	5.72	4.82	3.79	2.97
	Other	9.80/8.30	11.46	3.85[f]		6.00				
All modes	Commute				12.51					
	Other				5.71					

[a]For Switzerland, values are in CHF/h.
[b]For Germany, values are for short trips <50km (which corresponds well with trips in current sample).
[c]Official values aggregated for all modes.
[d]Implied by a meta-model by Wardman et al. (2016)
[e]For Austria, Schmid et al. (2019) distinguish leisure and other respectively.
[f]For leisure trips.
[g]In most studies defined as a bus.

If one compares VTTS of visitors to Austria with those of Austrian nationals, one can observe that time tourists spend on car trips in summer is valued almost identically (app. 10 EUR/h) as time Austrian workers spend on leisure trips, while winter trips have only a slightly lower value (app. 9 EUR/h). Also, the Dutch exhibit VTTS for car close to 10 EUR/h, and the British a bit more.

However, if compared with typical values from Germany, the VTTS of tourists is much higher than that of German residents. This is interesting, given that the dominating majority of tourist visiting Tyrol in both winter and summer are German citizens. It might indicate that their perception of travel time and travel cost changes for the duration of the vacation stay.

The results obtained and the comparison with the international values suggest that the VTTS is rather determined by local circumstances and factors characterizing the area of the vacation stay and is not origin-specific and brought by visitors “from home”. However, to validate this hypothesis and acquire a deeper understanding of monetary valuations of travel time among tourists, it would be necessary to compare the VVTS of tourists stratified by country of residence (which was not possible due to sample size) with VTTS reported in studies from these countries (e.g. VTTS of Dutch tourists in the Austrian Alps and VTTS of Dutch residents in the Netherlands). In addition, this hypothesis might hold only for car travel because for transit trips, VTTS of visitors to Austria is almost two times lower than VTTS for leisure and other trips amid Austrian workers and resembles more the figures reported in the UK, Benelux or Italy.

5 Conclusion

5.1 Contribution and findings

Several contributions were possible by means of this doctoral thesis. The author managed to be probably one of the first:

- to design and conduct a complex bespoke travel-activity survey among visitors of tourist destinations.
- to analyze and thoroughly compare the seasonal differences between mode choice behavior of tourists in summer and winter.
- to develop econometrics models of mode choice accounting for additional factors, typically not considered in daily travel context
- to calculate both direct and cross, aggregate time and cost elasticities for all modes of transport at a tourist destination.
- to calculate VTTS values for tourists at the destinations, which has not been analyzed by researchers from either transport planning, tourism or economics, yet.

The thesis provides transport planners and policy makers with a broad set of tools for analyzing tourist mode choice behavior and gives recommendations about which and how to use (see section 5.2 for a discussion on that).

The thesis provides also answers to the specific research questions posed in section 1.2.

1. **What factors determinate travel decisions of tourists staying in alpine regions in terms of mode choice?**

   Travel time and travel cost play a role in mode choice decisions of tourists traveling within the destination. The perception of time differs between the modes whilst the sensitivity to cost is generic among modes. Access and in particular egress time have a stronger effect than in-vehicle time on choosing transit alternative. Number of transfers has a strong negative effect too, whereas the frequency of connections not. The reaction to an increase in travel time becomes less negative with an increasing length of stay in both seasons, and an increasing age and income in winter. Tourists staying in more expensive accommodations exhibit a lower preference for cycling than for driving in summer and prefer transit to driving in winter. In terms of time of day, morning hours are associated with high probability of choosing transit, followed by driving, walking and cycling in the last place. In summer, sport activities correlate positively with choice of transit over car, whereas social activities have a negative effect. Tourists performing many discrete activities are more likely to walk or cycle than drive, but are less likely to use transit. Opposite to that, those performing fewer but longer activities are more likely to choose transit. Prior knowledge about the mobility services at the destination plays in favor of using transit during the stay, while better knowledge about the trip to the destination has a negative effect on the utility of transit or walking in winter. As far as the fitness level is concerned, it increases the odds of choosing cycling in summer and walking in winter.

2. **Is there a visible impact of the accompanying party size and composition?**

Furthermore, tourists rarely travel alone. The majority of activities is performed within the family circle or in the company of friends and so the trips to the activities involve traveling with company. The influence of size and composition of group members staying together on vacation is substantial. In particular children under 6 years old have a large positive effect on choosing private car for travel in summer. The presence of other household members is an influencing factor only in summer. Neither length nor duration of trips seem to be affected by size or composition of the travel party. However, a destination choice model would be necessary to estimate this effect precisely.

3. **Is there a visible impact of weather conditions?**

The non-significant response to temperature and sunshine in mode choice models contradicts somewhat the effects known from daily travel behavior, which suggest that temperature becomes significant after crossing some (negative or positive) threshold. However, it complies with the results of descriptive studies on weather adaptation in tourism and is in line with the literature (cf. section 2.8) suggesting that, on one hand, other factors might prevail over weather and, on the other hand, tourists are more forgiving of weather in regions where weather is generally unstable. They also declare it explicitly in the survey that weather did not make them choose alternative transport mode than planned. Unfortunately, due to insufficient data in the sample, the precipitation impact on cycling remains unknown. What is known, however, is that precipitation has a negative effect on walking in winter, which was anticipated, and a positive effect on walking in summer, which raises doubts about the plausibility of this outcome (however a similar finding was reported also by Saneinejad et al. (2012)). It is postulated that a joint model for the activity, destination and mode choice may explain the underlying dependencies more precisely. Not accounting for interference of weather on the activity and destination choice, can lead to questionable results at the mode choice level – an issue that has also been raised by Liu et al. (2015).

4. **How do tourists valuate their travel time savings depending on transport mode?**

   The willingness-to-pay indicators yield higher values for car travel than for transit, which is particularly visible in the summer season. Tourists also valuate higher the time spent on access and egress walk travel from and to public transportation than the in-vehicle time. The outcomes are in line with the numbers for daily leisure travel of Austrian residents reported recently.

5. **How might tourists respond to policy measures oriented on changing the modal split in tourist regions?**

   The elasticity measures explicitly indicate that tourist mode choice behavior is very inelastic to changes in the cost of travel. Neither the higher fuel cost nor the transit fare can induce a substantial shift from car to transit and vice versa, which should serve as a suggestion for policy makers e.g. when evaluating transit pricing policies. However, the response with respect to travel time is much more distinct. It indicates that tourists are more likely to switch from transit to car if the travel time gets worse than when the ticket prize is increased.

5.2 DISCUSSION AND IMPLICATIONS FOR SCIENCE, ECONOMY AND POLICY

Although the work presented is explorative in its essence, a few interesting presumptions (e.g. influence of weather conditions) and theories (i.e. vacation relaxation effect) have been tested on this occasion. Also the data collection process itself, though not ground-braking and to some extent building on the design of established travel behavior surveys, is applied in a novel context and to an unconventional population. It is argued that a survey of tourist travel behavior should collect disaggregate data on trips and activities of single respondents using a diary-based approach, if possible accompanied by GPS tracking.

The thesis presents probably the first applications of DCA methods to intra-destination tourist movements in a peculiar Alpine environment. Many model specifications were tested, out of which the Nested Logit formulations (section 4.4) are recommended since they can account for the substitution between transit and walking in summer and driving and walking in winter and thus deliver more accurate results (within reasonable computation time).

The modeling results support the use of additional explanatory variables beyond the typical ones like travel time, travel cost and level of service. The estimated models prove that the effects of group composition, trip purpose and weather in summer, and trip purpose, information about the destination, fitness level and weather in winter are significant and of not negligible magnitude. Thus, although accounting for these factors results in an increase in data collection cost, complexity and response burden, it is strongly advised to do it already at the survey design stage. Models equipped with additional variables significantly outperform the base models. That is, models typically used in the context of daily travel, operating only with time, cost and LOS variables, will not deliver precise results and are not recommended.

The reported VTTS and elasticity values are of importance for future policy design and infrastructure project appraisal. In regions with large tourist markets and where tourist traffic is considerable, not only the VTTS of local populations, but also those of tourist visitors should be used for cost-benefit analyses and appraisal of transport investments. Tourists can spend their saved travel time on other activities at the destinations, which can result in more consumption of local services and products and higher satisfaction from the stay, from which local tourist businesses will benefit. Incorporating this aspect into evaluation of transport projects and policies will lead to better understanding of the monetary benefits of transport investments and policy changes.

Hopefully, it will contribute to a paradigm change in policy-making in tourist regions, where many decision so far are not evidence-based and are not supported by comprehensive analyses, but rather focus on short-term horizons and do not reach beyond the political tenure of local leaders (Elliott, 1997; Head, 2010). As Eaton and Holding (1996) point out, these are often ad-hoc actions, not based on empirical analysis and not followed by proper evaluation, which often fail due to problems with funding and limited (or unmeasured) impact on behavior.

Nevertheless, it should be borne in mind that transport policies, whilst tailored to the peculiarities of tourist visitors, may not neglect the basic needs of local residents. Free transit and similar products aimed solely at visitors do not always meet social acceptance of local communities in tourist regions (Gronau, 2017a). Considering also the needs of residents when designing transport policies should help alleviate the conflicts arisen and lead to better reciprocal understanding (an issue broadly documented in tourism literature, cf. Harrill (2004) or Sharpley (2014)).

5.3 LIMITATIONS

It was shown in the thesis that is necessary to account for the fitness-, sport- or health-related character of trips and precisely differentiate between activities involving movement (e.g. cycling for pleasure) and movements to activities (e.g. cycling to a supermarket), i.e. relocation to a place where the activity is performed. However, including the former ones in the data would require developing a method to measure their positive part of the utility, as mentioned in section 2.10. Otherwise, the results might contradict the theory of rational consumer behavior and utility maximization.

Some specific information that could have presumably contributed to a deeper understanding of tourists' mobility choices was not collected in the survey. This is in particular the following:

- If respondents needed to carry baggage on their trip to the activity start location (e.g. climbing equipment, snow sledges for kids, baby carriage) and if it was bulky and troublesome or not.
- If they brought their own bicycles with them.
- If their hotel offers them bicycles for rent or free of charge.
- If they bought any kind of regional guest card in the summer season like the *PremiumCard* in the Ötztal or the *AktivCard* in the Zillertal.
- The precise age of children or at least stratified 0-6, 7-15 and 16-20 so that it would comply with VVT single ticket rates and would allow more precise cost calculations.

Sample size is another clear limitation of the study. With 849 respondents, it is rather small (approx. 2.5%) in relation to on average 34,000 tourists staying in all three regions at any time (given over 85,000 beds available and an average load factor of around 40%). It is also and not representative since data was collected mostly through convenience sampling and the response rate from questionnaires distributed in hotels was very small (which otherwise would allow control over the sampling process). It must be borne in mind that results based on a sample of this kind cannot be generalized to larger or different study populations.

As discussed in section 3.7, a large share of trips within the tourist destination are shorter than 2km and are made on foot. The accuracy of distance and travel time calculation for short trips using *Google Maps* API might become questionable as factors other than pure walking speed[12] come into play. Walking speed may depend on altitude difference, age, trip purpose, carried items (baby carriage, groceries) or sidewalk surface conditions (snow layer). This might have an effect on model results given the considerable share of short walking trips in the current dataset.

[12] Google does not disclose what speed they use in their routing system. As long as transit is concerned, it is based on timetable, car speeds are mostly based on live traffic data, but the assumptions behind walking and cycling are unknown. It is however observable that the speed variates depending on the altitude difference.

6 Outlook and future work

6.1 Detailed modes of transport

As introduced in section 3.8, the survey data contains information on whether the trip was undertaken as a driver or as a passenger. This concept was then desisted and modes were aggregated into four main segments: driving, transit, walking, cycling (Table 4.1). It would be however interesting to precisely derive the availabilities and occupancies of private vehicles and estimate models for a full choice set as proposed in the survey. It would provide more insights into the behavior of single household/group members. In particular, it could explain the interactions between car drivers and car passengers, parents and children as well as holders and non-holders of a driver's license and their effect on the use of private transportation on vacation. Eventually, it could help capture differences in household fleet management during vacation – when most visitors have usually one private car available at the destination – and at home – where households often have more than one private car at their disposal. This is however a very challenging task, as noticed by Miller et al. (2005), since it requires considering various facets of intra-household activity scheduling, like fully and partially joint tours, fully and partially joint trips and activities, escorting children and managing chauffeuring tasks between the household members.

6.2 Model for joint trips, tours and household members' daily schedules

Going on a vacation is mostly a social and family experience. The spouses must arrange their leave in advance and synchronize it with their kids' school breaks. Planning a holiday trip is therefore a complex and time-consuming task, the more household members or the larger the travel group, the more complex it becomes. One can argue that the situation at the destination is not simpler at all. Accounting for these intra-household effects only by incorporating company size and structure variables into the models, as it is done in this thesis, is a rather superficial approach and not capable of capturing the underlying complexity of decision-making.

Although not managed within this thesis, it is scheduled as the next research task to model joint travel of group members using group utility functions as introduced in section 2.9.

6.3 MODEL FOR JOINT CHOICE OF ACTIVITY, DESTINATION AND TRANSPORT MODE

Besides the modal split issues at the vacation destinations, troubling the local transit companies and the hotel industry and driving political discussions, it is also important to know where tourist travel within the regions and what affects their destination choice decisions. It is assumed that the choice of a destination is not a self-contained and autonomous decision and depends not only on the destination attributes, but also on the planned activity and available transport modes. Therefore, the basic model should definitely allow for joint modeling of the choice of activity type, destination and transport mode. Further levels of precision can be added through accounting for the departure time (Hess et al., 2007b; Hess et al., 2007a) and travel party (Wu et al., 2011). A conceptually suitable tool for this task would be a multi-level Nested or Cross-Nested Logit model as proposed by Ding et al. (2014) and Ding et al. (2015). A conceivable model structure capable of accommodating all three decision components: activity, destination and mode choice, is illustrated in Figure 6.1.

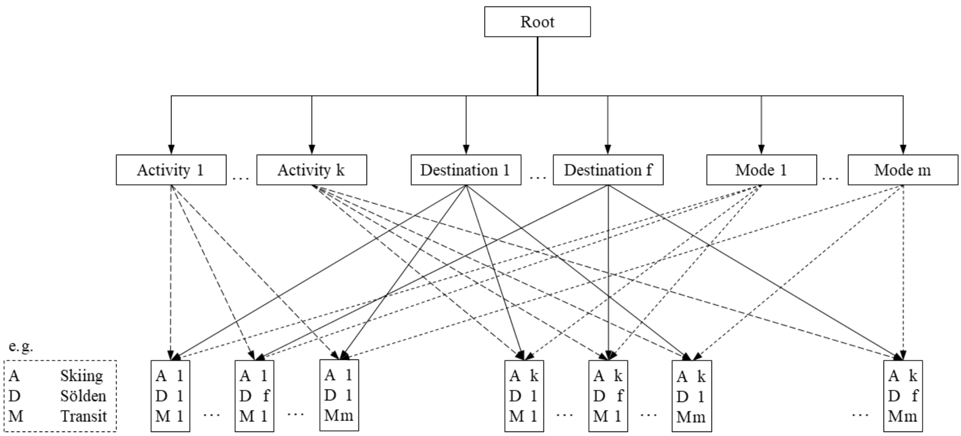


Figure 6.1 Cross-nested model for joint choice of activity, destination and transport mode

6.4 MODEL FOR ROUTE CHOICE

The analysis of routing decisions sets higher requirements on the spatial accuracy of the trip information that cannot be fulfilled by the current dataset. High-resolution data with GPS traces (preferably acquired through a mobile app accompanied by survey questions of an activity-diary-type) of tourist trips would be necessary to perform the analysis as well as precise data on the road network including cycle and foot paths. Information about the terrain topography, toll roads, snow clearing and de-icing of roads should be incorporated in the model to properly account for all peculiarities of route choice in a mountain environment.

6.5 Model for tourists' budget and time consumption at the destination

Apart from looking only at the choice between discrete and exclusive alternatives like mode, destination or route, it would be also insightful to analyze the tourist choices of continuous goods like income or time. These goods typically have very precise constraints during a vacation stay since tourists come to a destination for a given period of time limited by a hotel booking or flight tickets and mostly have a certain money budget that is prepared beforehand and that they do not want to exceed. Using the Multiple Discrete-Continuous Extreme Value (MDCEV) model developed by Bhat (2005) one could model not only the type, but also the duration of different out-of-hotel leisure activities undertaken by tourists during the stay. This could give an insight into tourist activity behavior at the destination from the economic consumer demand perspective.

6.6 Tourist self-selection

In the mode choice models, decision-makers have a very limited and precisely defined choice set, that is, they can choose only from the transport modes available for them for a particular trip. Considering a very low share of rental car users among the respondents and no functional car-sharing or bike-sharing systems in any of the surveyed areas, the transport mode chosen for the trip to the destination strongly determines the set of the alternatives available for travel at the destination.

Thus, it would be interesting to investigate whether, besides all factors found significant in the models (see Section 4.3), there is a self-selection phenomenon present amid tourists as it is known from studies of daily travel behavior (van Wee, 2009). That is, whether there is any tendency among car-users to choose a destination allowing very comfortable use of a car on-site or whether transit users incline towards vacations resorts offering high quality public transport services. If so, the on-site transport choices of tourists would be influenced not only by the mode chosen for the vacation trip from home to the destination, but also, at a deeper level, by the underlying attitudes.

6.7 Integration with transport modeling software

In order to use the proposed model in a large-scale scenario, an integration with a disaggregate transport modeling software is essential. As a further research step, it is planned to incorporate the developed discrete choice model into a large-scale transportation model for the province of Tyrol, e.g. within the *MATSim* agent-based environment (Horni et al., 2016). This could allow to test the developed hypotheses in real cases and check if the discrete choice model helps the global transportation model validate better. Similar work has been already done, e.g., for shopping and leisure destination choice (Horni, 2013).

However, a major obstacle is that, as for now, the province of Tyrol does not have a disaggregate transportation model. Until a complete large-scale (agent-based) model for Tyrol will be created, the following temporary solution is conceivable. A small-scale local agent-based model for a chosen tourist region (Ötztal, Zillertal, etc.) should be created. The model will produce traffic flows based on tourist activities in the region, which will be transferred to the existing aggregate model. A final global validation for a given region could be carried out in the aggregated model.

Summary

Although tourism is responsible for a large part of traffic load, in particular in the Alpine countries, travel decisions of tourists and non-local residents remain underrepresented in the research. There is a lack of knowledge on travel patterns of tourists staying at the destination and factors influencing their intra-destination travel behavior. Consequently, local authorities and administration do not have the empirical evidence necessary for policy-making and -evaluation and must base their decisions on conjectures. The thesis combines data collection and modeling techniques developed in transportation research with existing knowledge in the field of tourism and travel to fill this research gap.

The data was collected through a complex survey conducted in summer and winter in highly-frequented alpine tourist regions in Austria. The survey employed a travel-activity diary and was complemented with secondary data from external sources. Through the application of disaggregate discrete choice models, it was possible to identify the determinants of the transport mode choices of tourists at the destination for both seasons.

The outcomes reveal, as expected, a significantly negative effect of travel time and travel cost. Furthermore, a substantial influence of children on transport mode choice is found, albeit not on length or duration of trips. Also travel purpose, price segment of the accommodation, prior knowledge about the destination and fitness level of tourists prove to have a significant impact on mode choice. In terms of weather, tourists are generally forgiving of unfavorable weather conditions and adapt easily. However, the separate effects of weather elements (temperature, precipitation, sunshine, wind) are ambiguous and require further investigation.

