Dipartimento Interateneo di Scienze, Progetto e Politiche del Territorio
Eccellenza MIUR 2018-2022

Doctoral Dissertation
Doctoral Program in Urban and Regional Development (34^{th} Cycle)

Using attitudes and green consciousness as a determinant of travel behaviour and market segmentation

By

Pinky Kumawat

******

Supervisor(s):
Prof. Cristina Pronello, Supervisor
Prof. Silvia Chiusano, Co-Supervisor

Doctoral Examination Committee:
Prof. Shlomo Bekhor, Referee, Technion - Israel Institute of Technology Haifa
Prof. Fabien Leurent, Member, Ecole des Ponts – Paris Tech
Prof. Yannis Tyrinopoulos, Member, University of West Attika, Athens, Greece
Prof. Roberto Fontana, Member, Politecnico di Torino
Dr. Dominique Mignot, Referee, IFSTTAR – Director of Dept. Transport Santé Sécurité

Politecnico di Torino
March 2022

Politecnico di Torino
UNIVERSITÀ DEGLI STUDI DI TORINO
ScuDo
Scuola di Dottorato – Doctoral School
WHAT YOU ARE, TAKES YOU FAR
Dipartimento Interateneo di Scienze, Progetto e Politiche del Territorio
Eccellenza MIUR 2018-2022

Declaration

I hereby declare that the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Pinky Kumawat
March 2022

* This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

I would like to dedicate this thesis to my loving family.

Acknowledgment

First and foremost, a great thanks to my supervisor, mentor, and guide prof. Cristina Pronello for her important suggestions, response for my queries, doubts, providing valuable insights at each step of the way, and let me do many different experiences during the PhD period. I will always be grateful for her support, guidance, efforts, and the trust she showed in me.

A special thanks to my dear father and husband who is always standing behind me to support, motivate, help, improve, focus, encourage in moving forward, and making me more and more strong.

Thanks to my dear parents, in-laws, brothers, and sister for their constant support in completing my education and PhD degree.

A warm thanks to my department and research group colleagues Jean-Baptiste, Davide, Valerio, Deepan, Ximena, and Valentina for their assistance, information, time and help they provided me whenever I asked to them for any kind of help throughout the PhD journey.

I would also like to thank Dr. William Boone who is a professor of educational Psychology (Miami University, USA), for answering my queries on Rasch analysis by email.

At last, I am very grateful to SmartData Polito and all people who helped me in anyway throughout the PhD journey.

Executive Summary

Transport and urban planning is vital to ensure appropriate spending of funds for infrastructure development and maintenance, to ensure sustainability and economic competitiveness. Implementing measures to improve transport systems requires in-depth knowledge of potential travellers' behaviour and underlying psychological factors. Transport planners are concerned to know the choices of people: their daily life and travel habits because insights into such choices, obtained from data, could assist in improving services offered to citizens.

Nowadays, there are several potential new sources and collection methods for travel data: mobile apps, innovative web surveys, payment methods, mobile network data, social media, in-vehicle equipment, and roadside equipment. Thence, data is identified as a new form of oil for future transport where information extraction and data analytics can improve the understanding of urban mobility by enhancing knowledge, improving customer service, and providing efficient operation. Therefore, understanding various available travel data sources and issues in data collection is fundamental by evaluating their quality, reliability, use and purpose. The understanding of available data sources helps to select appropriate data source for data collection and purpose of the study.

This research aims, at first, to identify various travel data sources, through a review and benchmark of mobility apps, identifying apps as a tool to understand if they can properly track the mobility patterns. Secondly, after the analysis of apps, the research work has focused on the selection of set of data allowing to: a) understand the travel behaviour through the market segmentation, identifying key factors behind the decision making; b) assess the General Ecological Behaviour (GEB) of users and obtain a valid measure of the attitude towards the environment to understand if pro-environment activism could be one of the important factors in the market segmentation; and finally c) statistically validate the identified (in market segmentation and GEB measure) main psychological determinants of modal choice. The focus of this research is to analyse the main determinants of travelling decision making mainly using attitudes and preferences to: a) better understanding the user's needs; b) developing targeted strategies to offer proper infrastructures, improve services, and travel solutions to support transport planners and decision makers; and c) better planning and programming transport systems with the main attention to Public Transport (PT) and soft modes.

The adopted methodology is composed by five main steps: (1) review and benchmark of current mobility apps to identify, through a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis, what could be used as a tool for travel data collection; (2) travel survey design; (3) survey administration and sample selection; (4) data analysis design to understand travel behaviour mainly using attitudes and preferences; (5) mode choice modelling to identify the main psychological determinants behind the mode choice using Structural Equation Model (SEM).

The review of apps allowed to select Travel Surveys (TS) as the most suitable tool for the purpose of this research. Information was collected using a web survey called “Come Ci Muoviamo”, which was an advanced survey compared to the traditional TS, allowing to collect detailed information related to cognitive aspects, attitudes, preferences, perceptions, habits together with geolocations and travel diary information.

Piedmont region (Italy) has been selected as the study area of the survey to perform the market segmentation, with focus on the Metropolitan area of Torino for both assessing GEB and mode choice modelling. A sample of 4473 respondents was collected administering a web questionnaire using multiple channels (e-mail, websites, social media).

The data analysis design provides a first descriptive analysis of socio-demographic characteristics and mobility patterns of respondents. Then, a cluster analysis has been carried out to identify different profiles suitable to a modal shift towards more sustainable modes of transport and to better understand their needs. To describe the identified profiles, Exploratory Factor Analysis (EFA) has been used to discover the major latent constructs on the attitudinal variables collected in the survey. Identifying pro-environment activism as one of the important factors present in all clusters, Rasch model analysis was used to obtain a valid unidimensional measure of pro-environment behaviour. Finally, SEM is used to identify and statistically validate the identified psychological determinants behind the mode choice decision making behaviour of users.

Results suggests that TS are the most reliable source of information to obtain a high level of detail and the only source able to collect stated preferences, perceptions, attitudes, and different cognitive aspects, as the automatic tools cannot capture the emotions of human beings.

The market segmentation shows that, among the six clusters formed according to 13 latent factors, trip chain is the most used mode for the most important trip, followed by car as a driver, except the cluster 2 (Pro-environment active car addicts). The main factor of choosing car is “Mode performance” that includes comfort, safety, and cleaning. Four factors – Travel pleasure, Improvement of onboard service quality, Pro-environment activism, and Mode pleasure – are present in all six clusters, showing the most important factors behind the decision making of users when choosing the transport mode. In contrast to this, presence in clusters of Pro-environment activism not impacting mode choice reveals that it is more an intention instead of a sense of respect towards environment. Comfort, cost, accessibility, reliability, and duration seemed to be the key attributes in choosing the travel mode. Moreover, the challenge for developing sustainable transport policies with respect to each identified travel group is discussed. The clusters are ranked according to the sustainability of their travel behaviour (mode choice) to show to policy makers how to focus on least sustainable groups to attract them towards more sustainable modes.

Using Rasch model, the proposed 26 items GEB questionnaire was able to effectively measure travellers’ pro-environment behaviour. Unidimensionality, perfect level of item reliability of 1 and huge item separation (34.22 with dichotomous scale and 43.39 with polytomous scale), absence of larger differential item functioning, local independence, and no overlap among item characteristics curves are all good indicators of a valid model. Comparing dichotomous and polytomous scale, polytomous scale gives higher item separation, revealing that more categories are better than only two categories to measure GEB.

Mode choice modelling using SEM allowed to obtain a good and acceptable model fit for both, binomial and trinomial mode choice model. The proposed hypotheses are found to be significant, proving the empirical support for model validation. Travel Pleasure (TP) and Mode Pleasure (MP) emerge as two important attitudes influencing travellers when choosing the mode because they prefer to use what they like and give them pleasure; such factors were also identified important in the market segmentation. In addition, residential location (Home), Perceived Accessibility (PAC), and AFF (I like to drive) variables were also found significant in affecting mode choice. In contrast to this, Subjective Norms (SN), Personal Norms (PN) and GEB do not influence the mode choice. This finding shows that the attitudes/preferences are the strong motivation for the population to select the mode.

Overall, we conclude that, the identification of main psychographic profiles and factors can help decision makers to plan a more sustainable mobility, tested on the population and on its specific living context.

At the end of the analysis, some suggestions and practical policy implications are provided, useful to decision makers and transport operators. Finally, some limitations and recommendations for future research are put forward.

Publications during PhD

1. Kumawat, P., Pronello, C., (**2022**) Validating Italian General Ecological Behaviour Questionnaire of Travellers using Dichotomous Rasch Model. Transportation Research Board 101st Annual meeting, Washington DC 9-13 January 2022.

2. Kumawat, P., Pronello, C., (**2021**) Validating Italian General Ecological Behaviour Questionnaire of Travellers Using Dichotomous Rasch Model. *Sustainability* 2021, 13, 11976. https://doi.org/10.3390/su132111976.

3. Pronello, C., Kumawat, P., (**2021**) Smartphone Applications Developed to Collect Mobility Data: A Review and SWOT Analysis. DOI:10.1007/978-3-030-55187-2_35. pp.449-467. In *Advances in Intelligent Systems and Computing* - ISSN:2194-5357 vol. 1251.

Dipartimento Interateneo di Scienze, Progetto e Politiche del Territorio
Eccellenza MIUR 2018-2022

Table of contents

List of Figures

List of Tables

Glossary of the acronyms

Acronym	Meaning
GEB	General Ecological Behaviour
PT	Public Transport
SWOT	Strengths, Weaknesses, Opportunities, Threats
SEM	Structural Equation Model
TS	Travel Surveys
EFA	Exploratory Factor Analysis
TP	Travel Pleasure
MP	Mode Pleasure
PAC	Perceived Accessibility
SN	Subjective Norms
PN	Personal Norms
SA	Smartphone Applications
AFC	Automated Fare Collection Systems
APC	Automatic Passenger Counter
CATI	Computer Assisted Telephone Interviewing
CAPI	Computer Assisted Personal Interviewing
CASI	Computer Assisted Self-Interviewing
GPS	Global Positioning System
GSM	Global System for Mobile Communications
SDKs	Software Development Kits
APIs	Application Programming Interface
TDCA	Travel Data Collection and Analysis
PSM	Promote Sustainable Mobility
AVL	Automated Vehicle Location
EPS	Electronic Payment Systems
ICT	Information and Communication Technology
IoT	Internet of Things
DCM	Discrete Choice Model
MNL	Multinomial Logit
MNP	Multinomial Probit model
TPB	Theory of Planned Behaviour
TIB	Theory of Interpersonal Behaviour
NAT	Norm Activation Theory
CAWI	Computer Assisted Web Interviewing

t-SNE	T-distributed Stochastic Neighbour Embedding
KMO	Kaiser-Meyer-Olkin
PAF	Principal Axis Factoring
KW	Kruskal-Wallis
AV	Autonomous Vehicles
DRM	Dichotomous Rasch Model
RSM	Rating Scale Model
PCM	Partial Credit Model
MNSQ	MeaN-SQuare
PCAR	Principal Component Analysis of Residuals
INFIT	INlier pattern sensitive FIT statistics
OUTFIT	OUTlier sensitive FIT statistics
ZSTD	Z-STanDardized
PCA	Principal Component Analysis
IRT	Item Response Theory
DIF	Differential Item Functioning
ICC	Item Characteristic Curve
MH	Mantel-Haenszel
AMOS	Analysis of a Moment Structure
CFA	Confirmatory Factor Analysis
ADF	Asymptotically Distribution Free
AVE	Average Variance Extracted
PBC	Perceived Behavioral Control
CFI	Comparative Fit Index
GFI	Goodness of Fit Index
RMSEA	Root Mean Square Error of Approximation
RMR	Root Mean Squared Residual
MLE	Maximum Likelihood Estimation

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

Chapter 1

Introduction

Transport and urban planning are vital to ensure appropriate spending of funds for infrastructure development and maintenance, to ensure sustainability and economic competitiveness (Gal-Tzur *et al.*, 2014). Thus, for transport planners is of utmost importance knowing the choices of people – how they move, where they live and where they work – to improve mobility services. Such knowledge can be obtained thanks to data.

Nowadays, massive data availability from the worldwide web allows tracking words, as well as locations, that are analysed and matched through several databases, allowing the prediction of people's activities and making obsolete the expensive and time-consuming statistical surveys (Hilbert, 2013).

Today there are several data sources, open data as well as the directed, automated or volunteered sources (Kitchin, 2014), including mobile phone data. The impressive growth of data volume generated annually (Manyika *et al.*, 2011) should have largely improved the knowledge of the urban mobility, but, nowadays, knowledge on the mobility is still scarce and fragmented, often too aggregated and used to specific goals or "spot-based" (e.g., automated sources as traffic sensors, cameras and automatic counters). Such data could give some support in understanding the reasons behind travel behaviour, till now investigated through ad hoc survey not allowing to reach a wide number of people.

There are several potential new sources and collection methods for travel data: mobile apps, innovative web surveys, payment methods, mobility network data, social media, in-vehicle equipment, and roadside equipment. The data sources and collection methods measure various parameters, primarily the movements of vehicles (traffic) or of people (mobility). They also measure subset (e.g., all modes of transport or individual vehicle types) and involve different samples (e.g., total populations and/or specific temporal and spatial samples of people).

Considering the potential of data in understanding mobility patterns and travel behaviour, first four data sources (having the possibility of data collection and availability in mind) – Travel Surveys (TS), Automated Fare Collection System (AFC), Automatic Passenger Counter (APC), and Smartphone Apps (SA) – were studied in terms of collection methods, tools, type of information collected, pros and cons. Despite of several advantages and disadvantages of each data source, the critical analysis allowed to understand that three data sources (AFC, APC and SA) collect mainly spatial and limited socio demographic information while TS can collect geolocation (origin and destination), detailed socio-demographic variables, perceptions, attitudes, preferences, and travel habits that serve for the purpose of this study. Nevertheless, identifying SA as a very recent tool for travel data collection, it was thought to use apps to collect spatial information in automatic way and attitudes/preferences by a questionnaire filled in through the app. To this end, before starting the data collection, the potential of using apps for the purpose of the study was investigated. Therefore, a detailed case study of mobility apps was performed to understand if and how the apps can benefit the collection of mobility data. The case study revealed some problems in terms of data quality and reliability as well as the limited information collected by the surveys through the apps. Thus, the apps were not considered appropriate for the purpose of this research which focuses on identifying the psychosocial determinants behind the decision making of users, and not only the spatial analysis. Thanks to the case study of apps, we preferred to adopt a more innovative way as regards the traditional survey, adding some technological features allowing the geolocation (origin and destination coordinates), also for the different legs of the trip chain. Moreover, the survey allows to go in depth in attitudinal, cognitive, and behavioural aspects which is not possible with other sources as the apps. This was fundamental to validate a previous psychological model we developed and eventually define a model based on a large data base (differently from the previous one based on a small database). The survey design, administration, sample selection and data collection were already done by the research group, this research started by using the initially cleaned dataset for analysis and modelling.

The target stakeholders of the research work are transport companies, transport authorities and governing bodies at different geographical scales: municipalities, provinces, regions, state. The proposed theme of the research program has direct impact to social, political, and environmental domain of interest with the focus on transport system studies. One of the main concerns of European program HORIZON 2020 was the development of innovative solutions for sustainable transport and mobility (Anastasi *et al.*, 2013).