The econometric models were also used to produce estimates of willingness-to-pay indicators among tourists as well as to evaluate their responsiveness to changes on the supply side through elasticities.

The Value of Travel Time Savings (VTTS) among tourist visitors amounts to about 10 EUR/h for car in summer and about 9 EUR/h in winter, which is very close to the VTTS values (around 10 EUR/h) for leisure trips of Austrian residents reported in literature. However, the VTTS of tourists traveling on transit are much lower than

those of Austrian transit riders. When compared against the VTTS values reported in other European countries, tourists in Austria valuate their time very high.

Tourists traveling within the destinations are found to be very inelastic to changes in transit fare or fuel price. The obtained values range between -0.08 and -0.01, which is lower than typical values reported in Austrian and international studies. The reaction to changes in travel time is more visible and oscillates between -1.07 and -0.10 depending on transport mode and season. The elasticities are generally higher in winter than in summer. These are meaningful findings for designing transit pricing strategies in tourist regions since they indicate that tourists attach more importance to the level of service in the transport network than to the travel costs.

That is, except the contribution to science, the thesis provides decision- and policy-makers with valuable outcomes needed for project appraisal, cost-benefit-analyses and designing evidence-based transport policy as well as numbers necessary for effective mobility management in tourist regions that are struggling with transport problems and the resultant negative externalities.

Moreover, the thesis identifies new research gaps and defines directions for further research initiatives such as modeling daily schedules of tourist households, joint modeling of activity, destination and mode choice, modeling route choice and time use at the destination or accounting for tourist self-selection in models.

Bibliography

Abou-Zeid, M. and Ben-Akiva, M. (2014) Hybrid choice models, *Handbook of choice modelling* eds S. Hess and A.J. Daly, pp. 383–412. Cheltenham, UK: Edward Elgar.

Acheampong, R.A. and Silva, E. (2013) Land use–transport interaction modeling: A review of the literature and future research directions. *Journal of Transport and Land Use*.

Ahas, R., Aasa, A., Roose, A., Mark, Ü. and Silm, S. (2008) Evaluating passive mobile positioning data for tourism surveys: An Estonian case study. *Tourism Management*, *29*, 469–486.

Albert, A. and Anderson, J.A. (1984) On the Existence of Maximum Likelihood Estimates in Logistic Regression Models. *Biometrika*, *71*, 1.

Alegre, J. and Pou, L. (2006) The length of stay in the demand for tourism. *Tourism Management*, *27*, 1343–1355.

Algers, S., Daly, A., Kjellman, P. and Widlert, S. (1996) Stockholm Model System (SIMS): Application. Volume 2: Modelling Transport Systems, *World transport research: Proceedings of the 7th World Conference on Transport Research WCTRS* eds D.A. Hensher, J. King and T.H. Oum. Oxford: Pergamon.

Alin, A. (2010) Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*, 370–374.

Alivand, M., Hochmair, H. and Srinivasan, S. (2015) Analyzing how travelers choose scenic routes using route choice models. *Computers, Environment and Urban Systems*, *50*, 41–52.

Alpaydin, E. (2020). *Introduction to machine learning.* (Fourth edition). Adaptive computation and machine learning series. Cambridge Massachusetts, The MIT Press.

Anderson, J. (1971) Space-Time Budgets and Activity Studies in Urban Geography and Planning. *Environment and Planning A*, *3*, 353–368.

Anderson, S.P., Palma, A. de and Thisse, J.-F. (1992). *Discrete choice theory of product differentation*.

Andrey, J., Mills, B., Leahy, M. and Suggett, J. (2003) Weather as a chronic hazard for road transportation in Canadian cities. *Natural Hazards*, *28*, 319–343.

Andridge, R.R. and Little, R.J.A. (2010) A Review of Hot Deck Imputation for Survey Non-response. *International statistical review*, *78*, 40–64.

Anta, J., Pérez-López, J.B., Martínez-Pardo, A., Novales, M. and Orro, A. (2016) Influence of the weather on mode choice in corridors with time-varying congestion: a mixed data study. *Transportation*, *43*, 337–355.

Antoniou, C., Efthymiou, D. and Chaniotakis, E. (2019). *Demand for emerging transportation systems: Modeling adoption, satisfaction, and mobility patterns*. Amsterdam, Elsevier.

Arce, C.H. and Pisarski, A. (2009) Surveys of Tourists and Transients: Synthesis of a Workshop, *Transport survey methods: Keeping up with a changing world* eds P. Bonnel, M. Lee-Gosselin, J.P. Zmud and J.-L. Madre, pp. 243–248. Bingley, UK: Emerald.

Arentze, T. (2015) Individuals' social preferences in joint activity location choice: A negotiation model and empirical evidence. *Journal of Transport Geography*, *48*, 76–84.

Arentze, T., Hofman, F., van Mourik, H. and Timmermans, H. (2000) ALBATROSS: Multiagent, Rule-Based Model of Activity Pattern Decisions. *Transportation Research Record: Journal of the Transportation Research Board*, *1706*, 136–144.

Arentze, T. and Timmermans, H. (2008) Social Networks, Social Interactions, and Activity-Travel Behavior: A Framework for Microsimulation. *Environment and Planning B: Planning and Design*, *35*, 1012–1027.

Aribarg, A., Arora, N. and Kang, M.Y. (2010) Predicting Joint Choice Using Individual Data. *Marketing Science*, *29*, 139–157.

Armstrong, R.W. and Mok, C. (1995) Leisure Travel Destination Choice Criteria of Hong Kong Residents. *Journal of Travel & Tourism Marketing*, *4*, 99–104.

Aschauer, F., Rösel, I., Hössinger, R., Kreis, H.B. and Gerike, R. (2018) Time use, mobility and expenditure: An innovative survey design for understanding individuals' trade-off processes. *Transportation*.

Austrian National Tourist Office (2014). *T-MONA Urlauberbefragung*. Vienna.

Axhausen, K.W. (2008) Definition of Movement and Activity for Transport Modelling, *Handbook of transport modelling* eds D.A. Hensher and K. Button, pp. 329–343. Amsterdam, London: Elsevier.

Axhausen, K.W. (2015). *Kommentar SN 640003 Verkehrserhebungen: Methoden der Verkehrsbefragungen - Schlussbericht VSS 2009/103.* Arbeitsberichte Verkehrs- und Raumplanung, 1064, IVT, ETH Zürich.

Axhausen, K.W., Ehreke, I., Glemser, A., Hess, S., Jödden, C., Nagel, K., Sauer, A. and Weis, C. (2014). *Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf Basis der Schätzung eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung: FE-Projekt 96.996/2011 Zeitkosten Personenverkehr. Entwurf Schlussbericht*. Zürich, München, IVT, ETH Zürich; TNS Infratest.

Axhausen, K.W. and Fröhlich, P. (2012). *Übersicht zu Stated Preference-Studien in der Schweiz und Abschätzung von Gesamtelastizitäten: Statusbericht*, ETH Zurich.

Axhausen, K.W., Schmid, B. and Weis, C. (2015). *Predicting response rates updated.* Arbeitsberichte Verkehrs- und Raumplanung, 1063, IVT, ETH Zürich.

Axhausen, K.W., Schönfelder, S., PTV AG and Fell, B. (2000). *Mobidrive questionnaires*, ETH Zurich.

BAK Economics AG (2019). *Performance des alpinen Tourismus in der Schweiz im internationalen Vergleich*.

Balbi, S., Giupponi, C., Perez, P. and Alberti, M. (2013) A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination. *Environmental Modelling & Software*, *45*, 29–51.

Ball, D.J. and Machin, N. (2006) Foreign travel and the risk of harm. *International journal of injury control and safety promotion*, *13*, 107–115.

Barber, J.R., Burdett, C.L., Reed, S.E., Warner, K.A., Formichella, C., Crooks, K.R., Theobald, D.M. and Fristrup, K.M. (2011) Anthropogenic noise exposure in protected natural areas: estimating the scale of ecological consequences. *Landscape Ecology*, *26*, 1281–1295.

Barchiesi, D., Moat, H.S., Alis, C., Bishop, S. and Preis, T. (2015) Quantifying International Travel Flows Using Flickr. *PloS one*, *10*, e0128470.

Basso, L.J. and Jara-Díaz, S.R. (2012) Integrating congestion pricing, transit subsidies and mode choice. *Transportation Research Part A: Policy and Practice*, *46*, 890–900.

Bates, J. (2008) History of demand modeling, *Handbook of transport modelling* eds D.A. Hensher and K. Button, pp. 11–33. Amsterdam, London: Elsevier.

Beard, J.G. and Ragheb, M.G. (1983) Measuring Leisure Motivation. *Journal of Leisure Research*, *15*, 219–228.

Beck, M.J. and Rose, J.M. (2017) Stated preference modelling of intra-household decisions: Can you more easily approximate the preference space? *Transportation*, *48*, 76.

Becken, S. and Wilson, J. (2013) The impacts of weather on tourist travel. *Tourism Geographies*, *15*, 620–639.

Becker, F. and Axhausen, K.W. (2017) Literature review on surveys investigating the acceptance of automated vehicles. *Transportation*, *44*, 1293–1306.

Bellemans, T., Kochan, B., Janssens, D., Wets, G., Arentze, T. and Timmermans, H. (2010) Implementation Framework and Development Trajectory of FEATHERS Activity-Based Simulation Platform. *Transportation Research Record: Journal of the Transportation Research Board*, *2175*, 111–119.

Bellos, V., Ziakopoulos, A. and Yannis, G. (2020) Investigation of the effect of tourism on road crashes. *Journal of Transportation Safety & Security*, *12*, 782–799.

Ben-Akiva, M. (1973). *Structure of passenger travel demand models*. PhD Thesis,Massachusetts Institute of Technology.

Ben-Akiva, M., Bergman, M.J., Daly, A.J. and Ramaswamy, R. (1984) Modelling interurban route choice behaviour, *Proceedings of the ninth international symposium on transportation and traffic theory* eds R. Hamerslag and J. Volmuller, pp. 299–330. Utrecht: VNU Science Press.

Ben-Akiva, M. and Boccara, B. (1995) Discrete choice models with latent choice sets. *International Journal of Research in Marketing*, *12*, 9–24.

Ben-Akiva, M. and Lerman, S.R. (1985). *Discrete choice analysis: Theory and application to travel demand*. Cambridge, Mass., London, MIT Press.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T. and Polydoropoulou, A. (2002) Integration of Choice and Latent Variable Models, *Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges* ed H.S. Mahmassani, pp. 431–470. Bingley: Emerald.

Bhat, C., Paleti, R., Pendyala, R. and Goulias, K.G. (2013). *SimAGENT Activity-Based Travel Demand Analysis: Framework, Behavioral Models, and Application Results*. Report prepared for the Southern California Association of Governments.

Bhat, C.R. (2005) A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions. *Transportation Research Part B: Methodological*, *39*, 679–707.

Bhat, C.R., Astroza, S. and Bhat, A.C. (2016) On allowing a general form for unobserved heterogeneity in the multiple discrete–continuous probit model: Formulation and application to tourism travel. *Transportation Research Part B: Methodological*, *86*, 223–249.

Bhat, C.R. and Koppelman, F.S. (1999) Activity-Based Modeling of Travel Demand, *Handbook of Transportation Science* ed R.W. Hall, pp. 35–61. Boston, MA: Springer US.

Bhat, C.R. and Koppelman, F.S. (2006). *A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models*.

Bhat, C.R. and Pendyala, R.M. (2005) Modeling intra-household interactions and group decision-making. *Transportation*, *32*, 443–448.

Bieger, T. and Laesser, C. (2013) Future Living Conditions and Mobility: Travel Behavior of Alpine Tourists, *The tourism and leisure industry: Shaping the future* eds K. Weiermair and C. Mathies, pp. 253–270. New York: Abingdon; Routledge.

Bieger, T. and Laesser, C. (2016) Information Sources for Travel Decisions: Toward a Source Process Model. *Journal of Travel Research*, *42*, 357–371.

Björk, P. and Jansson, T. (2008). *Travel Decision-making: The Role of Habit*. MPRA Paper.

Böcker, L., Dijst, M. and Prillwitz, J. (2013) Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review. *Transport Reviews*, *33*, 71–91.

Böhler, S., Grischkat, S., Haustein, S. and Hunecke, M. (2006) Encouraging environmentally sustainable holiday travel. *Transportation Research Part A: Policy and Practice*, *40*, 652–670.

Bovy, P.H.L. (2009) On Modelling Route Choice Sets in Transportation Networks: A Synthesis. *Transport Reviews*, *29*, 43–68.

Bovy, P.H.L. and Stern, E. (1990). *Route Choice: Wayfinding in Transport Networks.* Studies in Operational Regional Science, 9. Dordrecht, Springer.

Bowman, J. and Ben-Akiva, M. (2001) Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, *35*, 1–28.

Bowman, J.L. (1998). *The Day Activity Schedule Approach to Travel Demand Analysis*. Doctoral Thesis,Massachusetts Institute of Technology. Boston, USA.

Bowman, J.L., Bradley, M., Shiftan, Y., Lawton, T.K. and Ben-Akiva, M. (1999) Demonstration of an activity based model system for Portland, *World transport research: Proceedings of the 8th World Conference on Transport Research WCTRS* eds H. Meersman, E. de van Voorde and W.E. Winkelmans.

Bradley, M., Bowman, J.L. and Griesenbeck, B. (2010) SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. *Journal of Choice Modelling*, *3*, 5–31.

Bradley, M. and Vovsha, P. (2005) A model for joint choice of daily activity pattern types of household members. *Transportation*, *32*, 545–571.

Brewer, A.M. and Hensher, D.A. (2000) Distributed work and travel behaviour: The dynamics of interactive agency choices between employers and employees. *Transportation*, *27*, 117–148.

Brög, W. (2009) The New KONTIV® Design. http://www.social-data.de/info/KONTIV_engl.pdf. Accessed 30.08.2018.

Bundesamt für Statistik (BFS) (2017). *Verkehrsverhalten der Bevölkerung: Ergebnisse des Mikrozensus Mobilität und Verkehr 2015.* Statistik der Schweiz. Neuchâtel, CH.

Bundesministerium für Verkehr und digitale Infrastruktur (2018). *Mobilität in Deutschland – MiD: Ergebnisbericht*. Bonn.

Bursa, B. and Mailer, M. (2018) Car-less on holiday: Sustainable tourist travel in Alpine Regions, *Tourism Naturally Conference 2018*.

Cambridge Systematics Inc. (1996). *Travel Survey Manual*. United States.

Cascetta, E. and Papola, A. (2009) Dominance among alternatives in random utility models. *Transportation Research Part A: Policy and Practice*, *43*, 170–179.

Castillo-Manzano, J.I., Castro-Nuño, M., López-Valpuesta, L. and Vassallo, F.V. (2020) An assessment of road traffic accidents in Spain: the role of tourism. *Current Issues in Tourism*, *23*, 654–658.

Cavallaro, F., Ciari, F., Nocera, S., Prettenthaler, F. and Scuttari, A. (2017) The impacts of climate change on tourist mobility in mountain areas. *Journal of Sustainable Tourism*, *25*, 1063–1083.

Cervero, R. (1990) Transit pricing research. *Transportation*, *17*, 117–139.

Chalasani, V.S., Engebretsen, Ø., Denstadli, J.-M. and Axhausen, K.W. (2004). *Precision of geocoded locations and network distance estimates.* Arbeitsberichte Verkehrs- und Raumplanung. Zürich, ETH Zurich.

Champ, P.A., Boyle, K.J. and Brown, T.C. (2017). *A primer on nonmarket valuation.* The Economics of Non-Market Goods and Resources, 1571-487X, 13. Dordrecht, Springer.

Chatterjee, S. and Hadi, A.S. (2006). *Regression Analysis by Example*. Hoboken, NJ, USA, John Wiley & Sons.

Chen, C., Ma, J., Susilo, Y., Liu, Y. and Wang, M. (2016) The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation research. Part C, Emerging technologies*, *68*, 285–299.

Cherchi, E. and Ortúzar, J.d.D. (2002) Mixed RP/SP models incorporating interaction effects. *Transportation*, *29*, 371–395.

Chorus, C.G. (2012). *Random regret-based discrete choice modeling: A tutorial.* SpringerBriefs in business. Berlin, New York, Springer.

Chow, L.-F., Zhao, F., Li, M.-T. and Li, S.-C. (2005) Development and Evaluation of Aggregate Destination Choice Models for Trip Distribution in Florida. *Transportation Research Record: Journal of the Transportation Research Board*, *1931*, 18–27.

Christensen, L. and Nielsen, O.A. (2018) What Do European Tourism Demand Surveys Tell About Long Distance Travel?, *TRB 97th Annual Meeting Compendium of Papers*.

Chua, A., Servillo, L., Marcheggiani, E. and Moere, A.V. (2016) Mapping Cilento: Using geotagged social media data to characterize tourist flows in southern Italy. *Tourism Management*, *57*, 295–310.

Ciari, F. and Axhausen, K.W. (2012) Choosing carpooling or carsharing as a mode: Swiss stated choice experiments, *TRB 91st Annual Meeting Compendium of Papers*: Transportation Research Board.

Cooley, D. (2018). *googleway: Accesses Google Maps APIs to Retrieve Data and Plot Maps*.

Cooper, C.P. (1978). *The spatial behaviour of tourists on the Island of Jersey*. PhD,University College London. London.

Corfman, K.P. and Gupta, S. (1993) Chapter 3 Mathematical models of group choice and negotiations, *Marketing* ed J. Eliashberg, pp. 83–142. Amsterdam: Elsevier.

Crompton, J. (1992) Structure of vacation destination choice sets. *Annals of Tourism Research*, *19*, 420–434.

Crompton, J.L. (1979) Motivations for pleasure vacation. *Annals of Tourism Research*, *6*, 408–424.

Cullinane, S. and Cullinane, K. (1999) Attitudes towards traffic problems and public transport in the Dartmoor and Lake District National Parks. *Journal of Transport Geography*, *7*, 79–87.

Daly, A. (1987) Estimating "tree" logit models. *Transportation Research Part B: Methodological*, *21*, 251–267.

Daly, A., Hess, S. and Jong, G. de (2012) Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological*, *46*, 333–341.

Davidson, W., Donnelly, R., Vovsha, P., Freedman, J., Ruegg, S., Hicks, J., Castiglione, J. and Picado, R. (2007) Synthesis of first practices and operational research approaches in activity-based travel demand modeling. *Transportation Research Part A: Policy and Practice*, *41*, 464–488.

Day, J., Chin, N., Sydnor, S. and Cherkauer, K. (2013) Weather, climate, and tourism performance: A quantitative analysis. *Tourism Management Perspectives*, *5*, 51–56.

Daziano, R.A. and Rizzi, L.I. (2015) Analyzing the impact of a fatality index on a discrete, interurban mode choice model with latent safety, security, and comfort. *Safety Science*, *78*, 11–19.

De Knop, P. (2007) Sport tourism in Belgium. Opinion paper. *Journal of Sport & Tourism*, *9*, 291–292.

De Witte, A., Hollevoet, J., Dobruszkes, F., Hubert, M. and Macharis, C. (2013) Linking modal choice to motility: A comprehensive review. *Transportation Research Part A: Policy and Practice*, *49*, 329–341.