Transport is an important factor in the context of *sustainable development* due to the pressure it places on the environment, its economic and social impacts, and its relationships with other sectors. The sector has been growing continuously in recent years and this trend is forecasted to continue, making a strategy for sustainable transport a priority at local, national, European, and global level.[1]

The *environmental impacts* of eco-innovations in transport fall under at least one of the seven following categories: climate impact of greenhouse gas emissions, air pollution, noise, energy, and material resources demand (upstream and downstream impacts), accidents, impacts on nature and the landscape as well as urban separation. Usually, an eco-innovation will address more than one of these environmental impacts at the same time (Schade and Rothengatter, 2011).

The *economic impacts* of sustainable mobility can be analysed and measured from six different perspectives: user (individual user and industry), sectoral, macro-economy, societal, distributional, authority and government. Assessment methods differ for the different perspectives, as do their results (Schade and Rothengatter, 2011). Our focus is on the user to better understand the user needs. In summary, the economic aspects of sustainable mobility are undoubtedly relevant for supporting policy choices. Therefore, in the end, based on the findings of the research, some policy implications are proposed.

To this end, the PhD research work aims to:

- performing a case study of mobility apps by identifying apps as a recent tool for travel data collection to understand if and how they can benefit the transport sector;
- investigate the mobility patterns of users in the study area to understand when, how, why and where they travel;
- define a market segmentation using preferences and attitudes to understand travel behaviour and their influence on mode choice and investigate how the users can be attracted towards sustainable modes;
- assess the General Ecological Behaviour (GEB) of users to obtain a valid measure of the attitude towards the environment and its impact on mode choice;
- investigate the main psychological determinants behind the mode choice of users.

To reach the goals, the proposed methodology is composed by five main phases:

- case study of mobility apps;

[1] http://www.fgcsic.es/lychnos/en_EN/articles/transport_and_mobility, accessed on September 25, 2019.

- survey design;
- survey administration and sample selection;
- data analysis design;
- mode choice modelling.

The thesis is formed by five chapters, following the introduction.

In the second chapter, an overview of state of the art over time is presented related to various mobility data collection sources, issues of information extraction and data collection in transport. Along with this a literature review of travel behaviour understanding using market segmentation, GEB and mode choice modelling is presented.

The third chapter illustrates the objectives and methodology adopted in this research. This chapter gives information about the various steps of methodology from data collection to data analysis which allows the reader to fully understand the outcomes in chapter 4 “Results”. To conclude, last chapters are dedicated to the discussion and conclusions following the references used in the research work and appendices for additional details.

Chapter 2

Literature Review

Transport planning is a challenging task and digitalisation is currently reshaping the transport sector. Indeed, there is a lack of reliable data of transport demand, due to the complexity of mobility patterns. Data is identified as a new form of oil for future transport where information extraction and data analytics can improve the understanding of urban mobility by enhancing knowledge, improving customer service, and providing efficient operation. Therefore, understanding various available travel data sources is a first important step in transport data analysis. Thus, the sections from 2.1 to 2.3 will focus on the evolution of travel data collection, the analysis of the different methods and the critical analysis of the main issues. Section 2.4 will deal with travel behaviour, analysing the market segmentation according to different variables and the General Ecological Behaviour (GEB), to finish with a presentation of different modelling approaches.

2.1 Travel data collection: evolution over time

It is important that government funds are invested in areas that provide the greatest return. Capital investment in transport infrastructure projects must be underpinned by good information on travel demand patterns (how, why, when and where people travel). Effective allocation of resources to manage and operate transport systems requires good information on the transport system performance. This information can only be obtained from comprehensive and regularly updated surveys of travel activity and transport demand.

The availability of reliable existing transport demand data, together with the costs involved in collecting new data, may dictate the specification and structure of the transport modelling system. Attempts should always be made to make best use of available demand data. The appropriateness of available data (for example, its coverage, robustness, and reliability) should be ascertained early in any model development and application undertaking. Therefore, the first step of this research work is aimed to understand different travel data sources, their evolution with time, assess their appropriateness and type of information collected in order to select appropriate source of information for further data analysis steps.

The study of mobility patterns is not new, but it has recently experienced a reappearance, mainly due to the technological advancements that facilitate the tracking of individual travels (Borsellino *et al.*, 2018). Self-reporting in the format of travel diaries have been used since the 1930s to obtain information about people's travel patterns (Rieser-Schüssler and Axhausen, 2014). Since the 1950s, the workhorse for the collection of transport demand data at regional scale has been the household surveys. Initially administered in person, face-to-face interviews were replaced in the 1970s with telephone interviews, eventually assisted with computers (Thakuriah, 2001). Computer Assisted Telephone Interviewing (CATI), Computer Assisted Personal Interviewing (CAPI), and Computer Assisted Self-Interviewing (CASI) started in late 1970s. Since the late 1990s, mobile tracking technologies have emerged as an important mechanism to capture space-time data. These technologies offer the possibility of collecting high resolution location information in real time (Birenboim and Shoval, 2016). More recently, smartphone-based data collection has been tested as it offers the opportunity to combine Global Positioning System (GPS) tracks with data from other smartphone sensors such as accelerometer, Wi-Fi, and Global System for Mobile Communications (GSM) (Thomas *et al.*, 2018). The development of smartphone applications for travel data collection and to promote sustainable mobility started in late 2000s that is one of the hot data collection method these days (Table 1).

Table 1: Evolution of data collection in transport over time

Data Source	Start Year
Travel Diaries	1930
Household Surveys	1950
Face to face interviews	1970
Telephone interviews	1970
Computer Assisted Telephone Interviews (CATI)	1970
Computer Assisted Personal Interviews (CAPI)	1970
Computer Assisted Self Interviews (CASI)	1970
Mobile Tracking	1990
Smart Card	1990
Global Positioning System (GPS)	1996
Smartphone Applications (SA)	2000

2.2 Understanding travel data collection methods

Before proceeding for data collection and analysis, it is of utmost importance to understand various available data sources, their pros, and cons, and how they can help in better understanding mobility patterns and travel behaviour. After giving background about data collection with the time, the next section explains typology of each studied data source in detail.

2.2.1 Travel Surveys (TS)

TS are a type of investigation that has been historically used by Public Transport (PT) authorities in order to gather specific information related to some individual's typical travel behaviours (Cui, 2006). This kind of method is usually made up of a questionnaire that is designed by the authority itself, which is then distributed to a selected sample of individuals.

The most common type of information that is usually gathered includes personal information of the surveyed individual, such as demographic and socioeconomic data as well as household characteristics and, most importantly, a travel diary of a typical day (start and end locations and times, mode of transport, purpose). Thanks to the flexibility of the support, this type of manual data collection procedure can be used for different purposes and at different scopes, potentially leading to very precise analyses.

In fact, due to their overall complexity, TS are a method that presents several inherent problems. Previous research show that several problems can be encountered in the answers, such as biased responses and missing or partial responses (Barry *et al.*, 2002; Zhao *et al.*, 2007). On top of that, studies show that they are usually very expensive, as well as time consuming and thus very infrequent (Barry *et al.*, 2002; Cui, 2006; Zhao *et al.*, 2007; Zhang *et al.*, 2011). Finally, surveys are not an easily updatable kind of information, due to their nature (Barry *et al.*, 2002; Cui, 2006).

Moreover, as time passes, new trends arise, and old methods may become inefficient or inappropriate, innovation in communication technology requires researchers to constantly update their approaches to sample selection and survey administration to gather insightful data. Finally, as shown by Kagerbauer *et al.,* (2015), new mobility patterns, such as inter-modality (the use of more than one mode within one Origin-Destination-trip) and multi-modality (to use different modes of transport for their trips over an extended period of time), are arising today in our societies and require new studies in order to be efficiently inspected through surveys. Considering all the above-said, a lot of actors grew their stake to find simpler, cheaper, more reliable, and more resilient methods to analyse mobility related data. As reported in Table 1, TS start with travel diaries in 1930s; adopting household travel surveys in 1950s and face-to-face/telephone interviews in 1970s which are called CATI, CAPI and CASI.

2.2.2 Smartphone Applications (SA)

SA have become one of the key tools used both in our personal and professional lives (Siuhi and Mwakalonge, 2016). They are software applications designed to run on smart phones, tablets, and other mobile devices. Apps are one of the most comprehensive approaches to collect data from all the transport modes, even though most smartphone apps in the transport sector refer to travel planning, ridesharing/carpooling/vanpooling services, traffic safety, parking information, and vehicle fuel consumptions and emissions. A detailed study of smartphone apps in all over the world to collect mobility data is performed to support the app development in the research laboratory of the authors and to understand if and how, data collection from apps can benefit the transport sector. The methodology used and results of the review study will be presented in the next chapters.

Beside the apps, there are various platforms and software development kits (SDKs), mostly developed by companies for business and research purposes. SDKs can be divided into three categories[2]: 1) SDKs that bring together a group of tools enabling the programming of mobile applications (iOS, Android, etc.); 2) application maintenance SDKs; and 3) marketing and advertising SDKs. A platform, instead, is a group of technologies that are used as a base upon which other applications, processes or technologies are developed.[3]

The evolution of smartphone apps in the transport sector started in year 2007 with the development of the first application. Then, since 2007, a slow progress was recorded until 2011, when the number of apps rapidly grew (figure 1), the apps being identified as a useful method to collect data compared to traditional TS. In the years 2015 and 2017, the maximum number of apps developed and used was recorded while, there on, a marked decline occurred. However, in figure 1 not all the surveyed apps are depicted as the year of their development was missing. The mobility app developed firstly in the research lab for data collection was Mobilité

[2] https://www.atinternet.com/en/glossary/sdk/, accessed on July 10, 2019.
[3] Platform?, https://www.techopedia.com/definition/3411/platform, accessed on July 10, 2019.

Dynamique. The app was allowing the users to keep track of their mobility patterns. Several statistics let the users understand their travel behaviours such as the number of daily trips and the mode used for travelling. Moreover, a heat map was showing the most visited or favourite places. The application was user friendly as it only requires the GPS sensor to work in the background (the smartphone screen is off or another app is running in foreground).

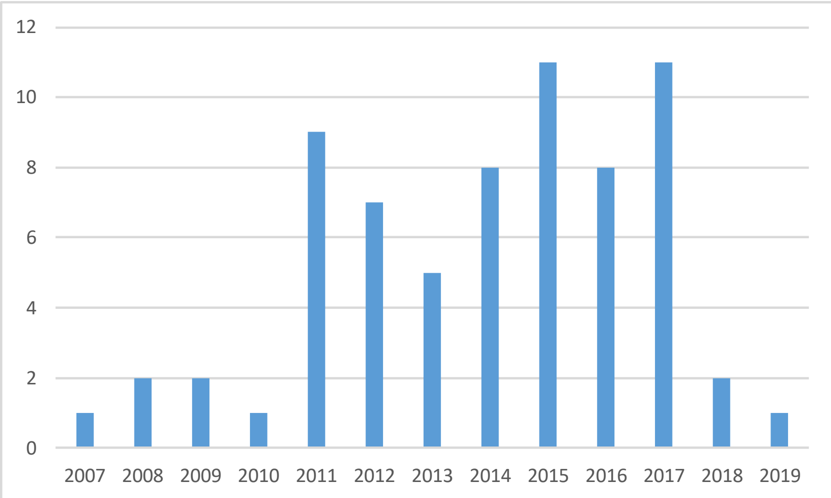


Figure 1: Number of smartphone applications on mobility data collection

The application was able to recognize still (no movement), walk, bike and vehicle (car, bus, train etc.) modes. To perform the mode detection, the Google (Application Programming Interface) APIs (Google APIs 2017) were used. Only low power sensors (not specified by Google) were used to retrieve the mode to save battery. Cardoso *et al.*, (2016) performed a test on the APIs and showed that the on-vehicle method does not have a good accuracy. For this reason, the application has been discontinued and it was decided to improve the currently used approach. This is also a practical example of decision behind using data from web survey for the research instead of apps which is limited to understand mobility patterns and not helping in understanding in-depth travel behaviour, specifically attitudes and preferences.

2.2.3 Automated Fare Collection Systems (AFC)

The purpose of this kind of systems is to replace old manual ticketing system with automated system, which automatically records the location and time of each customer's fare transactions (Zhao *et al.*, 2007). Indeed, AFC systems are usually tightly related to Automated Vehicle Location (AVL) systems, since, if both are present, allow to record both temporal and spatial information of the individual records without the need for additional data processing (Cui, 2006).

Usually, AFC systems are based on Electronic Payment Systems (EPS), which make use of contactless smart cards for the payment of the Public Transport (PT) fare. The ticket validation is performed by the user by presenting its smart card to the readers located on the bus. This validation can be performed in a completely autonomous way by the user, or under the control of some operator (usually the driver). This has clear implications on the number of readers present on board, as well as their positioning: the self-service interaction can be performed in an efficient way only if every boarding door is equipped with a reader.

Various studies using smart card data to extract the mobility patterns has been done. Pronello *et al.*, (2018) applied data mining to extract mobility patterns in province of Torino using smart card data. Smart cards present several advantages with respect to the traditional ticketing systems. Firstly, they improve the overall service reliability, reduce the users' boarding time, as well as the driver workload and the possibility of fare evasion. Moreover, the user perception of the service is improved thanks to the new technologies (Cui, 2006).

Finally, from the transit agency point of view, the possibility to access such kind of individual data allow them to reach some extremely valuable information that can be used in their planning operations (Cui, 2006; Barry *et al.*, 2009; Pelletier *et al.*, 2011; Wang *et al.*, 2011). In fact, from the data analysis point of view, smart card AFC data covers more larger samples, costs less money, and has different other advantages that are provided by its native digital nature.

On the other hand, the costs of research, development, and implementation of such systems are high, and the complexity related to the introduction of new components and processes into legacy systems imply a risk for the transport agencies when investing in this kind of technologies (Pelletier *et al.*, 2011). Furthermore, the original design requirements of the system will clearly affect the produced data quality. If the system is designed to only perform the fare collection, additional and sometimes difficult processing in order to obtain reliable data is required (Barry *et al.*, 2009). Finally, since classic flat fare rates are the most common around the globe, entry-only systems are very popular (Nunes *et al.*, 2016). Because of their nature, the alighting data is not recorded, and hence some kind of inferring mechanism is needed in order to retrieve the alight stop information (Cui, 2006; Barry *et al.*, 2009; Nunes *et al.*, 2016).

Nonetheless, as shown by Zhang *et al.*, (2011); Munizaga and Palma, (2012) and Munizaga *et al.*, (2014), smart card AFC systems are widely adopted all around the world, with high penetration rates, hence growing the interest in the research field in analysing the data produced by such systems. As shown by T. Li *et al.,* (2018), AFC data sources can be analysed for different purposes; they can be used to analyse transit riders' travel patterns and travel behaviour to assess the performance of the service and to plan and program the PT system.