Debbage, K.G. (1991) Spatial behavior in a bahamian resort. *Annals of Tourism Research*, *18*, 251–268.

Decrop, A. (2006). *Vacation decision making*. Wallingford, CABI.

Decrop, A. (2010) Destination Choice Sets: An Inductive Longitudinal Approach. *Annals of Tourism Research*, *37*, 93–115.

Denstadli, J.M. and Jacobsen, J.K.S. (2011) The long and winding roads: Perceived quality of scenic tourism routes. *Tourism Management*, *32*, 780–789.

Department for Transport (2015). *Understanding and valuing impacts of transport investment: values of travel time savings*.

Dickinson, J.E. and Dickinson, J.A. (2006) Local Transport and Social Representations: Challenging the Assumptions for Sustainable Tourism. *Journal of Sustainable Tourism*, *14*, 192–208.

Dickinson, J.E. and Robbins, D. (2007) Using the car in a fragile rural tourist destination: A social representations perspective. *Journal of Transport Geography*, *15*, 116–126.

Dickinson, J.E. and Robbins, D. (2008) Representations of tourism transport problems in a rural destination. *Tourism Management*, *29*, 1110–1121.

Dietvorst, A.G.J. (1994) Cultural tourism and time-space behaviour, *Building a new heritage: Tourism, culture, and identity in the new Europe* eds G.J. Ashworth and P.J. Larkham. London, New York: Routledge.

Díez-Gutiérrez, M. and Babri, S. (2020) Explanatory variables underlying the route choice decisions of tourists: The case of Geiranger Fjord in Norway. *Transportation Research Part A: Policy and Practice*, *141*, 398–409.

Ding, C., Mishra, S., Lin, Y. and Xie, B. (2015) Cross-Nested Joint Model of Travel Mode and Departure Time Choice for Urban Commuting Trips: Case Study in Maryland–Washington, DC Region. *Journal of Urban Planning and Development*, *141*, 4014036.

Ding, C., Xie, B., Wang, Y. and Lin, Y. (2014) Modeling the Joint Choice Decisions on Urban Shopping Destination and Travel-to-Shop Mode: A Comparative Study of Different Structures. *Discrete Dynamics in Nature and Society*, *2014*, 1–10.

Dolnicar, S., Laesser, C. and Matus, K. (2010) Short-haul city travel is truly environmentally sustainable. *Tourism Management*, *31*, 505–512.

Eaton, B. and Holding, D. (1996) The evaluation of public transport alternatives to the car in British National Parks. *Journal of Transport Geography*, *4*, 55–65.

Efron, B. and Tibshirani, R. (1986) Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy. *Statistical Science*, *1*, 54–75.

Elliott, J. (1997). *Tourism: Politics and public sector management*. London, Routledge.

Elsasser, H. and Bürki, R. (2002) Climate change as a threat to tourism in the Alps. *Climate Research*, *20*, 253–257.

Elvidge, A.D. and Renfrew, I.A. (2016) The Causes of Foehn Warming in the Lee of Mountains. *Bulletin of the American Meteorological Society*, *97*, 455–466.

Erhardt, G.D., Freedman, J., Stryker, A., Fujioka, H. and Anderson, R. (2007) Ohio Long-Distance Travel Model. *Transportation Research Record: Journal of the Transportation Research Board*, *2003*, 130–138.

Eymann, A. and Ronning, G. (1997) Microeconometric models of tourists' destination choice. *Regional Science and Urban Economics*, *27*, 735–761.

Federal Highway Administration (2017) National Household Travel Survey. https://nhts.ornl.gov.

Filimonau, V., Dickinson, J. and Robbins, D. (2014) The carbon impact of short-haul tourism: a case study of UK travel to Southern France using life cycle analysis. *Journal of Cleaner Production*, *64*, 628–638.

Fodness, D. and Murray, B. (1999) A Model of Tourist Information Search Behavior. *Journal of Travel Research*, *37*, 220–230.

Fosgerau, M., Hjorth, K. and Vincent Lyk-Jensen, S. (2007). *The Danish Value of Time Study: Final report*. Copenhagen.

Frank, L., Bradley, M., Kavage, S., Chapman, J. and Lawton, T.K. (2007) Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, *35*, 37–54.

Franke, V. (2017). *Das Tourismusmodell der BVG.* PTV ÖV-Forum: Modellbasierte Analyse & Optimierungsverfahren für den Öffentlichen Verkehr. Halle an der Saale.

Frejinger, E., Bierlaire, M., Stojanovic, J., Vrtic, M., Schüssler, N. and Axhausen, K.W. (2006). *A route choice model in Switzerland based on RP and SP Data*, ETH Zurich.

Gaviria, M. (1975). *El turismo de playa en España: Chequeo a 16 ciudades nuevas del ocio*. Madrid, Turner.

Gehrke, S.R. and Clifton, K.J. (2014) Operationalizing Land Use Diversity at Varying Geographic Scales and Its Connection to Mode Choice. *Transportation Research Record: Journal of the Transportation Research Board*, *2453*, 128–136.

Gerike, R. and Schulz, A. (2018) Workshop Synthesis: Surveys on long-distance travel and other rare events. *Transportation Research Procedia*, *32*, 535–541.

Gilbert, D. and Abdullah, J. (2004) Holidaytaking and the sense of well-being. *Annals of Tourism Research*, *31*, 103–121.

Gliebe, J.P. and Koppelman, F.S. (2002) A model of joint activity participation between household members. *Transportation*, *29*, 49–72.

Gliebe, J.P. and Koppelman, F.S. (2005) Modeling household activity-travel interactions as parallel constrained choices. *Transportation*, *32*, 449–471.

Golob, T.F. and Recker, W.W. (2003) Relationships Among Urban Freeway Accidents, Traffic Flow, Weather, and Lighting Conditions. *Journal of Transportation Engineering*, *129*, 342–353.

Gössling, S. and Hall, C.M. (2006). *Tourism and global environmental change: Ecological, social, economic and political interrelationships.* Contemporary geographies of leisure, tourism, and mobility. London, Taylor & Francis Group.

Gössling, S., Scott, D. and Hall, C.M. (2018) Global trends in length of stay: implications for destination management and climate change. *Journal of Sustainable Tourism*, *26*, 2087–2101.

Gössling, S., Scott, D., Hall, C.M., Ceron, J.-P. and Dubois, G. (2012) Consumer behaviour and demand response of tourists to climate change. *Annals of Tourism Research*, *39*, 36–58.

Graham, D.J. and Glaister, S. (2002) The Demand for Automobile Fuel: A Survey of Elasticities. *Journal of Transport Economics and Policy*, *36*, 1–25.

Graham, D.J. and Glaister, S. (2004) Road Traffic Demand Elasticity Estimates: A Review. *Transport Reviews*, *24*, 261–274.

Gronau, W. (2017a) Encouraging behavioural change towards sustainable tourism: a German approach to free public transport for tourists. *Journal of Sustainable Tourism*, *25*, 265–275.

Gronau, W. (2017b) On The Move: Emerging Fields of Transport Research in Urban Tourism, *Tourism in the City: Towards an Integrative Agenda on Urban Tourism* eds N. Bellini and C. Pasquinelli, pp. 81–91. Cham: Springer International Publishing.

Gross, S. and Grimm, B. (2018) Sustainable mode of transport choices at the destination – public transport at German destinations. *Tourism Review*, *73*, 401–420.

Gühnemann, A., Kurzweil, A. and Mailer, M. (2021) Tourism mobility and climate change - A review of the situation in Austria. *Journal of Outdoor Recreation and Tourism*, 100382.

Guiver, J., Lumsdon, L. and Weston, R. (2008) Traffic reduction at visitor attractions: the case of Hadrian's Wall. *Journal of Transport Geography*, *16*, 142–150.

Gursoy, D. and McCleary, K.W. (2004) An Integrative Model of Tourists' Information Search Behavior. *Annals of Tourism Research*, *31*, 353–373.

Gutiérrez, A. and Miravet, D. (2016) The Determinants of Tourist Use of Public Transport at the Destination. *Sustainability*, *8*, 908.

Haboucha, C.J., Ishaq, R. and Shiftan, Y. (2017) User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49.

Hardy, A. and Aryal, J. (2020) Using innovations to understand tourist mobility in national parks. *Journal of Sustainable Tourism*, *28*, 263–283.

Hardy, A., Hyslop, S., Booth, K., Robards, B., Aryal, J., Gretzel, U. and Eccleston, R. (2017) Tracking tourists' travel with smartphone-based GPS technology: a methodological discussion. *Information Technology & Tourism*, *17*, 255–274.

Harrell, F.E. (2015). *Regression modeling strategies: With applications to linear models, logistic and ordinal regression, and survival analysis.* Springer series in statistics, 0172-7397. Cham, Springer.

Harrill, R. (2004) Residents' Attitudes toward Tourism Development: a Literature Review with Implications for Tourism Planning. *Journal of Planning Literature*, *18*, 251–266.

Head, B.W. (2010) Reconsidering evidence-based policy: Key issues and challenges. *Policy and Society*, *29*, 77–94.

Heinen, E., van Wee, B. and Maat, K. (2010) Commuting by Bicycle: An Overview of the Literature. *Transport Reviews*, *30*, 59–96.

Heinze, G. and Dunkler, D. (2017) Five myths about variable selection. *Transplant international*, *30*, 6–10.

Hensher, D.A. (2001) Measurement of the Valuation of Travel Time Savings. *Journal of Transport Economics and Policy*, *35*, 71–98.

Hensher, D.A. and Li, Z. (2010) Accounting for differences in modelled estimates of RP, SP and RP/SP direct petrol price elasticities for car mode choice: A warning. *Transport Policy, 17*, 191–195.

Hensher, D.A., Rose, J.M. and Black, I. (2008) Interactive Agency Choice in Automobile Purchase Decisions: The Role of Negotiation in Determining Equilibrium Choice Outcomes. *Journal of Transport Economics and Policy*, *42*, 269–296.

Hess, S., Daly, A., Rohr, C. and Hyman, G. (2007a) On the development of time period and mode choice models for use in large scale modelling forecasting systems. *Transportation Research Part A: Policy and Practice*, *41*, 802–826.

Hess, S., Erath, A. and Axhausen, K.W. (2008). *Estimates of the valuation of travel time savings in Switzerland obtained from pooled data*, ETH Zurich.

Hess, S. and Palma, D. (2019) Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, *32*, 100170.

Hess, S., Polak, J.W., Daly, A. and Hyman, G. (2007b) Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands. *Transportation*, *34*, 213–238.

Hewer, M.J., Scott, D.J. and Gough, W.A. (2017) Differences in the importance of weather and weather-based decisions among campers in Ontario parks (Canada). *International journal of biometeorology*, *61*, 1805–1818.

Ho, C. and Mulley, C. (2015) Intra-household interactions in transport research: A review. *Transport Reviews*, *35*, 33–55.

Ho, C.Q., Hensher, D.A., Mulley, C. and Wong, Y.Z. (2018) Potential uptake and willingness-to-pay for Mobility as a Service (MaaS): A stated choice study. *Transportation Research Part A: Policy and Practice*, *117*, 302–318.

Hofer, K. (2015). *Nachfragemodellierung des touristischen Verkehrs im Bundesland Salzburg*. Master's Thesis,Graz University of Technology. Graz.

Hoogendoorn-Lanser, S., Schaap, N.T. and OldeKalter, M.-J. (2015) The Netherlands Mobility Panel: An Innovative Design Approach for Web-based Longitudinal Travel Data Collection. *Transportation Research Procedia*, *11*, 311–329.

Hörl, S., Balać, M. and Axhausen, K.W. (2019) Pairing discrete mode choice models and agent-based transport simulation with MATSim, *2019 TRB Annual Meeting Online,* pp. 19–2409: Transportation Research Board.

Horni, A. (2013). *Destination choice modeling of discretionary activities in transport microsimulations*. PhD Thesis,IVT, ETH Zürich.

Horni, A., Nagel, K. and Axhausen, K.W. (2016). *The Multi-Agent Transport Simulation MATSim*, Ubiquity Press.

Horowitz, J.L. and Louviere, J.J. (1995) What is the role of consideration sets in choice modeling? *International Journal of Research in Marketing*, *12*, 39–54.

Hranac, R., Sterzin, E.D., Krechmer, D., Rakha, H. and Farzaneh, M. (2006). *Empirical Studies on Traffic Flow in Inclement Weather*.

Hudson, S. (2005) Winter sports destinations: dealing with seasonality, *Sport tourism destinations: Issues, opportunities and analysis* ed J.E.S. Higham, pp. 188–204. Amsterdam, Oxford: Elsevier Butterworth Heinemann.

Iso-Ahola, S.E. (1984) Social psychological foundations of leisure and resultant implications for leisure counseling, *Leisure counseling: Concepts and applications* ed E.T. Dowd, pp. 97–125. Springfield, IL: C.C. Thomas.

Jacobsen, J.K.S. (1996) Segmenting the use of a scenic highway. *The Tourist Review*, *51*, 32–38.

Janzen, M., Vanhoof, M., Smoreda, Z. and Axhausen, K.W. (2018) Closer to the total? Long-distance travel of French mobile phone users. *Travel Behaviour and Society*, *11*, 31–42.

Järv, O., Aasa, A., Ahas, R. and Saluveer, E. (2007) Weather dependence of tourist's spatial behaviour and destination choices: Case study with passive mobile positioning data in Estonia, *Developments in tourism climatology: 3rd International Workshop on Climate, Tourism and Recreation* ed A. Matzarakis, pp. 221–227. Freiburg.

Jokubauskaitė, S., Hössinger, R., Aschauer, F., Gerike, R., Jara-Díaz, S., Peer, S., Schmid, B., Axhausen, K.W. and Leisch, F. (2019) Advanced continuous-discrete model for joint time-use expenditure and mode choice estimation. *Transportation Research Part B: Methodological*, *129*, 397–421.

Jones, P.M. (1979a) 'HATS': A Technique for Investigating Household Decisions. *Environment and Planning A: Economy and Space*, *11*, 59–70.

Jones, P.M. (1979b) New approaches to understanding travel behaviour: the human activity approach, *Behavioural travel modelling* eds D.A. Hensher and P.R. Stopher, pp. 55–80. London: Croom Helm.

Jong, G.C. de and Gunn, H.F. (2001) Recent Evidence on Car Cost and Time Elasticities of Travel Demand in Europe. *Journal of Transport Economics and Policy*, *35*, 137–160.

Kahle, D. and Wickham, H. (2013) ggmap: Spatial Visualization with ggplot2. *The R Journal*, *5*, 144.

Kang, H. and Scott, D.M. (2011) Impact of different criteria for identifying intra-household interactions: a case study of household time allocation. *Transportation*, *38*, 81–99.

Katoshevski, R., Glickman, I., Ishaq, R. and Shiftan, Y. (2013) Integrating activity-based travel-demand models with land-use and other long-term lifestyle decisions. *Journal of Transport and Land Use*.

Kim, J. and Lee, S. (2017) Comparative analysis of traveler destination choice models by method of sampling alternatives. *Transportation Planning and Technology*, *40*, 465–478.

Kinsella, J. and Caulfield, B. (2011) An Examination of the Quality and Ease of Use of Public Transport in Dublin from a Newcomer's Perspective. *Journal of Public Transportation*, *14*, 69–81.

Klassen, N. (2001). *Einfluss der Information auf die individuelle Freizeitmobilität: Anwendung der Stated Preference Methode auf die Potentialabschätzungen eines Freizeit- und Naherholungsinformationssystems*. PhD Thesis,Technische Universität München. München.

Koenig, U. and Abegg, B. (1997) Impacts of Climate Change on Winter Tourism in the Swiss Alps. *Journal of Sustainable Tourism*, *5*, 46–58.

Koetse, M.J. and Rietveld, P. (2009) The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, *14*, 205–221.

Köll, H. and Bader, M. (2011). *Auswertung Mobilitätserhebung Tirol 2011*. Reith bei Seefeld.

Kouwenhoven, M., Jong, G.C. de, Koster, P., van den Berg, V.A., Verhoef, E.T., Bates, J. and Warffemius, P.M. (2014) New values of time and reliability in passenger transport in The Netherlands. *Research in Transportation Economics*, *47*, 37–49.

Kowald, M. and Axhausen, K.W. (Eds.) (2015). *Social networks and travel behaviour*. Burlington, VT, Ashgate.

Kozak, M. (2002) Comparative analysis of tourist motivations by nationality and destinations. *Tourism Management*, *23*, 221–232.

Kristoffersson, I., Daly, A. and Algers, S. (2018) Modelling the attraction of travel to shopping destinations in large-scale modelling. *Transport Policy*, *68*, 52–62.

Krueger, R., Rashidi, T.H. and Rose, J.M. (2016) Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343–355.

LaMondia, J. and Bhat, C.R. (2013) A study of visitors' leisure travel behavior in the northwest territories of Canada. *Transportation Letters*, *3*, 1–19.

LaMondia, J., Snell, T. and Bhat, C.R. (2010) Traveler Behavior and Values Analysis in the Context of Vacation Destination and Travel Mode Choices. *Transportation Research Record: Journal of the Transportation Research Board*, *2156*, 140–149.

Landesstatistik Tirol (2021) Tourismus in Tirol. https://www.tirol.gv.at/statistik-budget/statistik/. Accessed March 2021.

Langer, G. (1995) Tourismus und Umwelt: Überlegungen zur relativen Gewichtung von Umweltbelastungen. *The Tourist Review*, *50*, 60–78.

Lanzendorf, M. (2002) Mobility Styles and Travel Behavior: Application of a Lifestyle Approach to Leisure Travel. *Transportation Research Record: Journal of the Transportation Research Board*, *1807*, 163–173.

Lau, G. and McKercher, B. (2006) Understanding Tourist Movement Patterns in a Destination: A GIS Approach. *Tourism and Hospitality Research*, *7*, 39–49.

Lavrakas, P.J. (2008). *Encyclopedia of survey research methods*. Thousand Oaks, Calif., SAGE Publications.

Lehto, X.Y., O'Leary, J.T. and Morrison, A.M. (2004) The effect of prior experience on vacation behavior. *Annals of Tourism Research*, *31*, 801–818.

Leiner, D.J. (2020). *SoSci Survey*.

Le-Klähn, D.-T. and Hall, C.M. (2013) Tourist use of public transport at destinations – a review. *Current Issues in Tourism*, *18*, 785–803.

Leong, W. and Hensher, D.A. (2012) Embedding Decision Heuristics in Discrete Choice Models: A Review. *Transport Reviews*, *32*, 313–331.

Lew, A. and McKercher, B. (2006) Modeling Tourist Movements: A local destination analysis. *Annals of Tourism Research*, *33*, 403–423.

Li, Y., Yang, L., Shen, H. and Wu, Z. (2019) Modeling intra-destination travel behavior of tourists through spatio-temporal analysis. *Journal of Destination Marketing & Management*.

Limtanakool, N., Dijst, M. and Schwanen, T. (2006) The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. *Journal of Transport Geography*, *14*, 327–341.

Lin, Y., Kerstetter, D., Nawijn, J. and Mitas, O. (2014) Changes in emotions and their interactions with personality in a vacation context. *Tourism Management*, *40*, 416–424.

Lindberg, K., Dellaert, B.G. and Rømer Rassing, C. (1999) Resident tradeoffs. *Annals of Tourism Research*, *26*, 554–569.

Litman, T. (2013) Changing North American vehicle-travel price sensitivities: Implications for transport and energy policy. *Transport Policy*, *28*, 2–10.