2.2.4 Automatic Passenger Counter (APC)

APC systems are primarily designed as data collection systems to provide data obtained previously through ride-checks or on-off counts. APC systems record the number of passengers boarding and alighting at each serviced stop together with the time and stop location (Cui, 2006). There are different methods to detect passenger boarding or alighting. The most common method uses infrared light beams which when broken in sequence indicate a passenger boarding or alighting. This method requires that the sensors are properly aligned. Another method is to use pressure sensitive mats to detect passengers stepping into or out of the bus. This method will not work with low floor buses. There is also the method to use passive infrared sensors to detect passengers based on the difference of body heat versus the ambient temperature. Methods also exist to use video images taken inside the bus and count the number of passengers through image recognition (Wilson 2006).[4]

APC equipment is the most useful in collecting ridership data at the trip level, although it received above average scores at all but the system level. Stop-level scores were slightly lower than other disaggregate scores, suggesting some concerns with correct stop identification. Among the technologies that were rated for usefulness, APCs scored highest at the route and trip levels. Agencies using APCs are satisfied with their performance. Four agencies reported that they were "very satisfied" with APCs. The satisfaction levels are closely tied to the benefits experienced by agencies who use or are testing APC units. Seventy percent of respondents cite the ability to collect a greater amount of data at more detailed levels with greater frequency (Boyle, 1998).

Detailed data collection is particularly valued by planning and scheduling departments. Cost savings are also mentioned by 30% of the agencies. However, APCs do have problems, and the most common is software related. Software

[4]https://sharecourseware.org/ShowLecture.aspx?ID=1594&CatID=1&SubCatID=37&AspxAutoDetectCookieSupport=1#, accessed on July 20, 2020.

appears to be the limiting factor in making use of APC capabilities. The increase in data flow often requires development or upgrading of analytical programs, and data processing can be time-consuming. In the other direction, APCs require consistent maintenance by the agency of databases containing schedule and bus stop information, including stop patterns and variations by trip, for each route. Next to software, hardware problems were reported most often, including equipment failure, maintenance problems, and the durability of APC units on the buses (Boyle, 1998).

The synthesis of overall analysis of abovementioned data sources is presented in Table 2. Looking at the summary of four analysed data sources (Table 2), AFC, APC and SA are limited to spatial and socio-economic information. For understating travel behaviour using attitudes, perceptions, preferences, and cognitive aspects, TS are the only way to collect this kind of detailed information. Even collecting this type of information with apps, TS need to be launched.

After having an idea about different travel data collection methods, it is important to address the challenges in data collection and using the collected data for the purpose of the research or study. The next section addressing these challenges and the solutions to use.

Table 2: Synthesis of various travel data collection methods

TS	**Collection method**: Manual (traditional), **Tool**: Questionnaire	
	Information	demographic, socio-economic, travel habits, preferences, attitudes, perceptions, geographic locations
	Pros	historically used, flexible and reliable, used for different purposes, lead precise analyses, enrich information
	Cons	biased/missing responses, expensive, time consuming, infrequent, not easily updatable, create burden on users
SA	**Collection method**: Automatic (New), **Tool**: Sensors, APIs, GPS	
	Information	limited demographic and socio-economic information, precise locations, details of each trip legs, preferences/attitude/perception using survey only by the apps
	Pros	user friendly, easily updatable, continuous, burden free on users, support different geographical territories, used for launch surveys
	Cons	missing details, face technical issues, heavy processing power, require advanced analytical methods, time consuming analyses
AFC	**Collection method**: Automatic (New), **Tool**: Sensors, contactless smart cards, EPS	
	Information	number of readers present on board, positioning of boarding stop, location and time of each customer's fare transactions, temporal, and spatial information
	Pros	improve service reliability, reduce users' boarding time, driver workload and possibility of fare evasion, user perception improved, covers more samples, costs less money, worldwide adopted, high penetration rates growing interest in analysing the data produced
	Cons	cost of research, development, and implementation are high, complexity to introduce new components and processes into legacy systems imply risk, original design requirements affect data quality, difficult processing to obtain reliable data, alighting data is unrecorded require inferring mechanism to retrieve alight stop information
APC	**Collection method**: Automatic (New), **Tool**: passive infrared sensors, infrared light beams, sensitive mats, video images	
	Information	ridership data at the trip level, number of passengers boarding and alighting at stops with the time and stop location
	Pros	collect greater amount of data at more detailed levels with greater frequency, cost saving, agencies satisfied with performance
	Cons	Software appears as limiting factor in making use of APC capabilities, requires upgrading of analytical programs, time-consuming data processing, require consistent maintenance hardware problems (equipment failure, maintenance problems, durability)

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

2.3 Main issues in data collection

Data collection of mobility patterns is a time-consuming and expensive activity and, so far, monitoring mobility on a regular basis is still a future scenario. The previous section has shown which are the methods to collect data, each having pros and cons. This section presents which are the main issues to solve to make data collection effective.

2.3.1 Increasing volumes and accelerating sample rates of data

Increasing rates of transport data collection will continue to be facilitated by anticipated growth in the speed and coverage of wireless communication technologies, computer processing power, and data handling capacity. The key driving forces are the proliferation of devices and Information and Communication Technology (ICT) applications connected to the internet based on sensor networks and machine-to-machine communication[5], the number of networked sensors and information generators that are growing at over 30% per annum, creating a rapidly expanding Internet of Things (IoT) (Hung, 2017) that is projected to contain around 75 billion devices in 2025.

The combined effect of the two trends described above is that the size of transport related datasets - in line with those held in other industry sectors - is set to grow significantly over the next 10 years. The volume of all digital data being created and stored on servers and in the cloud is doubling almost every 1.2 years, and the volume of newly created data was estimated to have exceeded 1,000 exabytes in 2013 alone. These big datasets are increasingly beyond the capacity of conventional databases; requiring new techniques, tools, and computing systems to store, manage and utilise them. In transport related data terms, a key trend will be the adaptation of existing non-data-driven processes, and currently closed operational datasets; to capture, curate, store, search, share, transfer, analyse and visualise datasets so they are converted into actionable insight and usable information. Such data driven insights will also require new human intelligence and understanding to ensure the wisdom is applied in an informed manner. The

[5] https://www.oecd-ilibrary.org/science-and-technology/exploring-data-driven-innovation-as-a-new-source-of-growth_5k47zw3fcp43-en, accessed on July 22, 2020.

capabilities for exploiting big transport data will therefore be needed at both managerial/leadership levels as well as analytical and statistical roles.

2.3.2 Issues of transport related information extraction

The vast activity evinced in the literature survey made in previous sections is a clear exponent of the technical advances attained lately with big data applied to the transport and mobility domains. However, not only a number of open research issues remain unsolved and not addressed to date, but also new challenges appear as a result of the exchange of data and their exploitation across heterogeneous transportation areas (Torre-Bastida *et al.*, 2018) as follows:

- **Availability of data**: the non-standardised formats and incompleteness of available environmental data and lack of user data creates a problem to make data available. There is a need to make some common standards to make data available in a standard and useful format.
- **Privacy/Security**: the data we use to analyses contain sensitive information of the users. This poses a security and privacy risk for the users participating in the program. We need to implement some measures to safely store and analyse user data.
- **Heterogeneity and Incompleteness:** the difficulties of big data analysis derive from its large scale as well as the presence of mixed data based on different patterns or rules (heterogeneous mixture data) in the collected and stored data. In the case of complicated heterogeneous mixture data, the data has several patterns and rules, and the properties of the patterns vary greatly. Data can be both structured and unstructured. 80% of the data generated by organizations are unstructured. They are highly dynamic and does not have a particular format. It may exist in the form of e-mail attachments, images, pdf documents, medical records, X-rays, voice mails, graphics, video, audio etc., and they cannot be stored in row/column format as structured data. Transforming this data to structured format for later analysis is a major challenge in big data mining. So new technologies must be adopted for dealing with such data. Incomplete data creates uncertainties during data analysis, and it must be managed during data analysis. Doing this correctly is also a challenge. Incomplete data refers to the missing of data field values for some samples. The missing values can be caused by different realities, such as the malfunction of a sensor node, or some systematic policies to intentionally skip some values. While most modern data

mining algorithms have inbuilt solutions to handle missing values (such as ignoring data fields with missing values), data imputation is an established research field which seeks to impute missing values to produce improved models (compared to the ones built from the original data). Many imputation methods exist for this purpose, and the major approaches are to fill most frequently observed values or to build learning models to predict possible values for each data field, based on the observed values of a given instance.