Liu, C., Susilo, Y.O. and Karlström, A. (2015) Investigating the impacts of weather variability on individual's daily activity–travel patterns: A comparison between commuters and non-commuters in Sweden. *Transportation Research Part A: Policy and Practice*, *82*, 47–64.

Liu, C., Susilo, Y.O. and Karlström, A. (2017) Weather variability and travel behaviour – what we know and what we do not know. *Transport Reviews*, *37*, 715–741.

Liu, C., Susilo, Y.O. and Termida, A.N. (2016). *Subjective perception towards uncertainty on weather conditions and its impact on out-of-home leisure activity participation decisions*.

Llorca, C., Ji, J., Molloy, J. and Moeckel, R. (2018) The usage of location based big data and trip planning services for the estimation of a long-distance travel demand model. Predicting the impacts of a new high speed rail corridor. *Research in Transportation Economics*, *72*, 27–36.

Llorca, C., Winkler, C., Mocanu, T. and Moeckel, R. (2019) Long-distance and daily travel demand: integration of various travel markets and modelling approaches. *Procedia Computer Science*, *151*, 788–793.

Louviere, J.J. (1984) Hierarchical information integration: A new method for the design and analysis of complex multiattribute judgement problems. *ACR North American Advances*.

Louviere, J.J., Hensher, D.A. and Swait, J.D. (2000). *Stated choice methods: Analysis and applications*. Cambridge, Cambridge University Press.

Lu, X. and Pas, E.I. (1999) Socio-demographics, activity participation and travel behavior. *Transportation Research Part A: Policy and Practice*, *33*, 1–18.

Luce, R.D. and Suppes, P. (1965) Preference, utility, and subjective probability, *Handbook of Mathematical Psychology* eds R.D. Luce, R.R. Bush and E.H. Galanter, pp. 249–410. New York: John Wiley & Sons.

Lumsdon, L.M. (2006) Factors affecting the design of tourism bus services. *Annals of Tourism Research*, *33*, 748–766.

Mailer, M., Abegg, B., Jänicke, L. and Bursa, B. (2019) Mobilitätsbedingte Klimawirkung einer alpinen Tourismusdestination. *Zeitschrift für Tourismuswissenschaft*, *11*, 211–236.

Mäler, K.-G. and Vincent, J.R. (2005). *Valuing environmental changes: Volume 2: Valuing Environmental Changes.* Handbook of environmental economics, 2. Amsterdam, Boston, North-Holland/Elsevier.

Manski, C.F. (1977) The structure of random utility models. *Theory and Decision*, *8*, 229–254.

Mantel, N. (1970) Why Stepdown Procedures in Variable Selection. *Technometrics*, *12*, 621–625.

Marschak, J. (1959). *Binary Choice Constraints on Random Utility Indicators*. Cowles Foundation Discussion Papers.

Martín-Cejas, R.R. (2015) The environmental impact caused by road access to Timanfaya Natural Park on Lanzarote Island. *Transportation Research Part D: Transport and Environment*, *41*, 457–466.

Martínez-Garcia, E. and Raya, J.M. (2008) Length of stay for low-cost tourism. *Tourism Management*, *29*, 1064–1075.

Maryland State Highway Administration (2013). *The Maryland Statewide Transportation Model: Model Documentation (version 1.0)*.

Masiero, L. and Zoltan, J. (2013) Tourists intra-destination visits and transport mode: A bivariate probit model. *Annals of Tourism Research*, *43*, 529–546.

Mason, P. and Cheyne, J. (2000) Residents' attitudes to proposed tourism development. *Annals of Tourism Research*, *27*, 391–411.

Maze, T., Agarwai, M. and Burchett, G. (2006) Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow. *Transportation Research Record: Journal of the Transportation Research Board*, *1948*, 170–176.

McFadden, D. (1973) Conditional Logit Analysis of Qualitative Choice Behaviour, *Frontiers in Econometrics* ed P. Zarembka, pp. 105–142. New York, NY, USA: Academic Press New York.

McFadden, D. (1977a). *Modelling the Choice of Residential Location*. Cowles Foundation Discussion Papers.

McFadden, D. (1977b) Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments. *Cowles Foundation Discussion Papers*.

McFadden, D. (1981) Econometric models of probabilistic choice, *Structural Analysis of Discrete Data and Econometric Applications* eds C.F. Manski and D. McFadden, pp. 198–272. Cambridge: MIT Press.

McFadden, D. and Train, K. (2000) Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*, 447–470.

McGehee, N.G. and Andereck, K.L. (2004) Factors Predicting Rural Residents' Support of Tourism. *Journal of Travel Research*, *43*, 131–140.

MCI (2014). *Tourismussatellitenkonto Tirol*. Innsbruck.

McKercher, B., Hardy, A. and Aryal, J. (2019) Using tracking technology to improve marketing: insights from a historic town in Tasmania, Australia. *Journal of Travel & Tourism Marketing*, *36*, 823–834.

McKercher, B. and Lau, G. (2008) Movement Patterns of Tourists within a Destination. *Tourism Geographies*, *10*, 355–374.

McKercher, B. and Lau, G. (2009) Methodological Considerations when Mapping Tourist Movements in a Destination. *Tourism Analysis*, *14*, 443–455.

McKercher, B., Shoval, N., Park, E. and Kahani, A. (2014) The [Limited] Impact of Weather on Tourist Behavior in an Urban Destination. *Journal of Travel Research*, *54*, 442–455.

McKercher, B. and Zoltan, J. (2014) Tourist Flows and Spatial Behavior, *The Wiley Blackwell Companion to Tourism* eds A.A. Lew, C.M. Hall and A.M. Williams, pp. 33–44. Oxford, UK: John Wiley & Sons.

McNally, M.G. (2000). *The Activity-Based Approach*.

Miller, E.J. (2004) The Trouble with Intercity Travel Demand Models. *Transportation Research Record: Journal of the Transportation Research Board*, *1895*, 94–101.

Miller, E.J. (2020) Travel demand models, the next generation, *Mapping the travel behavior genome* eds K.G. Goulias and A.W. Davis, pp. 29–46. Amsterdam, Netherlands: Elsevier.

Miller, E.J. and O'Kelly, M.E. (1983) Estimating Shopping Destination Choice Models from Travel Diary Data. *The Professional Geographer*, *35*, 440–449.

Miller, E.J., Roorda, M.J. and Carrasco, J.A. (2005) A tour-based model of travel mode choice. *Transportation*, *32*, 399–422.

Mishra, S., Wang, Y., Zhu, X., Moeckel, R. and Mahapatra, S. (2013) Comparison between gravity and destination choice models for trip distribution in Maryland, *TRB 92nd Annual Meeting Compendium of Papers*: Transportation Research Board.

Mokhtarian, P.L. (2018) Why travel surveys matter in the Age of Big Data?, *Transportation Research Circular E-C238*, pp. 2–4. Washington DC, United States.

Mokhtarian, P.L. and Salomon, I. (2001) How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation Research Part A: Policy and Practice*, *35*, 695–719.

Mokhtarian, P.L., Salomon, I. and Redmond, L.S. (2001) Understanding the Demand for Travel: It's Not Purely 'Derived'. *Innovation: The European Journal of Social Science Research*, *14*, 355–380.

Molin, E., Oppewal, H. and Timmermans, H. (1999) Group-Based versus Individual-Based Conjoint Preference Models of Residential Preferences: A Comparative Test. *Environment and Planning A: Economy and Space*, *31*, 1935–1947.

Monz, C., D'Antonio, A., Lawson, S., Barber, J. and Newman, P. (2016) The ecological implications of visitor transportation in parks and protected areas: Examples from research in US National Parks. *Journal of Transport Geography*, *51*, 27–35.

Morley, C. (2012) Technique and Theory in Tourism Analysis. *Tourism Economics*, *18*, 1273–1286.

Murphy, P.E. and Rosenblood, L. (1974) Tourism: an exercise in spatial research. *The Canadian Geographer/Le Géographe canadien*, *18*, 201–210.

NatCen Social Research (2019). *National Travel Survey 2018: Technical Report*. London.

Nawijn, J., Mitas, O., Lin, Y. and Kerstetter, D. (2013) How Do We Feel on Vacation? A Closer Look at How Emotions Change over the Course of a Trip. *Journal of Travel Research*, *52*, 265–274.

Newmark, G. (2014) Conducting Visitor Travel Surveys: A Transit Agency Perspective. *Journal of Public Transportation*, *17*, 136–156.

Nicholls, S., Amelung, B. and Student, J. (2016) Agent-Based Modeling: A Powerful Tool for Tourism Researchers. *Journal of Travel Research*, *56*, 3–15.

NobelPrize.org (2020) Nomination and selection of Laureates in Economic Sciences. https://www.nobelprize.org/nomination/economic-sciences. Accessed 14-Mar-20.

O'Fallon, C. and Sullivan, C. (2005) Trip chains and tours: definitional issues associated with household travel surveys, *28th Australian Transport Research Forum*. Sydney: Curtin University, Australia.

Ogrin, M. (2012) Sustainable mobility in Slovenian Julian Alps. *Dela*, 89–108.

Önder, I., Koerbitz, W. and Hubmann-Haidvogel, A. (2016) Tracing Tourists by Their Digital Footprints. *Journal of Travel Research*, *55*, 566–573.

Oppenheim, A.N. (1992). *Questionnaire design, interviewing and attitude measurement*, Pinter Publishers.

Orsi, F. and Geneletti, D. (2013) Using geotagged photographs and GIS analysis to estimate visitor flows in natural areas. *Journal for Nature Conservation*, *21*, 359–368.

Outwater, M., Bradley, M., Ferdous, N., Pendyala, R., Garikapati, V., Bhat, C., Dubey, S., LaMondia, J., Hess, S. and Daly, A. (2015a). *Foundational Knowledge to Support a Long-Distance Passenger Travel Demand Modeling Framework: Final Report*. Exploratory Advanced Research Program DTFH61-10-R-00036.

Outwater, M.L., Bradley, M., Ferdous, N., Bhat, C., Pendyala, R., Hess, S., Daly, A. and LaMondia, J. (2015b) Tour-Based National Model System to Forecast Long-Distance Passenger Travel in the United States, *TRB 94th Annual Meeting Compendium of Papers*: Transportation Research Board.

Páez, A., Scott, D.M. and Volz, E. (2008) A Discrete-Choice Approach to Modeling Social Influence on Individual Decision Making. *Environment and Planning B: Planning and Design*, *35*, 1055–1069.

Pagliara, F., Cascetta, E. and Axhausen, K.W. (2010a). *Can dominance affect spatial choices?*, IVT, ETH Zürich.

Pagliara, F., Preston, J. and Simmonds, D. (2010b). *Residential location choice: Models and applications / Francesca Pagliara, John Preston, David Simmonds, editors.* Advances in spatial science. Heidelberg, London, Springer.

Paulssen, M., Temme, D., Vij, A. and Walker, J.L. (2014) Values, attitudes and travel behavior: A hierarchical latent variable mixed logit model of travel mode choice. *Transportation*, *41*, 873–888.

Pearce, D.G. (1988) Tourist time-budget. *Annals of Tourism Research*, *15*, 106–121.

Pearce, P.L. (1981) "Environment shock": A study of tourists' reactions to two tropical islands. *Journal of Applied Social Psychology*, *11*, 268–280.

Pechlaner, H. and Hamman, E.-M. (2006). *The effects of traffic on alpine tourism*.

Peeta, S., Paz, A. and DeLaurentis, D. (2008) Stated preference analysis of a new very light jet based on-demand air service. *Transportation Research Part A: Policy and Practice*, *42*, 629–645.

Pegg, S., Patterson, I. and Gariddo, P.V. (2012) The impact of seasonality on tourism and hospitality operations in the alpine region of New South Wales, Australia. *International Journal of Hospitality Management*, *31*, 659–666.

Pettebone, D., Newman, P., Lawson, S.R., Hunt, L., Monz, C. and Zwiefka, J. (2011) Estimating visitors' travel mode choices along the Bear Lake Road in Rocky Mountain National Park. *Journal of Transport Geography*, *19*, 1210–1221.

Pickering, C. and Barros, A. (2013) Mountain environments and tourism, *The Routledge handbook of tourism and the environment* eds A. Holden and D.A. Fennell. New York: Routledge.

Pinjari, A.R. and Bhat, C. (2011) Activity-based Travel Demand Analysis, *A handbook of transport economics* ed A. de Palma. Cheltenham Glos U.K., Northampton Mass.: Edward Elgar.

Pozsgay, M. and Bhat, C. (2001) Destination Choice Modeling for Home-Based Recreational Trips: Analysis and Implications for Land Use, Transportation, and Air

Quality Planning. *Transportation Research Record: Journal of the Transportation Research Board*, *1777*, 47–54.

Prato, C.G. (2009) Route choice modeling: past, present and future research directions. *Journal of Choice Modelling*, *2*, 65–100.

Pratt, R.H., Turnbull, K.F., Evans, IV, John, E., McCollom, B.E., Spielberg, F., Vaca, E. and Kuzmyak, J.R. (2000). *Traveler response to transportation system changes: Interim handbook*. TCRP Project B-12.

Prelipcean, A.C., Susilo, Y.O. and Gidófalvi, G. (2018) Collecting travel diaries: Current state of the art, best practices, and future research directions. *Transportation Research Procedia*, *32*, 155–166.

Prillwitz, J. and Barr, S. (2011) Moving towards sustainability? Mobility styles, attitudes and individual travel behaviour. *Journal of Transport Geography*, *19*, 1590–1600.

Pröbstl-Haider, U., Haider, W., Wirth, V. and Beardmore, B. (2015) Will climate change increase the attractiveness of summer destinations in the European Alps? A survey of German tourists. *Journal of Outdoor Recreation and Tourism*, *11*, 44–57.

Provenzano, D., Hawelka, B. and Baggio, R. (2018) The mobility network of European tourists: a longitudinal study and a comparison with geo-located Twitter data. *Tourism Review*, *73*, 28–43.

Puckett, S.M. and Hensher, D.A. (2006) Modelling interdependent behaviour as a sequentially administered stated choice experiment: Analysis of freight distributions chains, *11th International Conference on Travel Behaviour Research*.

Quaile, E.L. (2001) Back to basics: Föhn and chinook winds. *Weather*, *56*, 141–145.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Vienna, Austria.

Rashedi, Z., Mahmoud, M., Hasnine, S. and Habib, K.N. (2017) On the factors affecting the choice of regional transit for commuting in Greater Toronto and Hamilton Area: Application of an advanced RP-SP choice model. *Transportation Research Part A: Policy and Practice*, *105*, 1–13.

Rasouli, S. and Timmermans, H. (2014) Activity-based models of travel demand: promises, progress and prospects. *International Journal of Urban Sciences*, *18*, 31–60.

Regnerus, H.D., Beunen, R. and Jaarsma, C.F. (2007) Recreational traffic management: The relations between research and implementation. *Transport Policy*, *14*, 258–267.

Rendeiro Martin-Cejas, R. and Ramirez Sanchez, P.P. (2010) Ecological footprint analysis of road transport related to tourism activity: The case for Lanzarote Island. *Tourism Management*, *31*, 98–103.

Rich, J. and Mabit, S.L. (2012) A Long-Distance Travel Demand Model for Europe. *European Journal of Transport and Infrastructure Research*, *12*, 1–20.

Rose, J.M. and Bliemer, M.C.J. (2009) Constructing Efficient Stated Choice Experimental Designs. *Transport Reviews*, *29*, 587–617.

Rugg, D. (1973) The Choice of Journey Destination: A Theoretical and Empirical Analysis. *The Review of Economics and Statistics*, *55*, 64.

Ryan, C. and Glendon, I. (1998) Application of leisure motivation scale to tourism. *Annals of Tourism Research*, *25*, 169–184.

Sabir, M. (2011). *Weather and travel behaviour*. Dissertation,Vrije Universiteit Amsterdam.

Sammer, G., Fellendorf, M., Herry, M., Karmasin, H., Klementschitz, R., Kohla, B., Meschik, M., Rehrl, K. and Reite, T. (2011). *KOMOD - KOnzeptstudie MObilitätsDaten Österreichs: Im Auftrag des Bundesministeriums für Verkehr, Innovation und Technologie, Programmlinie ways2go des Forschungs- und Technologieprogramms iv2splus*. Vienna.

Saneinejad, S., Roorda, M.J. and Kennedy, C. (2012) Modelling the impact of weather conditions on active transportation travel behaviour. *Transportation Research Part D: Transport and Environment*, *17*, 129–137.

Scarpa, R. and Thiene, M. (2004) Destination Choice Models for Rock Climbing in the Northeast Alps: A Latent-Class Approach Based on Intensity of Participation. *SSRN Electronic Journal*.

Scarpa, R., Thiene, M. and Train, K. (2008) Utility in Willingness to Pay Space: A Tool to Address Confounding Random Scale Effects in Destination Choice to the Alps. *American Journal of Agricultural Economics*, *90*, 994–1010.

Schlich, R., Schönfelder, S., Hanson, S. and Axhausen, K.W. (2004) Structures of Leisure Travel: Temporal and Spatial Variability. *Transport Reviews*, *24*, 219–237.

Schmid, B., Jokubauskaite, S., Aschauer, F., Peer, S., Hössinger, R., Gerike, R., Jara-Diaz, S.R. and Axhausen, K.W. (2019) A pooled RP/SP mode, route and destination choice model to investigate mode and user-type effects in the value of travel time savings. *Transportation Research Part A: Policy and Practice*, *124*, 262–294.

Scott, D., Gössling, S. and Freitas, C.R. de (2008) Preferred climates for tourism: case studies from Canada, New Zealand and Sweden. *Climate Research*, *45*, 61–73.

Scott, D.M. and Kanaroglou, P.S. (2002) An activity-episode generation model that captures interactions between household heads: Development and empirical analysis. *Transportation Research Part B: Methodological*, *36*, 875–896.

Scuttari, A. and Isetti, G. (2019) E-mobility and Sustainable Tourism Transport in Remote Areas. *Zeitschrift für Tourismuswissenschaft*, *11*, 237–256.

Scuttari, A., Orsi, F. and Bassani, R. (2019) Assessing the tourism-traffic paradox in mountain destinations. A stated preference survey on the Dolomites' passes (Italy). *Journal of Sustainable Tourism*, *27*, 241–257.

Scuttari, A., Volgger, M. and Pechlaner, H. (2016) Transition management towards sustainable mobility in Alpine destinations: realities and realpolitik in Italy's South Tyrol region. *Journal of Sustainable Tourism*, *24*, 463–483.

Seltenhammer, K., Dietrich, B., Coudek, E., Feiel, S., Kalisch, M. and Wanner, A. (2018). *Easy Travel - Ergebnisse AP3: Mobilitätsketten und Kundenbedürfnisse*. Vienna.

Sharaby, N. and Shiftan, Y. (2012) The impact of fare integration on travel behavior and transit ridership. *Transport Policy*, *21*, 63–70.

Sharpley, R. (2014) Host perceptions of tourism: A review of the research. *Tourism Management*, *42*, 37–49.

Shiftan, Y., Ben-Akiva, M., Proussaloglou, K., Jong, G. de, Popuri, Y., Kasturirangan, K. and Bekhor, S. (2003) Activity-Based Modeling as a Tool for Better Understanding Travel Behaviour, *10th International Conference on Travel Behaviour Research*.