- **Scale and Complexity:** managing large and rapidly increasing volumes of data is a challenging issue. Traditional software tools are not enough for managing the increasing volumes of data. Data analysis, organization, retrieval, and modelling are also challenging due to scalability and complexity of data that needs to be analysed.
- **Timeliness:** as the size of the data sets to be processed increases, it will take more time to analyse. In some situations, results of the analysis are required immediately.
- **Data quality:** detection of inconsistencies, missing data, disambiguation, validation errors, data gaps are the issues which directly impacts the results and their implications. This is a major problem in the data science world which remained to be solved and considered.
- **Ease of use:** with the invention of new technologies by the time, the lack of knowledge about the use of these new tools creates a problem for data collection or sample selection. There is a need to focus on user experience of the use of new tools and techniques.
- **Technical:** lack of appropriate skills and a lack of common standards and challenges in connecting data silos. Insufficient interdisciplinary knowledge and cooperation between transport and computer science experts poses a barrier to get real valued insights from the available data.
- **Commercial:** lack of understanding of the value of data, a lack of clear business models, commercial sensitivities that prevent sharing of data and the need for upfront investment to develop and store data.

A recent trend (within the last 5 years) is observed for companies that have traditionally dealt with data and converted it into information that is useful to people or used it to provide virtual services, to get directly involved in the provision of mobility services for users - particularly those involving personal use of car. Examples include Parkopedia/Park@MyHouse (Parkopedia to offer parking information services to BMW, 2013)[6], Tom Tom (Garside, 2011), Google, which was originally a data and information company, now investing in numerous technologies in the transport sector as, for example, Uber (Techcrunch, 2013)[7], driverless cars (BBC, 2014)[8], cashless payment systems (New York Times, 2014)[9]. This evolution shows how it is primed to become a mobility service provider drawing on its vertically integrated stack of maps, places, and search-driven data.

The benefits resulting from big data and IoT applications in smart cities could be significant for transport sector and span a wide range of areas including economic and social improvements. However, while there is general agreement on the types of benefits and opportunities in this area, there is still a lack of research on the economic value associated with the use of big data in transport. Indeed, it is difficult to put a value on data if there are no existing examples demonstrating its usefulness, which in turn makes impossible to make optimal decisions about how to develop, trade and exploit such data. Gaps also exist regarding the potential environmental and social impacts associated with using big data to support the transport sector. The private sector is a big generator of data, and their role as suppliers may be an untapped source of significant future value. Yet, many organisations do not necessarily understand the value of releasing it (Bonina, 2013)[10]. Since governments and public agencies do not control all the relevant information, getting private companies to share relevant data is highly important. The availability of reliable data from multiple sources creates a fertile environment for developing new and smart urban transport solutions. This is an unpredictable process, as it is not always possible to foresee what solutions could be developed.

2.4 Travel behaviour

There is substantial consent that, besides socio-economic and trip characteristics, psycho-attitudinal factors play a key role in influencing people's mode choice and travel behaviour (Koppelman and Pas, 1980; Gärling *et al.*, 1998). In the last few

---

[6] http://www.roadtraffic-technology.com/news/newsparkopedia-offer-parking-information-services-bmw, accessed on September 15, 2020.

[7] https://techcrunch.com/2013/08/22/google-ventures-puts-258m-into-uber-its-largest-deal-ever/, accessed on September 15, 2020.

[8] https://www.bbc.com/news/technology-27587558, accessed on September 15, 2020.

[9] https://www.nytimes.com/2014/07/16/world/africa/transit-cards-to-replace-cash-on-kenyan-minibuses-a-hard-sell.html, accessed on September, 2020.

[10] https://zenodo.org/record/1322706#.Xp3t2lMzZQI, accessed on September, 2020.

decades, several researchers argued that individuals' personality, attitudes, and perceptions have a great influence in predicting travel behaviour. Implementing measures to improve transport systems requires in-depth knowledge of potential travellers' behaviour and underlying psychological factors (von Behren *et al.*, 2018). Therefore, the following sections present state of the art approaches to understand travel behaviour, mainly focusing on market segmentation, GEB and mode choice models using psycho-attitudinal variables.

2.4.1 Market segmentation

Market segmentation has been one of the primary contributors to the development of effective marketing programs (Pizam and Calantone, 1987). It provides a unique identification method to separate a specific group of users having similar behaviours and attitudes (March, 1997; Pronello and Camusso, 2011). The primary objective of segmentation is to partition the total market into relatively homogeneous clusters with similar patterns (Díaz and Koutra, 2013). A certain amount of marketing information collected about a particular market segment plays a crucial part in the overall corporate strategy (Guo *et al.*, 2013). Through the process of market segmentation, firms can divide large heterogeneous tourist markets into small ones that can be reached more efficiently (Chen *et al.*, 2013). For example, market segmentation could be implemented to better understand the competitive landscape since it can provide insightful information on visitor preferences and behaviour and strive to match tourism demand by enhancing product offerings.

Travel behaviour can be analysed by reducing the complexity of different individuals' behaviour. Segmenting data in groups with similar characteristics has recently become an established approach in travel behaviour research (von Behren *et al.*, 2018) and well known in market research. To segment population in groups, cluster analysis methods are often used. Considering influences on travel behaviour of different peer groups is essential to develop targeted strategies to offer proper infrastructure, services, tailored policies (Pronello and Camusso, 2011) and travel solutions. This can affect people's mode choice and travelling (von Behren *et al.*, 2018).

One of the first studies to define transport user's segmentation using attitudes, by Pas and Huber (1992), defined the rail users' group in relation to their willingness to change behaviour. Haustein (2021) created five segments of car shares based on a longitudinal survey including psychological constructs in Copenhagen. Kim *et al.*, (2020) identified six segments to understand the activity patterns by using self-driving cars in the state of Georgia using survey data. De Angelis *et al.*, (2021) identified five groups of commuters of academic institution, based on their modal choice and then compared the groups through socio-demographic and psychosocial variables, specifically attitudes, personal norms, personal constraints, and travel satisfaction. De Angelis *et al.*, (2021) suggested that higher institutions can become a prominent player in promoting sustainable mobility, providing the contextual and instrumental basis for the adoption of more sustainable travel behaviour. Pronello and Camusso (2011) identified four travellers' profiles in the Italian city of Alessandria, which are quite informative and policy relevant, highlighting the importance of attitudinal items. Four devised clusters by Pronello and Camusso (2011) were Travel pleasure addicts, Paying ecologists, Time addicts and Timeservers. The important four factors identified in determining clusters were Travel Pleasure, High time saving desirability, environmental willingness to pay, and Low time saving desirability, while mode performance and mode pleasure were less significant. Analyses by Pronello and Camusso (2011) showed that the travel pleasure addicts manifest the highest attitude to change mode while time addicts and timeservers displays the highest dependence on car, and low intention to use alternative modes.

Overall, the literature suggests that the main purpose of market segmentation is to understand the mode choice behaviour of users. The abovementioned studies are significant in defining which behavioural mechanisms policy makers must consider in transport planning, in order to address user choices towards sustainable transport. Therefore, this research utilized the method of market segmentation to understand travel behaviour of users, specifically the mode choice and investigate how the users can be attracted towards sustainable modes.