Shoval, N. and Ahas, R. (2016) The use of tracking technologies in tourism research: the first decade. *Tourism Geographies*, *18*, 587–606.

Shoval, N., Isaacson, M. and Chhetri, P. (2014) GPS, Smartphones, and the Future of Tourism Research, *The Wiley Blackwell Companion to Tourism* eds A.A. Lew, C.M. Hall and A.M. Williams, pp. 251–261. Oxford, UK: John Wiley & Sons.

Simma, A., Schlich, R. and Axhausen, K.W. (2002). *Destination choice modelling of leisure trips: The case of Switzerland.* Arbeitsberichte Verkehrs- und Raumplanung. Zürich.

Singleton, P.A. (2020) Exploring the positive utility of travel and mode choice, *Mapping the travel behavior genome* eds K.G. Goulias and A.W. Davis, pp. 259–277. Amsterdam, Netherlands: Elsevier.

Sirakaya, E., McLellan, R.W. and Uysal, M. (1996) Modeling Vacation Destination Decisions. *Journal of Travel & Tourism Marketing*, *5*, 57–75.

Sirakaya-Turk, E., Uysal, M., Hammitt, W.E. and Vaske, J.J. (2017). *Research methods for leisure, recreation and tourism.* (2nd edition). CABI tourism texts. Wallingford, Oxforshire, UK, CABI.

Sirakaya-Turk, E. and Woodside, A.G. (2005) Building and testing theories of decision making by travellers. *Tourism Management*, *26*, 815–832.

Sirgy, M.J., Kruger, P.S., Lee, D.-J. and Yu, G.B. (2011) How Does a Travel Trip Affect Tourists' Life Satisfaction? *Journal of Travel Research*, *50*, 261–275.

Small, K.A. (2012) Valuation of travel time. *Economics of Transportation*, *1*, 2–14.

Sobolevsky, S., Bojic, I., Belyi, A., Sitko, I., Hawelka, B., Arias, J.M. and Ratti, C. (2015) Scaling of City Attractiveness for Foreign Visitors through Big Data of Human Economical and Social Media Activity, *2015 IEEE International Congress on Big Data (BigData Congress): June 27, 2015 - July 2, 2015, New York, New York, USA* ed B. Carminati, pp. 600–607. Piscataway, NJ: IEEE.

Statistics Austria (2020) STATcube: Statistical Database of Statistics Austria. http://www.statcube.at.

Steiger, R., Abegg, B. and Jänicke, L. (2016) Rain, Rain, Go Away, Come Again Another Day. Weather Preferences of Summer Tourists in Mountain Environments. *Atmosphere*, *7*, 63.

Stekhoven, D.J. and Bühlmann, P. (2012) MissForest--non-parametric missing value imputation for mixed-type data. *Bioinformatics*, *28*, 112–118.

Swait, J. (2001) Choice set generation within the generalized extreme value family of discrete choice models. *Transportation Research Part B: Methodological*, *35*, 643–666.

Sydsæter, K. and Hammond, P.J. (2016). *Essential mathematics for economic analysis.* (Fifth edition). Harlow United Kingdom, Pearson Education.

Termida, A.N., Susilo, Y.O. and Franklin, J.P. (2016) Observing dynamic behavioural responses due to the extension of a tram line by using panel survey. *Transportation Research Part A: Policy and Practice*, *86*, 78–95.

Terrier, C. (2009) Tourist Flows and Inflows: On Measuring Instruments and the Geomathematics of Flows, *Transport survey methods: Keeping up with a changing world* eds P. Bonnel, M. Lee-Gosselin, J.P. Zmud and J.-L. Madre, pp. 219–241. Bingley, UK: Emerald.

Thimm, T. and Seepold, R. (2016) Past, present and future of tourist tracking. *Journal of Tourism Futures*, *2*, 43–55.

Thompson, K. and Schofield, P. (2007) An investigation of the relationship between public transport performance and destination satisfaction. *Journal of Transport Geography*, *15*, 136–144.

Thornton, P.R., Williams, A.M. and Shaw, G. (1997) Revisiting Time—Space Diaries: An Exploratory Case Study of Tourist Behaviour in Cornwall, England. *Environment and Planning A: Economy and Space*, *29*, 1847–1867.

Thrane, C. (2015) Examining tourists' long-distance transportation mode choices using a Multinomial Logit regression model. *Tourism Management Perspectives*, *15*, 115–121.

Timmermans, H. and Arentze, T.A. (2011) Transport Models and Urban Planning Practice: Experiences with Albatross. *Transport Reviews*, *31*, 199–207.

Timmermans, H.J. and Zhang, J. (2009) Modeling household activity travel behavior: Examples of state of the art modeling approaches and research agenda. *Transportation Research Part B: Methodological*, *43*, 187–190.

Tischler, S. and Mailer, M. (2014) Sustainable Mobility and Living in Alpine Metropolitan Regions. *Transportation Research Procedia*, *4*, 140–153.

Tomschy, R., Herry, M., Sammer, G., Klementschitz, R., Riegler, S., Follmer, R., Gruschwitz, D., Josef, F., Gensasz, S., Kirnbauer, R. and Spiegel, T. (2016). *Österreich unterwegs 2013/2014: Ergebnisbericht zur österreichweiten Mobilitätserhebung*. im Auftrag von: Bundesministerium für Verkehr, Innovation und Technologie, Autobahnen- und Schnellstraßen-Finanzierungs-Aktiengesellschaft, Österreichische Bundesbahnen Infrastruktur AG, Amt der Burgenländischen

Landesregierung, Amt der Niederösterreichischen Landesregierung, Amt der Steiermärkischen Landesregierung und Amt der Tiroler Landesregierung. Vienna.

Ton, D., Duives, D.C., Cats, O., Hoogendoorn-Lanser, S. and Hoogendoorn, S.P. (2019) Cycling or walking? Determinants of mode choice in the Netherlands. *Transportation Research Part A: Policy and Practice*, *123*, 7–23.

TRACE Consortium (1999). *Costs of Private Road Travel and their Effects on Demand, Including Short and Long Term Elasticities*. Final Report.

Train, K. (2009). *Discrete choice methods with simulation.* (2nd ed.). Cambridge, Cambridge University Press.

Train, K., McFadden, D. and Ben-Akiva, M. (1987) The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *The RAND Journal of Economics*, *18*, 109.

Train, K.E. (1998) Recreation Demand Models with Taste Differences over People. *Land Economics*, *74*, 230.

Tschopp, M., Beige, S. and Axhausen, K.W. (2010). *Verkehrssysteme, Touristenverhalten und Raumstruktur in alpinen Landschaften*. Forschungsbericht NFP 48, vdf Hochschulverlag AG.

Unger, R., Abegg, B., Mailer, M. and Stampfl, P. (2016) Energy Consumption and Greenhouse Gas Emissions Resulting From Tourism Travel in an Alpine Setting. *Mountain Research and Development*, *36*, 475–483.

United Nations and World Tourism Organization (1994). *Recommendations on Tourism Statistics.* Statistical Papers. New York.

van Buuren, S. (2018). *Flexible imputation of missing data.* (Second edition). Chapman and Hall/CRC interdisciplinary statistics series. Boca Raton, CRC Press Taylor & Francis Group.

van Middelkoop, M., Borgers, A. and Timmermans, H. (2016) Inducing Heuristic Principles of Tourist Choice of Travel Mode: A Rule-Based Approach. *Journal of Travel Research*, *42*, 75–83.

van Nostrand, C., Sivaraman, V. and Pinjari, A.R. (2013) Analysis of long-distance vacation travel demand in the United States: a multiple discrete–continuous choice framework. *Transportation*, *40*, 151–171.

van Wee, B. (2009) Self-Selection: A Key to a Better Understanding of Location Choices, Travel Behaviour and Transport Externalities? *Transport Reviews*, *29*, 279–292.

Vij, A. and Walker, J.L. (2014) Hybrid choice models: The identification problem, *Handbook of choice modelling* eds S. Hess and A.J. Daly, pp. 519–564. Cheltenham, UK: Edward Elgar.

Vij, A. and Walker, J.L. (2016) How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, *90*, 192–217.

Vitins, B.J., Erath, A. and Axhausen, K.W. (2016) Integration of a Capacity-Constrained Workplace Choice Model: Recent developments and applications for an agent-based simulation in Singapore. *Transportation Research Record: Journal of the Transportation Research Board*, *2564*, 1–13.

Vovsha, P. (1997) Application of Cross-Nested Logit Model to Mode Choice in Tel Aviv, Israel, Metropolitan Area. *Transportation Research Record: Journal of the Transportation Research Board*, *1607*, 6–15.

Vrtic, M., Fröhlich, P., Schiller, C., Neuenschwander, R., Walker, P., Dijkstra, P. and Amstadt, D. (2010). *Gesamtverkehrsmodell Kanton Bern: Schlussbericht*.

Vu, H.Q., Li, G., Law, R. and Zhang, Y. (2018) Tourist Activity Analysis by Leveraging Mobile Social Media Data. *Journal of Travel Research*, *57*, 883–898.

Vuk, G., Bowman, J.L., Daly, A. and Hess, S. (2016) Impact of family in-home quality time on person travel demand. *Transportation*, *43*, 705–724.

Waddell, P., Bhat, C., Eluru, N., Wang, L. and Pendyala, R.M. (2007) Modeling Interdependence in Household Residence and Workplace Choices. *Transportation Research Record: Journal of the Transportation Research Board*, *2003*, 84–92.

Wang, Y., Veneziano, D., Russell, S. and Al-Kaisy, A. (2016) Traffic Safety Along Tourist Routes in Rural Areas. *Transportation Research Record: Journal of the Transportation Research Board*, 55–63.

Wardman, M. (1988) A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. *Journal of Transport Economics and Policy*, *22*, 71–91.

Wardman, M. (2001) A review of British evidence on time and service quality valuations. *Transportation Research Part E: Logistics and Transportation Review*, *37*, 107–128.

Wardman, M. (2004) Public transport values of time. *Transport Policy*, *11*, 363–377.

Wardman, M. (2012) Review and meta-analysis of U.K. time elasticities of travel demand. *Transportation*, *39*, 465–490.

Wardman, M. (2014) Price Elasticities of Surface Travel Demand A Meta-analysis of UK Evidence. *Journal of Transport Economics and Policy*, *48*, 367–384.

Wardman, M., Chintakayala, V.P.K. and Jong, G. de (2016) Values of travel time in Europe: Review and meta-analysis. *Transportation Research Part A: Policy and Practice*, *94*, 93–111.

Wardman, M., Toner, J., Fearnley, N., Flügel, S. and Killi, M. (2018) Review and meta-analysis of inter-modal cross-elasticity evidence. *Transportation Research Part A: Policy and Practice*, *118*, 662–681.

Washbrook, K., Haider, W. and Jaccard, M. (2006) Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. *Transportation*, *33*, 621–639.

Wen, C.-H. and Koppelman, F.S. (2001) The generalized nested logit model. *Transportation Research Part B: Methodological*, *35*, 627–641.

Wicki, M., Guidon, S., Becker, F., Axhausen, K.W. and Bernauer, T. (2019) How technology commitment affects willingness to use AVs: Results from realistic mode choice experiment for a self-driving shuttle service, *19th Swiss Transport Research Conference*.

Woodside, A.G. and Lysonski, S. (1989) A General Model Of Traveler Destination Choice. *Journal of Travel Research*, *27*, 8–14.

Wu, C.-L. and Carson, D. (2008) Spatial and Temporal Tourist Dispersal Analysis in Multiple Destination Travel. *Journal of Travel Research*, *46*, 311–317.

Wu, L., Zhang, J. and Fujiwara, A. (2011) Representing tourists' heterogeneous choices of destination and travel party with an integrated latent class and nested logit model. *Tourism Management*, *32*, 1407–1413.

Yang, L., Wu, L., Liu, Y. and Kang, C. (2017) Quantifying Tourist Behavior Patterns by Travel Motifs and Geo-Tagged Photos from Flickr. *ISPRS International Journal of Geo-Information*, *6*, 345.

Yasmin, F., Morency, C. and Roorda, M.J. (2017) Macro-, meso-, and micro-level validation of an activity-based travel demand model. *Transportmetrica A: Transport Science*, *13*, 222–249.

Zhang, J., Kuwano, M., Lee, B. and Fujiwara, A. (2009) Modeling household discrete choice behavior incorporating heterogeneous group decision-making mechanisms. *Transportation Research Part B: Methodological*, *43*, 230–250.

Zhang, J., Timmermans, H.J. and Borgers, A. (2005) A model of household task allocation and time use. *Transportation Research Part B: Methodological*, *39*, 81–95.

Zhao, X., Lu, X., Liu, Y., Lin, J. and An, J. (2018) Tourist movement patterns understanding from the perspective of travel party size using mobile tracking data: A case study of Xi'an, China. *Tourism Management*, *69*, 368–383.

Zheng, J. and Guo, J.Y. (2008) Destination choice model incorporating choice set formation, *TRB 87th Annual Meeting Compendium of Papers*: Transportation Research Board.

Zhong, L., Deng, J., Song, Z. and Ding, P. (2011) Research on environmental impacts of tourism in China: progress and prospect. *Journal of environmental management*, *92*, 2972–2983.

Zhou, B. and Kockelman, K.M. (2011) Opportunities for and Impacts of Carsharing: A Survey of the Austin, Texas Market. *International Journal of Sustainable Transportation*, *5*, 135–152.

Zoltan, J. and McKercher, B. (2014) Analysing intra-destination movements and activity participation of tourists through destination card consumption. *Tourism Geographies*, *17*, 19–35.

A Appendix: Survey questionnaires

A.1 PAPI questionnaire

universität innsbruck
Unit of Intelligent Transport Systems

MOBILITY SURVEY

Dear visitors to Ötztal,

This survey is part of an academic project focusing on the travel behavior of guests staying on vacation in Ötztal. The results of the survey will help provide better transportation services in tourist regions in the Alps. **Your participation is essential to achieve this goal!**

On the following pages, you will find an activity diary and a set of questions concerning you and your stay in Ötztal. On the last page, there is a filled example of the diary and below there are instructions for filling out the questionnaire. Please read them carefully.

We do care about data privacy at the University of Innsbruck – we work according to strict university standards as well as Austrian and European regulations. Your data will be used only and solely for academic work.
The survey should not take more than 20 minutes of your time.

Bartosz Bursa, MEng
Project leader
University of Innsbruck

Univ.-Prof. Dipl.-Ing. Dr. Markus Mailer
Head of department
University of Innsbruck

INSTRUCTIONS

In order to guarantee the highest quality of the data, we ask you to follow the instructions below:

1. Each family member older than 15 years should complete a separate questionnaire.
2. In the diary, **report on all activities that you carried out throughout the whole day outside of your hotel.** In other words, the activities for which you have left the accommodation, e.g. taking a walk, relaxing in a spa, visiting a museum, going for drinks or hiking in the mountains. **You will find an example of a filled diary on the last page of the questionnaire.**
3. You can choose any two days of your stay except the first and last one as these are influenced by your arrival/departure. Please fill the diary on the same day as you performed the activities – otherwise you might forget important details (e.g. exact time or location).
4. Write only one activity type in the activity box. If you have done more activities at the same location, use the next activity box and skip the trip box, which is between them.
5. If activity is a movement (e.g. cycling, hiking, skiing), write it in the activity box, not in the trip box. If you had to get to the start location of the activity (e.g. by car, bus, cable car or simply walking), write it in the trip box.
6. **Please provide the exact description and location of the activity.**
7. If you have any difficulties with filling the questionnaire, want to ask questions or give comments, please contact (in English or German):
   Bartosz Bursa
   +43 512 507-62405
   bartosz.bursa@uibk.ac.at

HOW TO ANSWER THE QUESTIONS

○ you can choose only one answer

☐ you can choose multiple answers

[ ] write your answer (in words or numbers)

SEE EXAMPLE ON THE LAST PAGE

Figure A.1 PAPI questionnaire – page 1

About you

1. **What year were you born in?** [ ]

2. **Your gender:** ◯ Male ◯ Female

3. **Your nationality:** [ ]

4. **Place of residence:**
   Country: [ ] Postal code: [ ]

5. **Which is the highest educational level you have completed?**
   - ◯ Primary level
   - ◯ Secondary level (high school)
   - ◯ A-levels / High school diploma
   - ◯ University degree (Bachelor's, Master's, PhD)

6. **Are you ...** *(multiple answers possible)*
   - ☐ Pupil or student
   - ☐ Apprentice or trainee
   - ☐ Doing housework, looking after the home or children
   - ☐ Part-time employed
   - ☐ Full-time employed
   - ☐ Self-employed / own business
   - ☐ Retired
   - ☐ Unemployed or looking for a job

7. **How many persons – including yourself – live in your household?**
   - [ ] adults
   - [ ] children under 6
   - [ ] children 6 – 17

8. **Do you have a spouse or a partner?**
   - ◯ Yes, I have a spouse / partner and we share the same household
   - ◯ Yes, I have a spouse / partner, but we don't share the same household
   - ◯ No, I don't have a spouse / partner

9. **What on average is the total net income of your household per month, after taxes and other deductions?**
   - ◯ Less than 1,000 EUR per month, net
   - ◯ 1,000 – 2,000 EUR
   - ◯ 2,001 – 3,000 EUR
   - ◯ 3,001 – 4,000 EUR
   - ◯ 4,001 – 5,000 EUR
   - ◯ 5,001 – 6,000 EUR
   - ◯ 6,001 – 7,000 EUR
   - ◯ 7,001 – 8,000 EUR
   - ◯ 8,001 – 9,000 EUR
   - ◯ 9,001 – 10,000 EUR
   - ◯ 10,001 – 12,000 EUR
   - ◯ 12,001 – 14,000 EUR
   - ◯ 14,001 – 16,000 EUR
   - ◯ 16,001 – 18,000 EUR
   - ◯ 18,001 – 20,000 EUR
   - ◯ More than 20,000 EUR per month, net

10. **How many paid vacation days are you entitled to each year?**
    [ ] days ◯ Does not apply

11. **In the last 12 months, how many nights altogether did you stay away from home for holidays or social visits?**
    - ◯ I did not go away
    - ◯ 1-5 nights
    - ◯ 6-10 nights
    - ◯ 11-20 nights
    - ◯ 21-30 nights
    - ◯ More than 30 nights

12. **Do you own a driver's license?**
    ◯ Yes ◯ No

13. **In a typical week, how often is a private car available to you?**
    - ◯ Always
    - ◯ Sometimes
    - ◯ Never

14. **In a typical week, how often do you drive a private car?**
    - ◯ Daily
    - ◯ 4-6 days a week
    - ◯ 1-3 days a week
    - ◯ 1-3 times a month
    - ◯ Less than once a month
    - ◯ Does not apply

15. **How is your health in general?**
    (This refers to both physical and mental health)
    - ◯ Very good
    - ◯ Good
    - ◯ Fair
    - ◯ Bad
    - ◯ Very bad

16. **Are you limited because of a health problem in activities people usually do?**
    - ◯ Severely limited
    - ◯ Limited but not severely
    - ◯ Not limited at all

17. **In a typical week, on how many days do you carry out sports, fitness or recreational (leisure) physical activities for at least 10 continuous minutes?**
    Number of days: [ ] (1-7) per week
    ◯ I never carry out such physical activities

18. **How much time in total do you spend on sports, fitness or recreational (leisure) physical activities in a typical week?**
    [ ] hours