2.4.2 General Ecological Behaviour (GEB)

People's ecological behaviour and the impact of human activities on the natural environment are subjects of public concern and have been largely studied in the psychological research. Many environmental psychologists acknowledge the need to spur more ecological behaviours or lifestyles (Howard, 2000; Otto *et al.*, 2014). The ecological behaviour means the actions which contribute towards environmental preservation and conservation (Axelrod and Lehman, 1993;

Maloney and Ward, 1973; Pickett *et al.*, 1993; Scott and Willits, 1994; Weigel, 1977); it includes behaviours such as recycling and composting, energy and water conservation, political activism, consumerism, commitment to environmental organizations, and so forth (Kaiser and Wilson, 2000).

Beforehand the ecological problems were identified as a crisis of maladaptive behaviour in the early 1970s (Nilsson and Küller, 2000). It was also recognised that ecologically responsible patterns of human behaviour were required to solve the problems (Oskamp and Stern, 1987). The attitude most often discussed is environmental concern, a general attitude against environmental deterioration (Fransson and Tommy, 1999). Gagnon-Thompson and Barton (1994) reported that environmental concern is stimulated either by a real care for the nature or by a care for nature as a human resource. Previous studies demonstrated that environmental concern, at least to some extent, would determine actions encouraging the sustainable environment (Arbuthnot, 1977; Kallgren and Wood, 1986; Oskamp and Stern, 1987). Perceived risk of environmental deterioration was another factor, which appeared to be important for pro-environmental behaviour (Baldassare and Katz, 1992; Campbell, 1983; Fridgen, 1994; Schmidt and Gifford, 1989). Also knowledge of environmental impact caused by human activities has been suggested as a motive for actions by, among others, Gamba and Oskamp, (1994); Krause, (1993).

It seems, albeit, that what people choose to do to reduce their environmental impact often does not correspond well with what research in industrial ecology suggests they should be doing (Stern, 2000; Gatersleben *et al.*, 2002). This apparent lack of correspondence has called into question the criterion validity of behavioural measures of ecological lifestyles (Gifford *et al.*, 2011; Steg and Vlek, 2009; Swim *et al.*, 2011). One problem that troubles the use of behavioural measures to estimate environmental impact is that contextual elements, such as the technologies people use in their everyday lives, mediate and amplify the environmental impact of people's behaviour (Midden *et al.*, 2007). For instance Carbon Dioxide (CO_2) emitted during a daily commute varies depending on whether a person uses a bike, a private vehicle or Public Transport (PT) (Arnold *et al.*, 2018). Another problem specific to behavioural measures of ecological lifestyles is that the circumstances surrounding individual's lifestyles may have different and sometimes even opposed implications for different actions encompassed by such measures (Arnold *et al.*, 2018).

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

It is presumed that individuals who have greater environmental awareness are more likely to travel by PT or cycling if the physical conditions allow using these modes (Hamidi and Zhao, 2020). In this regard, the proper measurement of GEB of users can serve as a powerful tool for policy makers to assess and particularly to impose more user-focused policies to engage them in their daily ecological habits. For that a well-designed GEB questionnaire with proper items, that match the real lifestyle habits of users is also a precondition and require attention, considering different cultural and geographical contexts. Furthermore, whether the goal of the research is a behavioural change (Leeming *et al.*, 1993) or the evaluation of different determinants of ecological behaviour (Hines *et al.*, 1987), the accurate measurement of ecological behaviour is a precondition for positive change in human behaviour. Therefore, various studies in the literature used GEB to asses sustainable behaviour, such as Arnold *et al.,* (2018) used GEB measurement to asses electricity consumption of German adults. Kaiser and Wilson (2000) used sample of two transport associations: one aims to promote a transport system that has as little negative impact on humans and nature, the other represents automobile drivers' interests, such as proper road maintenance, allowing higher speed limits on freeways, and fighting gasoline-tax increases. Two versions of GEB questionnaire were proposed in Italian context to assess pro-environment travel behaviour. The first version was proposed by Gaborieau and Pronello (2021) based on Kaiser and Wilson (2000), which we call GEB-40 (40 dichotomous items); the second version was proposed by Duboz (2018) as an extended version of GEB-40, which we call GEB-51 (51 dichotomous items). One of the weaknesses of previous two Italian GEB versions (GEB-40 and GEB-51) was the inclusion of irrelevant and redundant items that were excluded in this study. Hergesell (2017) examined differences in holiday transport mode choices by persons' general level of environmental commitment across lifestyle domains and found that train users tend to be more environmentally committed while car users less.

At best of our knowledge, the studies measuring GEB questionnaire using the Rasch model (Rasch, 1961), whether in different cultural contexts or in single area, used limited and small sample size. Kaiser and Biel (2000) compared ecological behaviour of 247 Swedish and 445 Swiss people; Kaiser and Wilson (2000) compared 686 Californian students and 443 Swiss participants; Gaborieau and Pronello (2021) compare 131 Italian, 445 Swiss, and 247 Swedish participants; Hergesell (2014) collected sample of 349 German participants, although the sample size is still within acceptable boundaries according to Linacre (1994). Nevertheless, replication in a larger sample of population is highly desirable and the use of small sample was reported as one of the limitations of previous researches (Arnold *et al.*, 2018; Gaborieau and Pronello, 2021). The current research focused to obtain high item reliability, good separation indexes, and well-functioning items with a larger sample size. In addition, to reduce the fatigue of respondents, it has been paid attention to use comparatively few (26) and highly reliable items to assess the GEB, as explained in Chapter 3.

2.4.3 Mode choice modelling

Mode choice is one of the most vital stages in transport planning process and it has direct impact on the policy making decisions. Mode choice models deals very closely with the decision making and continue to explore the process of commuter's choice (Sekhar, 2014).

Mode choice analysis has received the attention among discrete choice problems in travel behaviour literature. Most traditional mode choice models are based on the principle of random utility theory (Zenina and Borisov, 2011). The most widely used Discrete Choice Model (DCM) is the Multinomial Logit (MNL). A limitation of MNL models is that they assume that the probabilities of each pair of alternatives are independent of the presence or characteristics of all other alternatives (Daniel Mcfadden, 1973). Other DCMs, such as the Multinomial Probit model (MNP), do not make this independence assumption, but parameter estimation is more difficult than MNL model, which weakens their use (Dow and Endersby, 2004). Since last decades the machine learning methods (classification techniques) (Zenina and Borisov, 2011; Hagenauer and Helbich, 2017) and data mining methods (Xie *et al.*, 2003) are widely used for mode choice analysis.

A large body of literature shows that travel mode choice is affected by different factors including individual and household characteristics (Dieleman *et al.*, 2002; Schwanen and Mokhtarian, 2005; Böcker *et al.*, 2017), built environment (Ewing and Cervero, 2010; Helbich, 2017), weather conditions (Böcker *et al.*, 2013), and trip characteristics (Racca and Ratledge, 2004). However, these are not the only variables that explain heterogeneity in the mode preferences. It has been well accepted that attitudes and perceptions play an important role in the decision-making process (McFadden, 1986; Atasoy *et al.*, 2013). According to Beirão and Sarsfield Cabral (2007) the choice of the mode of transport is highly influenced by the perception of the services' quality comparing to other characteristics. Attitudes and perceptions cannot be directly observed from the data and hence considered latent variables (Atasoy *et al.*, 2013).

Despite of these existing techniques, Structural Equation Model (SEM) provides a powerful methodology to translate attitudes and other latent variables into a statistical model (Bollen, 1989). SEM has been widely applied in social sciences (Bielby and Hauser, 1977). In transport research, attitudinal variables are studied to explain the travel behaviour of individuals through SEM (Atasoy *et al.*, 2013). Golob (2003) provides a detailed literature review on numerous applications of SEM in transport. The SEM of attitudinal variables are integrated into choice models, in order to make use of simultaneous estimation of choice and attitudinal variables (Atasoy *et al.*, 2013). These integrated models are called hybrid choice models, which are introduced by Ben-Akiva *et al.,* (1999) and Walker and Ben-Akiva (2002). They provide a general framework where attitudinal variables are considered as latent variables. These variables are introduced in the choice context through latent variable models and latent classes.