Figure A.2 PAPI questionnaire – page 2

Your stay in Ötztal

19. Date of arrival: ______

20. Date of departure: ______

21. Place where you are staying:
(name of the accommodation and village)

______

22. Who is accompanying you during your stay in Ötztal?
(multiple answers possible)

- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6 → *How many?* ______
- ☐ Children 6-17 → *How many?* ______
- ☐ Other household members → *How many?* ______
- ☐ Other known person → *How many?* ______

23. Type of holiday:

- ○ Organized travel (by tour operator, school, club, etc.)
- ○ Individual trip

24. Is it your first visit to Ötztal?

- ○ Yes
- ○ No, I have been here ______ times before

25. Is Ötztal the main destination of your stay?

- ○ Yes
- ○ No, I am on a stopover here and will be moving to another place later

26. What is the main purpose of your visit in Ötztal?
(choose only one)

- ○ Sport, recreation
- ○ Culture, heritage, sightseeing
- ○ Rest, relaxation
- ○ Health, wellness
- ○ Social (time with family, friends)
- ○ Business
- ○ Conference/congress
- ○ Shopping, fun, entertainment
- ○ Other: ______

27. Which transport mode have you mainly used to come to Ötztal? *(choose only one)*

- ○ Private car
- ○ Rented car, car-sharing
- ○ Motorcycle
  - *please indicate*: ○ as a driver ○ as a passenger
- ○ Train
- ○ Coach
- ○ Airplane
- ○ Bicycle

28. Why did you choose this transport mode for your journey?
(multiple answers possible)

- ☐ No other mode was available
- ☐ Because of the distance of the journey
- ☐ Fastest mode
- ☐ Cheapest mode
- ☐ Safest mode
- ☐ Most convenient mode (direct, accessible, flexible)
- ☐ Most comfortable mode (e.g. cleanliness, seats, ventilation)
- ☐ Personal mobility constraints (e.g. disabled)
- ☐ Luggage transport (bulky, heavy)
- ☐ Weather conditions
- ☐ Other: ______

29. How informed do you feel about the journey options (arrival) to Ötztal?

- ○ Very well informed
- ○ Well informed
- ○ Somewhat informed
- ○ Slightly informed
- ○ Not informed at all

30. How have you informed yourself in advance about the journey to Ötztal? *(multiple answers possible)*

- ☐ On websites/mobile app of the region/destination
- ☐ On websites/mobile app of the hotel
- ☐ On online/mobile map services (i.e. GoogleMaps)
- ☐ At the travel agency
- ☐ From travel guidebooks
- ☐ From friends and relatives
- ☐ Other: ______
- ☐ I have not informed myself in advance

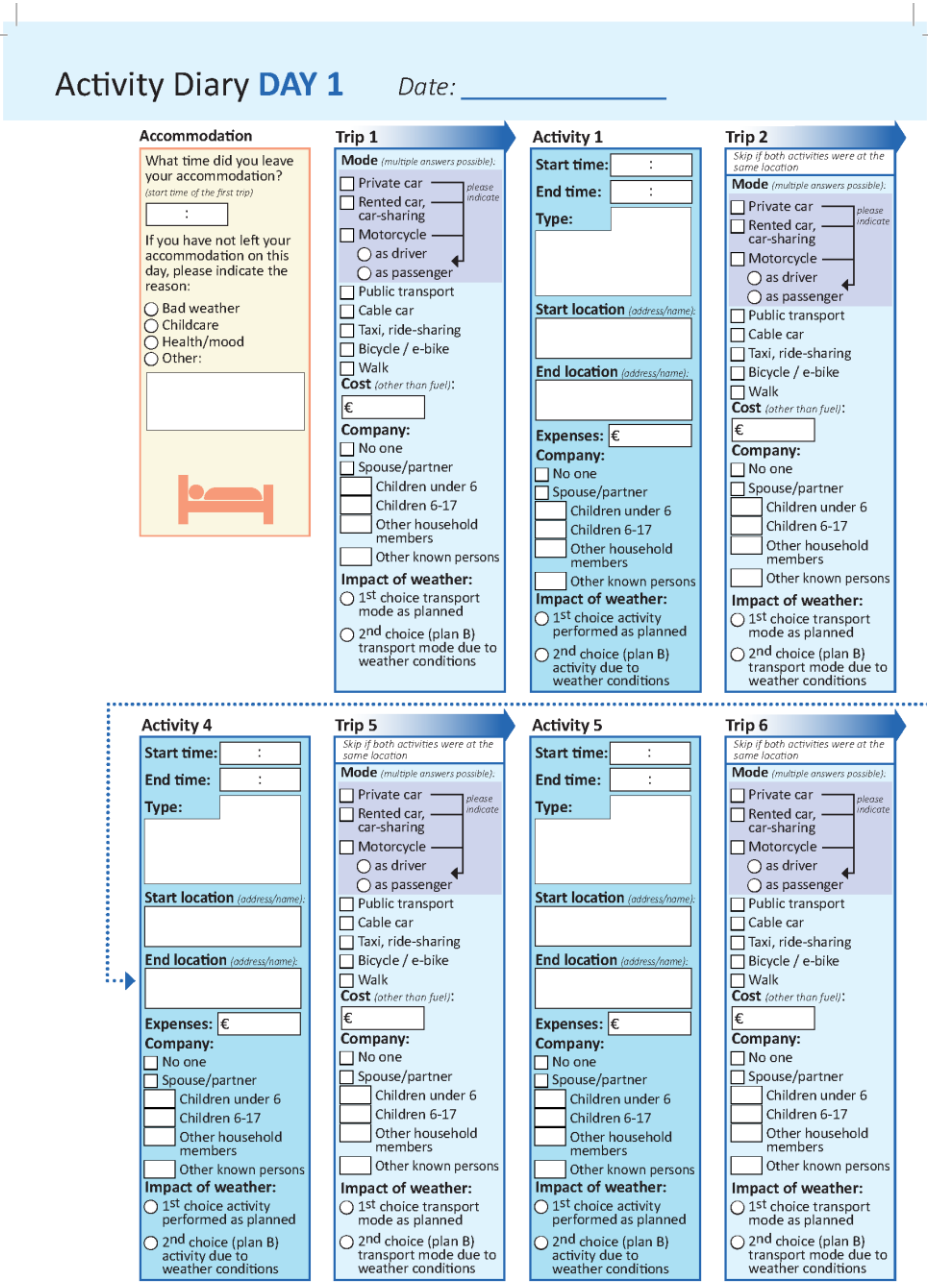
31. How informed do you feel about the on-site mobility services in Ötztal?

- ○ Very well informed
- ○ Well informed
- ○ Somewhat informed
- ○ Slightly informed
- ○ Not informed at all

32. How have you informed yourself in advance about the on-site mobility services in Ötztal? *(multiple answers possible)*

- ☐ On websites/mobile app of the region/destination
- ☐ On websites/mobile app of the hotel
- ☐ On websites/mobile apps of the local public transport operator
- ☐ On online map services (i.e. GoogleMaps)
- ☐ At the travel agency
- ☐ From travel guidebooks
- ☐ From friends and relatives
- ☐ Other: ______
- ☐ I have not informed myself in advance

Figure A.3 PAPI questionnaire – page 3



Activity Diary DAY 1 Date: ______________

Accommodation

What time did you leave your accommodation?
(start time of the first trip)
[:]

If you have not left your accommodation on this day, please indicate the reason:
- ○ Bad weather
- ○ Childcare
- ○ Health/mood
- ○ Other:

Trip 1

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

  please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 1

Start time: [:]
End time: [:]
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 2

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

  please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 4

Start time: [:]
End time: [:]
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 5

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

  please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 5

Start time: [:]
End time: [:]
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 6

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

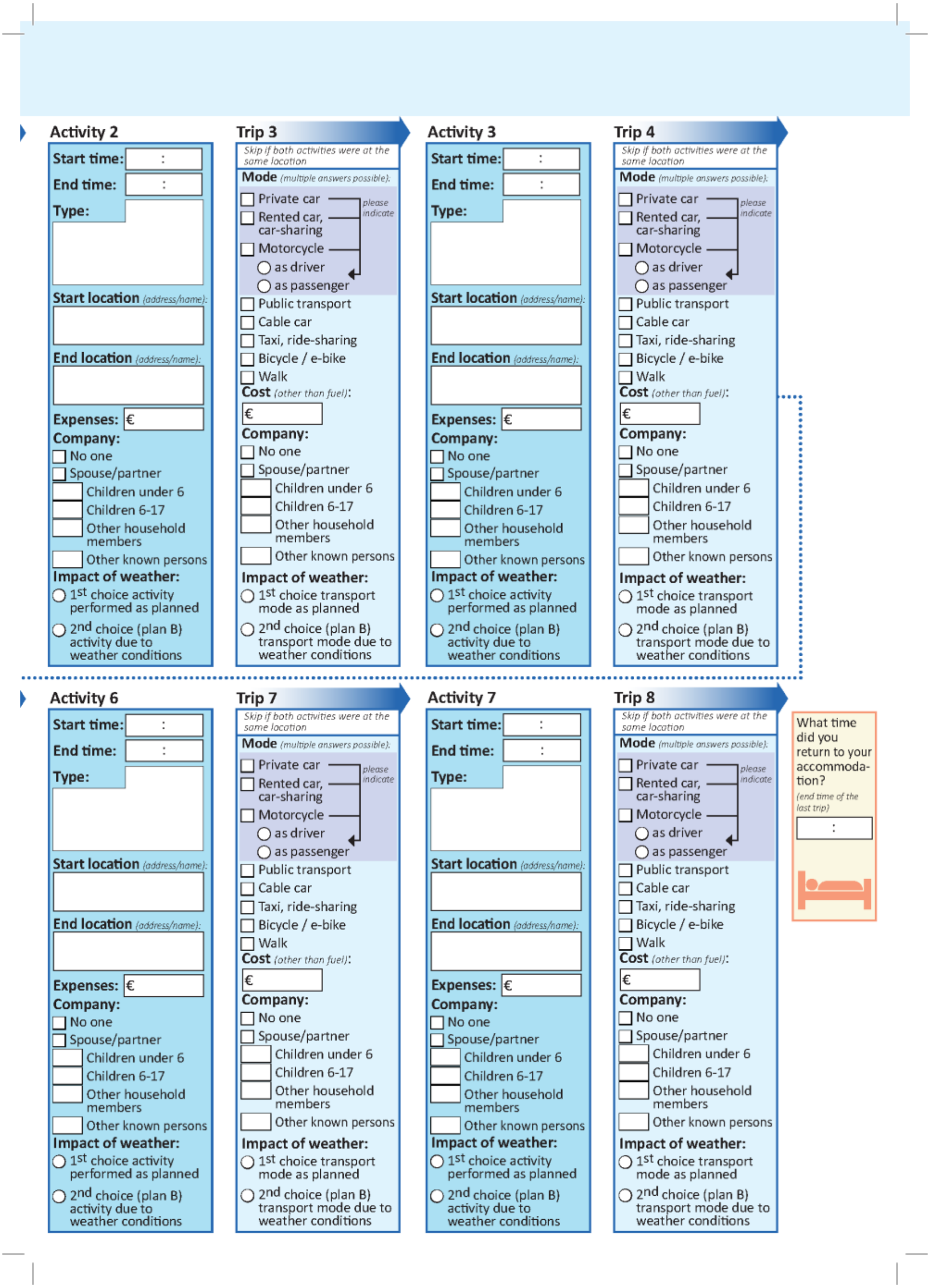
  please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Figure A.4 PAPI questionnaire – page 4



Activity 2
Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice activity performed as planned
- 2nd choice (plan B) activity due to weather conditions

Trip 3
Skip if both activities were at the same location
Mode *(multiple answers possible)*:
- Private car
- Rented car, car-sharing
- Motorcycle
  - as driver
  - as passenger
- *please indicate*
- Public transport
- Cable car
- Taxi, ride-sharing
- Bicycle / e-bike
- Walk

Cost *(other than fuel)*: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice transport mode as planned
- 2nd choice (plan B) transport mode due to weather conditions

Activity 3
Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice activity performed as planned
- 2nd choice (plan B) activity due to weather conditions

Trip 4
Skip if both activities were at the same location
Mode *(multiple answers possible)*:
- Private car
- Rented car, car-sharing
- Motorcycle
  - as driver
  - as passenger
- *please indicate*
- Public transport
- Cable car
- Taxi, ride-sharing
- Bicycle / e-bike
- Walk

Cost *(other than fuel)*: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice transport mode as planned
- 2nd choice (plan B) transport mode due to weather conditions

Activity 6
Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice activity performed as planned
- 2nd choice (plan B) activity due to weather conditions

Trip 7
Skip if both activities were at the same location
Mode *(multiple answers possible)*:
- Private car
- Rented car, car-sharing
- Motorcycle
  - as driver
  - as passenger
- *please indicate*
- Public transport
- Cable car
- Taxi, ride-sharing
- Bicycle / e-bike
- Walk

Cost *(other than fuel)*: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice transport mode as planned
- 2nd choice (plan B) transport mode due to weather conditions

Activity 7
Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice activity performed as planned
- 2nd choice (plan B) activity due to weather conditions

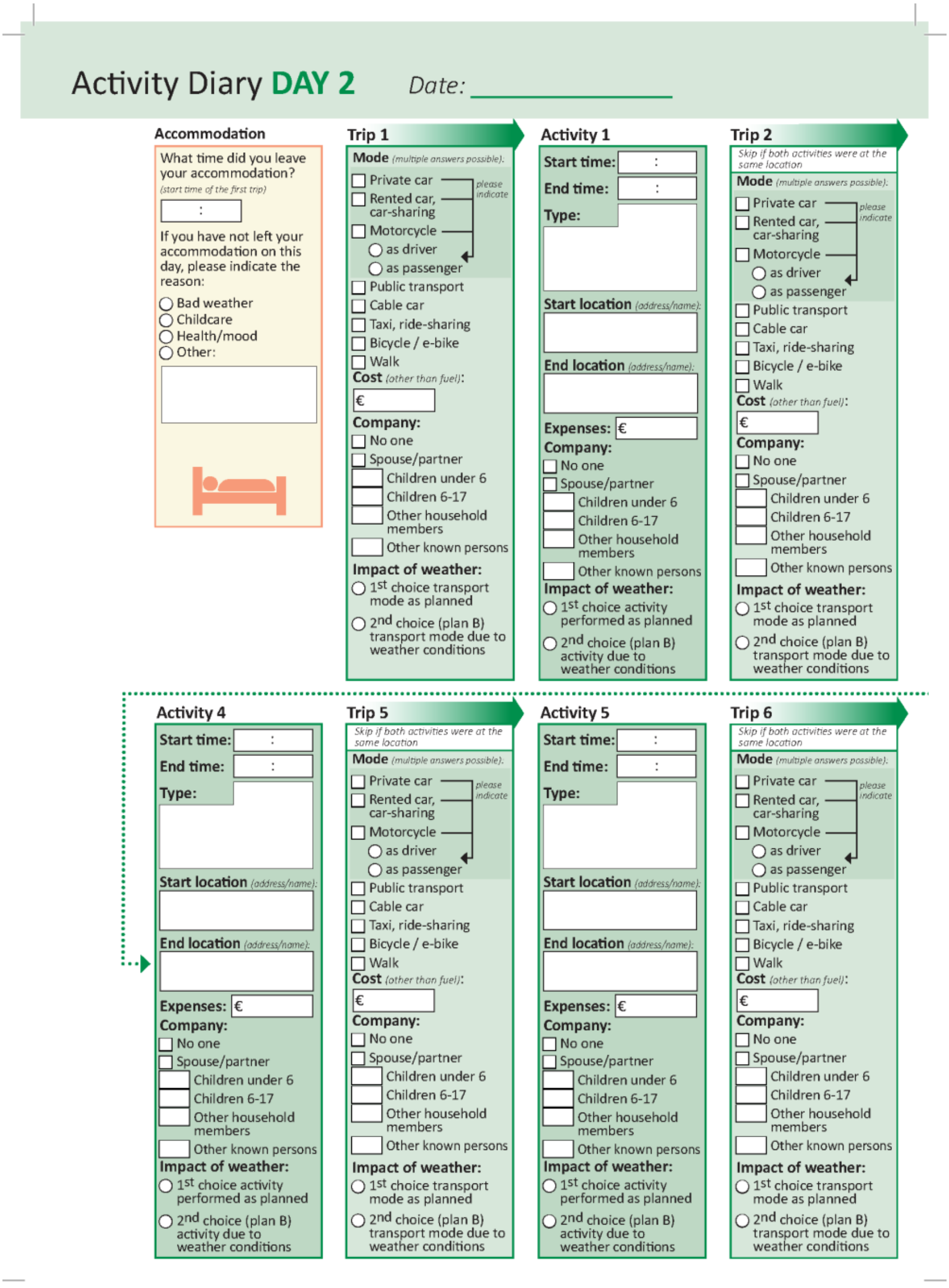
Trip 8
Skip if both activities were at the same location
Mode *(multiple answers possible)*:
- Private car
- Rented car, car-sharing
- Motorcycle
  - as driver
  - as passenger
- *please indicate*
- Public transport
- Cable car
- Taxi, ride-sharing
- Bicycle / e-bike
- Walk

Cost *(other than fuel)*: €
Company:
- No one
- Spouse/partner
- Children under 6
- Children 6-17
- Other household members
- Other known persons

Impact of weather:
- 1st choice transport mode as planned
- 2nd choice (plan B) transport mode due to weather conditions

What time did you return to your accommodation?
(end time of the last trip)
:

Figure A.5 PAPI questionnaire – page 5



Activity Diary **DAY 2** Date: ____________

Accommodation

What time did you leave your accommodation?
(start time of the first trip)
:

If you have not left your accommodation on this day, please indicate the reason:
- ○ Bad weather
- ○ Childcare
- ○ Health/mood
- ○ Other:

Trip 1

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 1

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 2

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 4

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 5

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 5

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 6

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

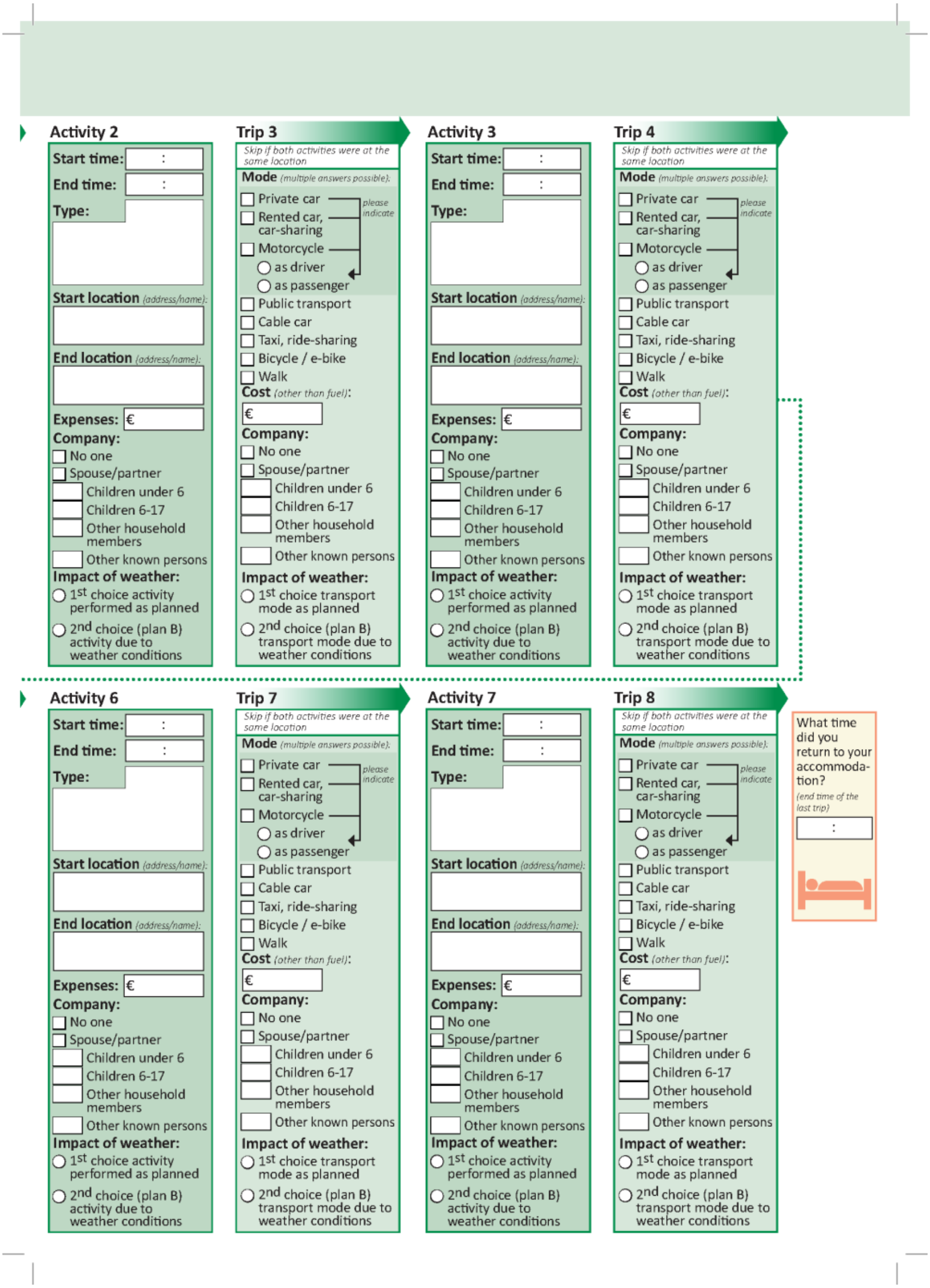
please indicate
- ☐ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☐ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: €

Company:
- ☐ No one
- ☐ Spouse/partner
- ☐ Children under 6
- ☐ Children 6-17
- ☐ Other household members
- ☐ Other known persons

Impact of weather:
- ○ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Figure A.6 PAPI questionnaire – page 6



Activity 2

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice activity performed as planned
2nd choice (plan B) activity due to weather conditions

Trip 3

Skip if both activities were at the same location
Mode *(multiple answers possible)*:
Private car
Rented car, car-sharing
Motorcycle
please indicate
as driver
as passenger
Public transport
Cable car
Taxi, ride-sharing
Bicycle / e-bike
Walk
Cost *(other than fuel)*:
€
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice transport mode as planned
2nd choice (plan B) transport mode due to weather conditions

Activity 3

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice activity performed as planned
2nd choice (plan B) activity due to weather conditions

Trip 4

Skip if both activities were at the same location
Mode *(multiple answers possible)*:
Private car
Rented car, car-sharing
Motorcycle
please indicate
as driver
as passenger
Public transport
Cable car
Taxi, ride-sharing
Bicycle / e-bike
Walk
Cost *(other than fuel)*:
€
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice transport mode as planned
2nd choice (plan B) transport mode due to weather conditions

Activity 6

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice activity performed as planned
2nd choice (plan B) activity due to weather conditions

Trip 7

Skip if both activities were at the same location
Mode *(multiple answers possible)*:
Private car
Rented car, car-sharing
Motorcycle
please indicate
as driver
as passenger
Public transport
Cable car
Taxi, ride-sharing
Bicycle / e-bike
Walk
Cost *(other than fuel)*:
€
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice transport mode as planned
2nd choice (plan B) transport mode due to weather conditions

Activity 7

Start time: :
End time: :
Type:
Start location *(address/name)*:
End location *(address/name)*:
Expenses: €
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice activity performed as planned
2nd choice (plan B) activity due to weather conditions

Trip 8

Skip if both activities were at the same location
Mode *(multiple answers possible)*:
Private car
Rented car, car-sharing
Motorcycle
please indicate
as driver
as passenger
Public transport
Cable car
Taxi, ride-sharing
Bicycle / e-bike
Walk
Cost *(other than fuel)*:
€
Company:
No one
Spouse/partner
Children under 6
Children 6-17
Other household members
Other known persons
Impact of weather:
1st choice transport mode as planned
2nd choice (plan B) transport mode due to weather conditions

What time did you return to your accommoda-tion?
(end time of the last trip)
:

Figure A.7 PAPI questionnaire – page 7

Activity Diary EXAMPLE

Accommodation

What time did you leave your accommodation?
(start time of the first trip)
8:20

If you have not left your accommodation on this day, please indicate the reason:
- ○ Bad weather
- ○ Childcare
- ○ Health/mood
- ○ Other:

Trip 1

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

please indicate
- ☒ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☒ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: € *0* *(Ötztal card)*

Company:
- ☐ No one
- ☒ Spouse/partner
- [ ] Children under 6
- [*2*] Children 6-17
- [ ] Other household members
- [ ] Other known persons

Impact of weather:
- ☒ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

Activity 1

Start time: *9:00*
End time: *12:30*
Type: *Mountain biking to Rofenhöfen*

Start location *(address/name)*: *Vent*
End location *(address/name)*: *Vent*

Expenses: € *45*

Company:
- ☐ No one
- ☒ Spouse/partner
- [ ] Children under 6
- [*2*] Children 6-17
- [ ] Other household members
- [ ] Other known persons

Impact of weather:
- ☒ 1st choice activity performed as planned
- ○ 2nd choice (plan B) activity due to weather conditions

Trip 2

Skip if both activities were at the same location

Mode *(multiple answers possible)*:
- ☐ Private car
- ☐ Rented car, car-sharing
- ☐ Motorcycle
  - ○ as driver
  - ○ as passenger

please indicate
- ☒ Public transport
- ☐ Cable car
- ☐ Taxi, ride-sharing
- ☒ Bicycle / e-bike
- ☐ Walk

Cost *(other than fuel)*: € *0* *(Ötztal card)*

Company:
- ☐ No one
- ☒ Spouse/partner
- [ ] Children under 6
- [*2*] Children 6-17
- [ ] Other household members
- [ ] Other known persons

Impact of weather:
- ☒ 1st choice transport mode as planned
- ○ 2nd choice (plan B) transport mode due to weather conditions

About you / Your stay in Ötztal EXAMPLE

3. Your nationality: *Dutch*

4. Place of residence:
Country: *the Netherlands* Postal code: *9171 MA*

5. Which is the highest educational level you have completed?
- ○ Primary level
- ○ Secondary level (high school)
- ☒ A-levels / High school diploma
- ○ University degree (Bachelor's, Master's, PhD)

7. How many persons – including yourself – live in your household?
- *2* adults
- *0* children under 6
- *2* children 6 – 17

8. Do you have a spouse or a partner?
- ☒ Yes, I have a spouse / partner and we share the same household
- ○ Yes, I have a spouse / partner, but we don't share the same household
- ○ No, I don't have a spouse / partner

19. Date of arrival: *08.11.2018*

20. Date of departure: *15.11.2018*

21. Place where you are staying:
(name of the accommodation and village)
Hotel Das Central, Sölden

22. Who is accompanying you during your stay in Ötztal?
(multiple answers possible)
- ☐ No one
- ☒ Spouse/partner
- ☐ Children under 6 → *How many?*
- ☒ Children 6-17 → *How many?* *2*
- ☐ Other household members → *How many?*
- ☐ Other known person → *How many?*

23. Type of your holiday:
- ☒ Organized travel (by tour operator, school, club, etc.)
- ○ Individual trip

Figure A.8 PAPI questionnaire – page 8

A.2 CAPI QUESTIONNAIRE

universität innsbruck
Unit of Intelligent Transport Systems

touristmobility → 1 27.02.2020, 16:26

Page 01

Dear visitors to Tyrol,

This survey is part of an academic project focusing on the travel behavior of guests staying on vacation in Tyrol. The results of the survey will help provide better transportation services in tourist regions in the Alps. Your participation is essential to achieve this goal!

We do care about data privacy at the University of Innsbruck – we work according to strict university standards as well as Austrian and European regulations. Your data will be used only and solely for academic work.

The survey should not take more than 20 minutes of your time.

Bartosz Bursa, MEng

Project leader

Univ.-Prof. Dipl.-Ing. Dr. Markus Mailer

Head of department

Figure A.9 CAPI questionnaire – page 1

Page 02
AY

1. What year were you born in?

2. Your gender:

- ◯ Male
- ◯ Female

3. Your nationality:

4. Place of residence:

Country:

Postal code:

5. Which is the highest educational level you have completed?

- ◯ Primary level
- ◯ Secondary level (high school)
- ◯ A-levels/High school diploma
- ◯ University degree (Bachelor's, Master's, PhD)

6. Are you...

- ◯ Pupil or student
- ◯ Apprentice or trainee
- ◯ Doing housework, looking after the home or children
- ◯ Part-time employed
- ◯ Full-time employed
- ◯ Self-employed / own business
- ◯ Retired
- ◯ Unemployed or looking for a job

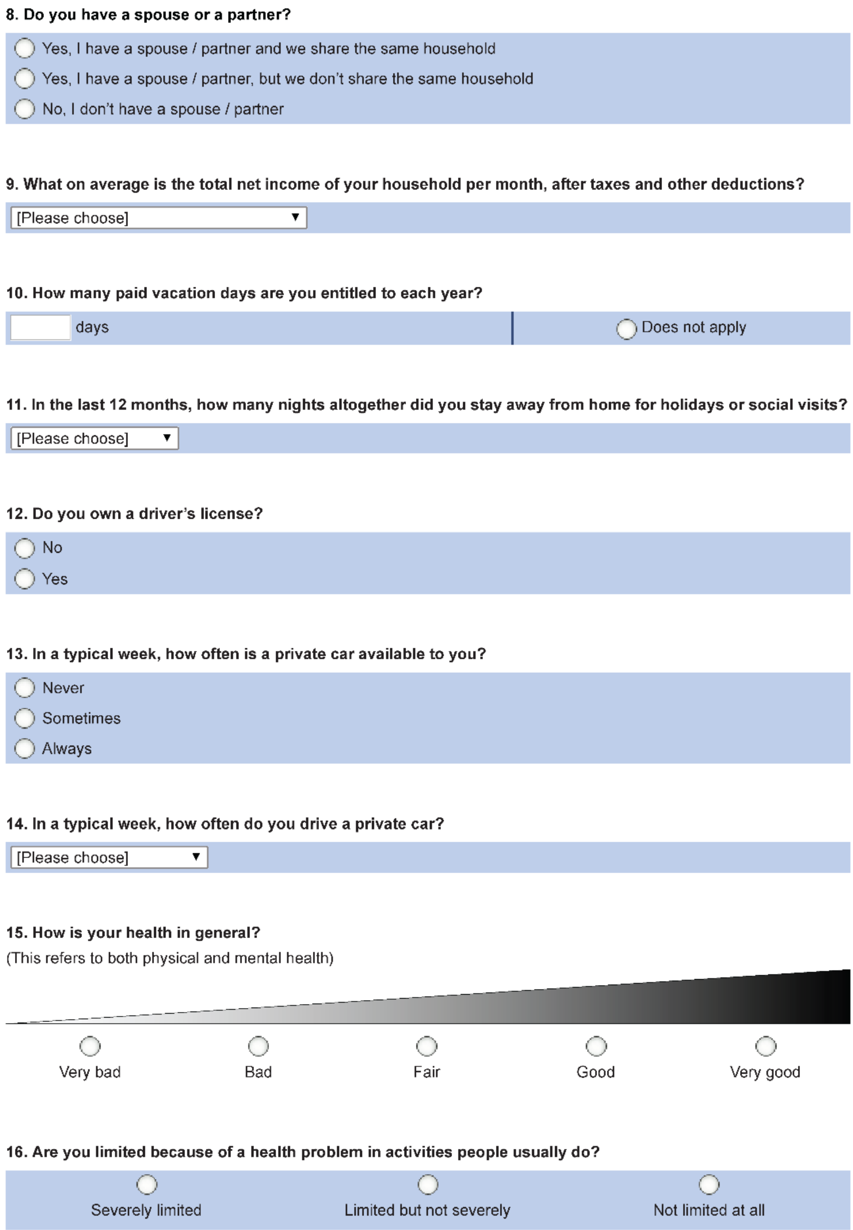
7. How many persons – including yourself – live in your household?

adults

children under 6

children 6 – 17

Figure A.10 CAPI questionnaire – page 2



8. Do you have a spouse or a partner?

- Yes, I have a spouse / partner and we share the same household
- Yes, I have a spouse / partner, but we don't share the same household
- No, I don't have a spouse / partner

9. What on average is the total net income of your household per month, after taxes and other deductions?

[Please choose]

10. How many paid vacation days are you entitled to each year?

days | Does not apply

11. In the last 12 months, how many nights altogether did you stay away from home for holidays or social visits?

[Please choose]

12. Do you own a driver's license?

- No
- Yes

13. In a typical week, how often is a private car available to you?

- Never
- Sometimes
- Always

14. In a typical week, how often do you drive a private car?

[Please choose]

15. How is your health in general?

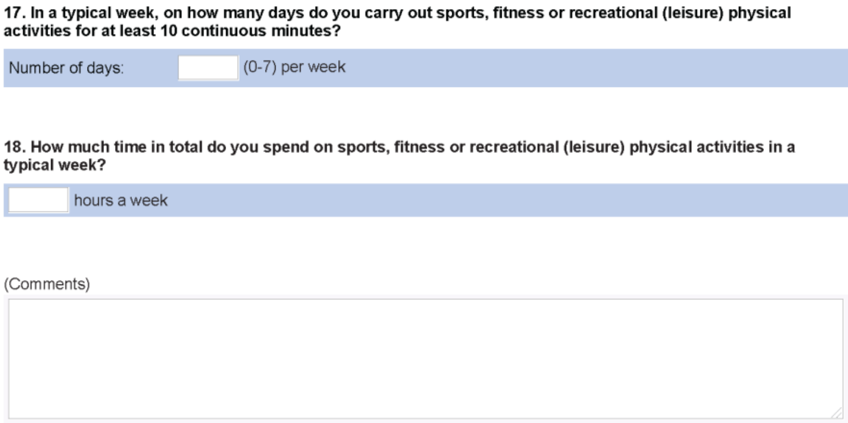
(This refers to both physical and mental health)

Very bad | Bad | Fair | Good | Very good

16. Are you limited because of a health problem in activities people usually do?

Severely limited | Limited but not severely | Not limited at all

Figure A.11 CAPI questionnaire – page 2 (continuation)



17. In a typical week, on how many days do you carry out sports, fitness or recreational (leisure) physical activities for at least 10 continuous minutes?

Number of days: ____ (0-7) per week

18. How much time in total do you spend on sports, fitness or recreational (leisure) physical activities in a typical week?

____ hours a week

(Comments)

Figure A.12 CAPI questionnaire – page 2 (continuation)

Page 03
YS

19. Date of arrival:

[ ]

20. Date of departure:

[ ]

21. Place where you are staying:

(name of the accommodation and village)

22. Who is accompanying you during your stay in Ötztal?

- ◯ No one
- ◯ Spouse / partner
- ◯ Children under 6 How many?
- ◯ Children 6-17 How many?
- ◯ Other household members How many?
- ◯ Other known persons How many?

23. Type of holiday:

- ◯ Organized travel (by tour operator, school, club, etc.)
- ◯ Individual trip

24. How many times have you been to Ötztal before?

[ ] times

25. Is Ötztal the main destination of your stay?

- ◯ Yes
- ◯ No, I am on a stopover here and will be moving to another place later

26. What is the main purpose of your visit in Ötztal?

[Please choose] ▼

27. Which transport mode have you mainly used to come to Ötztal?

[Please choose] ▼

Figure A.13 CAPI questionnaire – page 3

28. Why did you choose this transport mode for your journey?

- No other mode was available
- Because of the distance of the journey
- Fastest mode
- Cheapest mode
- Safest mode
- Most convenient mode (direct, accessible, flexible)
- Most comfortable mode (e.g. cleanliness, seats, ventilation)
- Personal mobility constraints (e.g. disabled)
- Luggage transport (bulky, heavy)
- Weather conditions
- Other:

29. How informed do you feel about the journey options (arrival) to Ötztal?

Not informed at all | Slightly informed | Somewhat informed | Well informed | Very well informed

30. How have you informed yourself in advance about the journey options to Ötztal?

- On websites/mobile app of the region/destination
- On websites/mobile app of the hotel
- On online/mobile map services (i.e. GoogleMaps)
- At the travel agency
- From travel guidebooks
- From friends and relatives
- Other:
- I have not informed myself in advance

31. How informed do you feel about the on-site mobility services in Ötztal?

Not informed at all | Slightly informed | Somewhat informed | Well informed | Very well informed

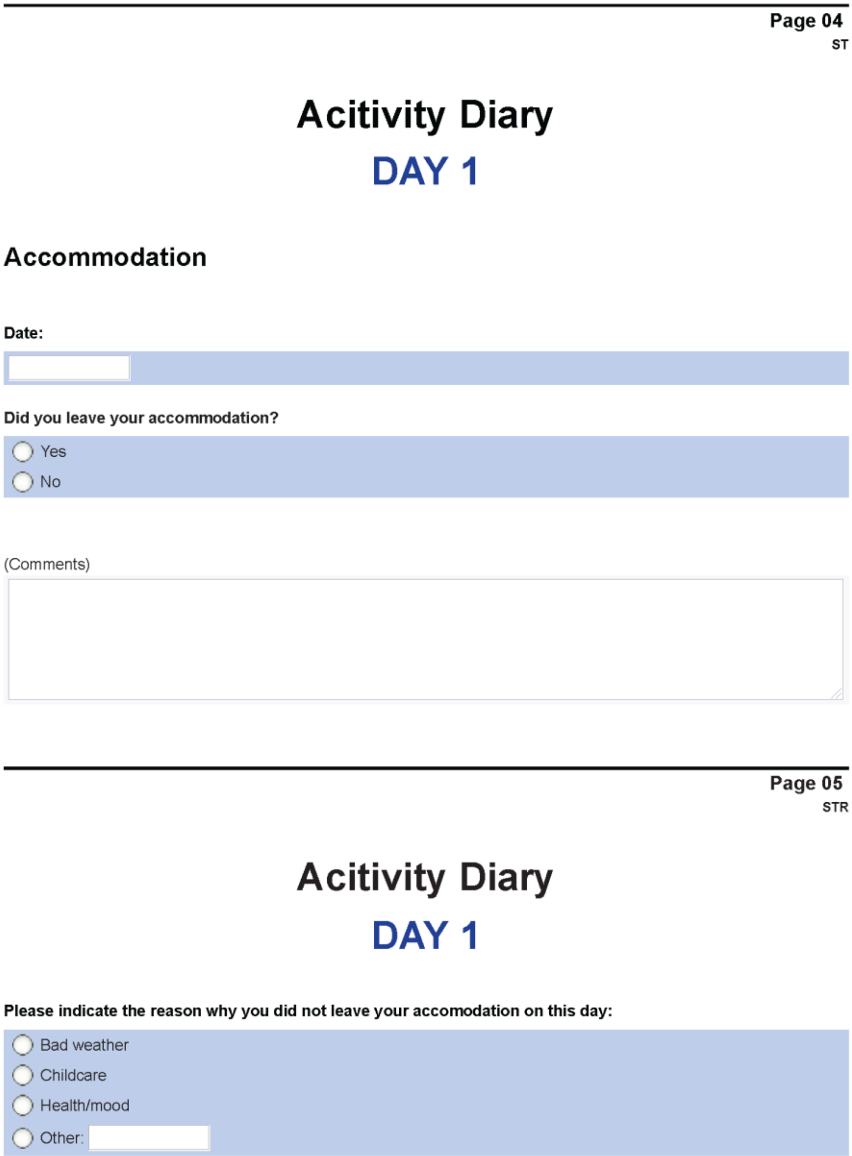
Figure A.14 CAPI questionnaire – page 3 (continuation)

32. How have you informed yourself in advance about the on-site mobility in Ötztal?

- ◯ On websites/mobile app of the region/destination
- ◯ On websites/mobile app of the hotel
- ◯ On websites/mobile apps of the local public transport operator
- ◯ On online map services (i.e. GoogleMaps)
- ◯ At the travel agency
- ◯ From travel guidebooks
- ◯ From friends and relatives
- ◯ Other: ________
- ◯ I have not informed myself in advance

(Comments)

Figure A.15 CAPI questionnaire – page 3 (continuation)



Page 04
ST

Acitivity Diary
DAY 1

Accommodation

Date:

Did you leave your accommodation?

- Yes
- No

(Comments)

Page 05
STR

Acitivity Diary
DAY 1

Please indicate the reason why you did not leave your accomodation on this day:

- Bad weather
- Childcare
- Health/mood
- Other:

Figure A.16 CAPI questionnaire – page 4 and 5

Page 06
STU

Acitivity Diary

DAY 1

What time did you leave your accommodation?
(start time of the first trip)
[Please choose] ▼

(Comments)

Figure A.17 CAPI questionnaire – page 6

Page 07
TA

Activity Diary

DAY 1

Trip 1

Mode

[Please choose] ▼

Cost (other than fuel): €

Company:

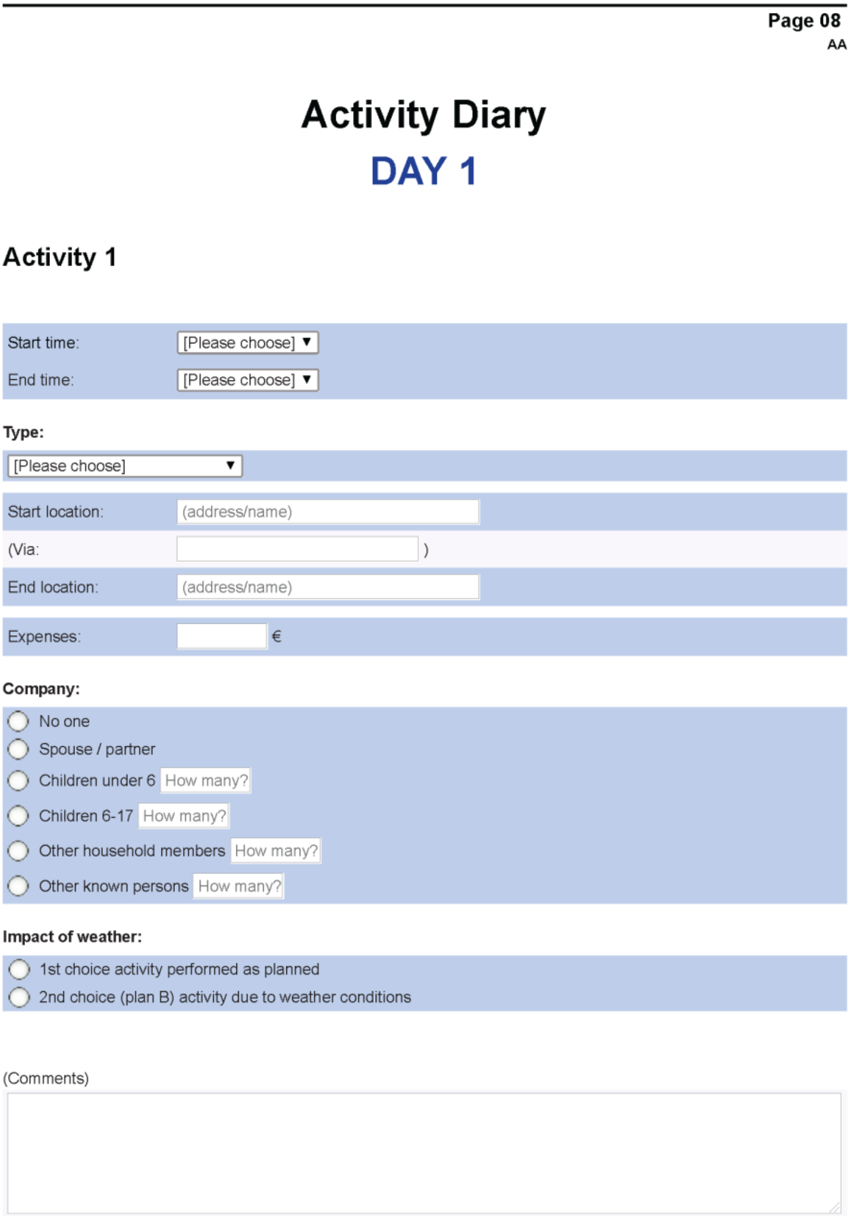
- No one
- Spouse / partner
- Children under 6 How many?
- Children 6-17 How many?
- Other household members How many?
- Other known persons How many?

Impact of weather:

- 1st choice transport mode as planned
- 2nd choice (plan B) transport mode due to weather conditions

(Comments)

Figure A.18 CAPI questionnaire – page 7. Pages for trips 2-8 (odd pages 9-21) are identical



Page 08
AA

Activity Diary

DAY 1

Activity 1

Start time:	[Please choose] ▼
End time:	[Please choose] ▼

Type:

[Please choose] ▼

Start location:	(address/name)
(Via:	)
End location:	(address/name)
Expenses:	€

Company:

- No one
- Spouse / partner
- Children under 6 How many?
- Children 6-17 How many?
- Other household members How many?
- Other known persons How many?

Impact of weather:

- 1st choice activity performed as planned
- 2nd choice (plan B) activity due to weather conditions

(Comments)

Figure A.19 CAPI questionnaire – page 8. Pages for activities 2-7 (even pages 10-20) are identical

Page 22
II

Activity Diary

DAY 1

What time did you return to your accomodation?

[Please choose] ▼

Page 23
SS

Acitivity Diary

DAY 2

Accommodation

Date:

Did you leave your accommodation?

- Yes
- No

(Comments)

Figure A.20 CAPI questionnaire – page 22 and 23

Page 24
STT

Acitivity Diary
DAY 2

Please indicate the reason why you did not leave your accomodation on this day:

- ◯ Bad weather
- ◯ Childcare
- ◯ Health/mood
- ◯ Other: ______

Page 25
STZ

Acitivity Diary
DAY 2

What time did you leave your accommodation?
(start time of the first trip)

[Please choose] ▼

(Comments)

Figure A.21 CAPI questionnaire – page 24 and 25

Page 26
TJ

Activity Diary

DAY 2

Trip 1

Mode

[Please choose] ▼

Cost (other than fuel): ______ €

Company:

- ◯ No one
- ◯ Spouse / partner
- ◯ Children under 6 [How many?]
- ◯ Children 6-17 [How many?]
- ◯ Other household members [How many?]
- ◯ Other known persons [How many?]

Impact of weather:

- ◯ 1st choice transport mode as planned
- ◯ 2nd choice (plan B) transport mode due to weather conditions

(Comments)

Figure A.22 CAPI questionnaire – page 26. Pages for trips 2-8 (even pages 28-40) are identical

Page 27
AJ

Activity Diary

DAY 2

Activity 1

Start time: [Please choose] ▼

End time: [Please choose] ▼

Type:

[Please choose] ▼

Start location: (address/name)

(Via:)

End location: (address/name)

Expenses: €

Company:

- ◯ No one
- ◯ Spouse / partner
- ◯ Children under 6 How many?
- ◯ Children 6-17 How many?
- ◯ Other household members How many?
- ◯ Other known persons How many?

Impact of weather:

- ◯ 1st choice activity performed as planned
- ◯ 2nd choice (plan B) activity due to weather conditions

(Comments)

Figure A.23 CAPI questionnaire – page 27. Pages for activities 2-7 (odd pages 29-39) are identical

Page 41
RR

Activity Diary
DAY 2

What time did you return to your accomodation?

[Please choose] ▼

Last Page

Thank you for completing this questionnaire!

We would like to thank you very much for helping us.

Your answers were transmitted, you may close the browser window or tab now.

MEng. Bartosz Bursa, Unit for Intelligent Transport Systems – University of Innsbruck – 2019

Figure A.24 CAPI questionnaire – page 41 (last page)

Curriculum Vitae

Personal data

Name and surname	Bartosz Bursa
Date of birth	December 4, 1988
Place of birth	Lapy, Poland
Citizen of	Poland

Education

2016 – 2020	University of Innsbruck (Innsbruck, AT)	
	Specialization:	Transport Planning
	Degree:	Doctor of Technical Sciences (equiv. to Doctor of Philosophy)
2011 – 2012	Wroclaw University of Technology (Wroclaw, PL)	
	Specialization:	Civil Engineering
	Degree:	Master of Engineering
2007 – 2011	Wroclaw University of Technology (Wroclaw, PL)	
	Specialization:	Civil Engineering
	Degree:	Bachelor of Engineering

Professional experience

2020 – today	University of Innsbruck (Innsbruck, AT), Unit of Intelligent Transport Systems	
	Position:	Senior Scientist

June 2016 – May 2020	University of Innsbruck (Innsbruck, AT), Unit of Intelligent Transport Systems *Position:* Scientific Assistant
2015 – 2016	JACOBS (London, UK) *Position:* Transport Planning Consultant
2013 – 2015	stadtraum GmbH (Poznan, PL / Berlin, DE) *Position:* Traffic Engineer
2012 – 2013	EGIS Poland (Wroclaw, PL) *Position:* Road Designer Assistant

Publications of the author

Refereed journal papers

Bursa, B., and Mailer M. (2020) Can large cycling events promote active mobility? Expectations versus reality on the example of the 2018 UCI Cycling World Championship. *Research in Transportation Business & Management*, https://doi.org/10.1016/j.rtbm.2020.100564

Blumthaler, W., Bursa, B., and Mailer, M. (2020) Influence of floating car data quality on congestion identification. *European Journal of Transport and Infrastructure Research 20(4)*, 22-37, https://doi.org/10.18757/ejtir.2020.20.4.5304

Bursa, B., Gajic, N. and Mailer, M. (2019) Insights into the congestion patterns on alpine motorways based on separate traffic lane analysis. *Transportation Research Procedia*, *37*, 441–448. https://doi.org/10.1016/j.trpro.2018.12.220

Mailer, M., Abegg, B., Jänicke, L. and Bursa, B. (2019) Mobilitätsbedingte Klimawirkung einer alpinen Tourismusdestination. *Zeitschrift für Tourismuswissenschaft*, *11*, 211–236. https://doi.org/10.1515/tw-2019-0013

Schlemmer, P., Blank, C., Bursa, B., Mailer, M. and Schnitzer, M. (2019) Does Health-Oriented Tourism Contribute to Sustainable Mobility? *Sustainability*, *11*, 2633. https://doi.org/10.3390/su11092633

Journal papers under review

Bursa, B., Mailer, M. and Axhausen, K.W. Travel behavior on vacation: transport mode choice of tourists at destinations. *Transportation Research Part A*

Bursa, B., Mailer, M. and Axhausen, K.W. Intra-destination travel behavior of alpine tourists. A literature review on choice determinants and the survey work. *Transportation*

Books

Bursa, B. (2021). *Modeling intra-destination travel behavior of tourists.* Innsbruck, Studia Verlag.

Refereed papers in proceedings

Bursa, B., Gajic, N. and Mailer, M. (2018) Classification of traffic jams on alpine motorways, *Proceedings of 7th Transport Research Arena*, https://doi.org/10.5281/zenodo.1441016

Refereed conference papers

Bursa, B. and Mailer, M. (2022) Challenges in surveying tourist on-site activity and travel behavior, to be presented at the *12th International Conference on Transport Survey Methods*, Lisbon, March 2022.

Bursa, B., Axhausen, K.W. and Mailer, M. (2021) Travel behaviour on vacation: mode choice and value of time of alpine tourists at the destination, presented at the *AIEST Conference*, Lucerne, Switzerland, August 2021.

Bursa, B., Axhausen, K.W. and Mailer, M. (2021) Modelling tourist on-site mode choice decisions during vacation stays, presented at the *International Symposium on Transportation Data and Modelling*, Ann Arbor, USA, June 2021.

Bursa, B. and Mailer, M. (2020) Car-less on holiday? Sustainable tourist travel in Alpine regions, presented at the *TTRA European Chapter Conference*, Innsbruck, September 2020.

Bursa, B. and Tischler, S. (2019) The role of destination accessibility in Alpine winter tourism, presented at the *NECTAR Cluster 5 Conference: Sustainable Tourism in the Digital World*, Visby, September 2019.

Bursa, B. (2019) Modeling the intra-destination travel behavior of tourists: mode choice, presented at the *40. Universitätstagung Verkehrswesen*, Fall/Lenggries, September 2019.

Blumthaler, W., Bursa, B. and Mailer, M. (2019) Evaluation of Floating Car Data quality for traffic congestion analysis on motorways, presented at the *Mobil.TUM International Scientific Conference on Mobility and Transport*, München, September 2019.

Bursa, B. (2019) Winter tourist on-site mobility patterns and travel decisions, presented at the *International Mountain Conference*, Innsbruck, September 2019.

Bursa, B., Gajic, N. and Mailer, M. (2018) Insights into the Congestion Patterns on Alpine Motorways Based on Separate Traffic Lanes Analysis, presented at the *21st EURO Working Group on Transportation Meeting*, Braunschweig, September 2018.

Schlemmer, P., Schnitzer, M., Blank, C., Bursa, B., and Mailer, M. (2018) Health-related mobility patterns of tourists in Western Austria, presented at the *Tourism Naturally Conference*, Kaprun, May 2018.

Bursa, B., Mailer, M. and Gajic, N. (2018) Classification of Traffic Jams on Alpine Motorways, presented at the *7th Transport Research Arena: A digital era for transport*, Vienna, April 2018.

Bursa, B. and Mailer, M. (2017) Easy travel – new mobility concepts in tourism, presented at the *XI. Österreichische Fachkonferenz für FußgängerInnen*, Klagenfurt, June 2017.

AUS DEN VERÖFFENTLICHUNGEN DES INSTITUTS

Schriftenreihe des Instituts für Infrastruktur, Arbeitsbereich Intelligente Verkehrssysteme der Universität Innsbruck

Band 1 (2015)
POSPISCHIL Ferdinand
Längsverschweißtes Gleis im engen Bogen: Eine Betrachtung der Gleislagestabilität

Band 2 (2021)
SARKER Rumana
Application of behavioral theories to increase the resilience of transit systems based on user-operator interaction

Band 3 (2021)
BURSA Bartosz
Modeling the intra-destination travel behavior of tourists

Vorangehend zu dieser Schriftenreihe des Arbeitsbereichs Intelligente Verkehrssysteme stehen die beiden früheren Schriftenreihen

- des Arbeitsbereichs Eisenbahnwesen und Öffentlicher Verkehr sowie
- des Arbeitsbereichs für Verkehrsplanung und Straßenbau.

Bisher erschienen unter

Mitteilungen des Instituts für Infrastruktur AB Eisenbahnwesen und Öffentlicher Verkehr

Heft 1 (1986)
PRAGER Günter
Beanspruchung von Schienen mit Grenzverschleiß auf Gebirgsbahnen

Heft 2 (1987)
ABLINGER Peter
Krümmungsbildmethode für den rechnerunterstützten Gleisentwurf

Heft 3 (1988)
SCHÖCH Wolfgang
Beanspruchung von Schienen mit UIC- und Sonderprofilen in engen Bogen

Heft 4 (1990)
FISCHER Reinhard
Beurteilung von periodisch asymmetrisch reprofilierten Schienen in engen Bogen aufgrund durchgeführter Messungen

Heft 5 (1991)
STEINER Ekkehard
Betriebsfestigkeitsnachweis von Schienen mit großer Seitenabnützung in engen Bogen aufgrund gemessener Lastkollektive

Heft 6 (1994)
HALLER Michael
Der Einfluß von "weichen" Zwischenlagen bzw. der Veränderung von Schleifparametern auf die Entwicklung von Schlupfwellen in engen Bogen

Heft 7 (1996)
CASAZZA Walter
Anschlußoptimierung in Fahrplannetzen mit einer Fuzzy-Logik-Bewertung der Umsteigequalität

Heft 8 (1997)
PRAGER Günter
Festschrift zum 60. Geburtstag von o. Univ.-Prof. Dr.-Ing. Erich Kopp

Heft 9 (1998)
SCHABAUER Wolfgang
Untersuchung der Schienenverdrehung bei Verwendung von Schienenzwischenlagen mit unterschiedlichen Federsteifigkeiten

Heft 10 (1998)
LINTNER Alfred
Dynamische Beanspruchung des Eisenbahnoberbaus infolge Schlupfwellen in engen Bögen

Heft 11 (2006)
FEICHTER Roland
Ein Vergleich verschiedener Fester Fahrbahnen in einem engen Bogen im Hinblick auf Schlupfwellenbildung und daraus resultierenden Gleisbeanspruchungen

Heft 12 (2007)
PRAGER Günter
Messungen am Eisenbahnoberbau – Habilitationsschrift

Heft 13 (2007)
PRAGER Günter
Zusammenstellung wissenschaftlicher Arbeiten – Eisenbahnwesen und Öffentlicher Verkehr – mit Kurzzusammenfassungen ausgewählter Projekte

Heft 14 (2010)
LOY Harald
Ein Beitrag zur Analyse der vertikalen Lastabtragung im Weichenbereich und Optimierung der Auflagerbedingungen durch besohlte Schwellen

Although tourism is responsible for a large part of traffic load, in particular in the Alpine countries, there is a lack of knowledge on travel patterns of tourists staying at the destination and factors influencing their intra-destination travel behavior. Consequently, local authorities and administration do not have the empirical evidence necessary for policy-making and -evaluation and must base their decisions on conjectures. This work combines data collection and modeling techniques developed in transportation research with existing knowledge in the field of tourism and travel research to fill this gap. Based on unique survey data collected with the use of bespoke travel-activity diaries, the thesis employs Discrete Choice models for the analysis of tourist transport mode decisions for intra-destination trips, identifies the impactful factors and measures their effect size within the collected sample. The work also reports elasticities with respect to changes in travel time and travel cost, and estimates of Value of Travel Time Savings among tourists. This provides decision- and policy-makers with valuable outcomes needed for project appraisal, cost-benefit-analyses and designing evidence-based transport policy, as well as numbers necessary for effective mobility management in tourist regions that are struggling with transport problems and the resultant negative externalities.

9 783991 050148