In integrated choice and latent variable models, the attitudinal variables are included as explanatory variables of the choice. Vredin Johansson *et al.,* (2006) analyse the effect of the latent variables of environmental preferences, safety, comfort, convenience, and flexibility on the mode choice using a sample of Swedish commuters. They provide insights for policy-makers so as to improve the transport systems through the use of the attitudinal variables. Espino *et al.,* (2006) study the mode choice behaviour for suburban trips by including the latent variable of comfort. Abou-zeid *et al.,* (2011) explain the variability in individuals' willingness to pay, with individuals' attitudes toward travel, through a latent variable model. They introduce a car-loving attitude and show that the individuals who dislike PT are more sensitive to the time and cost changes of public transport compared to others. This also confirms our choice of AFF (I like to drive) variable, which is affection towards car use as evidence in determining mode choice. Chen and Li (2017) integrates SEM and DCM for mode choice model for PT, which provides basis and inspiration for PT companies to improve the service quality (convenience, personal safety, and service environment) according to the perspective of passengers.

Residential location, neighbourhood type and urban form play a prominent role in determining the favoured travel mode (Wee *et al.*, 2003; Frank *et al.*, 2007; Pinjari *et al.*, 2007). This strengthens the choice of residential location (urban, suburban, and rural) variable in this study as one of the determinants in selecting the mode for commuting.

Different theoretical frameworks have been developed over the years for studying the effect of cognitive factors on behaviour, such as the Theory of Planned Behaviour (TPB) (Icek, 1991), Theory of Interpersonal Behaviour (TIB) (Triandis, 1980) and Schwartz's Norm Activation Theory (NAT) (Schwartz, 1978). However, a certain amount of criticism has been raised against attitude-based theories, partly because it is difficult to know whether attitudes control travel mode choice or vice versa. People do not always act as they say they will.

According to Devika *et al.*, (2020) attitude is the most significant factor in determining the mode choice behaviour. The private vehicle favouring attitude was found to have a stronger influence on the intention to use Public Transport (PT) as compared to that of PT favouring attitude of the people. They found that the PT attitude has a positive significant influence on the intention to use PT. It implies that as PT favouring attitude of the people increases, the intention to use it increases. The private vehicle attitude has a negative significant influence on the intention to use PT. This implies that as the private vehicle dependency of people increases, the intention to use PT decreases.

This is also confirmed in current study by using many environmental, subjective, and personal norm variables during iterative process of testing SEM model, which are not impacting the mode choice.

The aim of the inclusion of preferences is to better understand the underlying choice preferences of travellers and therefore increase the forecasting power of the choice model.

Chapter 3

Objectives and Methodology

Analyse and understand the key factors influencing mobility patterns and travel behaviour is a big challenge. The understanding of mobility patterns and travel behaviour helps to know the daily travel habits allowing to assess users' level of awareness about sustainable mobility behaviour, satisfaction and needs. Although, mobility pattern analysis just lets us to know where (origin-destination), when (time), why (purpose) and how (mode) people move, which is not sufficient to formulate the transport policies and making them more effective. The key is to identify what drives users to make these choices. To investigate these drivers, the understanding of human mind can help because the human mind is derived by their perceptions, habits, attitudes, experience, preferences, and cognitive aspects. A growing amount of literature identifies role of attitudes and cognitive aspects in understanding travel behaviour and, notably, mode choice.

Therefore, the focus of this research is to analyse what are the main determinant factors behind the travel decision making process of individuals, mainly using attitudes and preferences. To serve the purpose of the research it is fundamental to select appropriate data source among the available sources. For that, this research work firstly explores the understanding of different travel data sources reported in literature research section. Secondly, a case study of mobility apps was carried out to understand their use for travel data collection and analysis. As reported in literature review section, apps are limited to spatial and socio-demographic information collection, therefore detailed data collected from web survey (which can collect different types of detailed information) was mainly utilised in this research work to understand the mobility patterns and travel behaviour.

Thanks to the availability of detailed data collected from web survey, the current research has the following objectives:

- performing a case study of mobility apps by identifying smartphone apps as a recent tool for travel data collection and to understand if and how they can benefit the transport sector;
- investigate the mobility patterns of users in the study area to understand when, how, why and where they travel;
- define a market segmentation using preferences and attitudes to understand travel behaviour of users;
- assess the General Ecological Behaviour (GEB) of users to obtain a valid measure of the attitude towards the environment;
- investigate the main psychological determinants behind the mode choice of users.

The final research aim is to: a) propose solutions for better planning and programming transport systems with main attention to Public Transport (PT) and soft modes; to better understand the user's needs; b) develop targeted strategies to offer proper infrastructures, improve services, policies, and travel solutions to support transport planners and decision makers.

To reach the objectives, the proposed methodology has been defined in detail, providing five main stages:

- *case study of mobility apps*: this section describes in detail the review study done for all mobility apps for travel data collection and analysis;
- *survey design*: describing the design of survey with various sections included in the questionnaire;
- *survey administration and sample selection*: describing how the web survey was administered, the study area and sample selection;
- *data analysis design*: to understand mobility patterns of users; perform market segmentation by classifying the sample in groups of similar behaviour to understand their mode choice and investigate how the users can be attracted towards sustainable modes; Rasch measures estimate to assess the GEB of users to understand if this impacts the mode choice by obtaining a single measure of pro-environmental attitude after identifying pro-environment activism as one of the factors present in all clusters in market segmentation;
- *mode choice modelling* to identify the main psychological determinants behind the mode choice using SEM.

3.1 Case study of mobility apps

As explained in literature review section, Travel Surveys (TS) and other traditional methods have been used for travel data collection since 1930s but facing some difficulties with respect to the time, cost, respondent burden, etc. To overcome these limitations, digitalization opens the door for new travel data collection and analysis methods. To a large extent, the apps are, nowadays, one of the most comprehensive approach to collect data from all the transport modes. Stakeholders in several countries show a positive outlook towards the apps and have high expectation in terms of data collection in the future; however, they still hesitate because analyses about comparability with current methods in terms of accuracy have not been addressed yet. To fulfil this gap, a review of 81 apps developed in the transport sector has been performed in detail and the apps classified according to the purpose of development. Three main purposes have been identified and the apps evaluated according to their features and the methods used to collect the data. A SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis has then been performed to understand the strengths, weaknesses, opportunities, and threats of using the smartphone applications for understanding mobility patterns. Out of the 81 apps, only 24, providing a sufficient number of details, were considered for the SWOT analysis to assess their usefulness for researchers and practitioners.

SWOT analysis organizes thoughts and ideas into internal and external factors that may help and harm a company (Duxbury, 2012). This kind of analysis can be applied to transport decisions, allowing planning authorities to identify strengths and limitations of proposed data collection and analysis methods as well as possible opportunities and threats. Both strengths-weaknesses analysis, as well as the opportunities-threats analysis, have been based on the in-depth study of the 24 selected apps. They are based on the theoretical approach (Novicevic *et al.*, 2004) and are focused on three main topics: 1) data: availability and quality; 2) technical characteristics; and 3) design and user interface.

3.2 Survey design

The understanding of the various data sources and their pros, cons, and limitations allowed to select the most appropriate method to collect the data needed to the research. Thus, instead of apps, it has been decided to use innovative TS approach (web survey) to collect data because apps are not reliable yet and also limited to collect cognitive aspects. The quantitative approach has been adopted, collecting data through a web-questionnaire aimed to get in depth information related to opinions, intentions, attitudes, lifestyles, and preferences. To this end a self-administered web-questionnaire was previously designed (by the research group), named *"Come Ci Muoviamo?...ma soprattutto Come Vorremmo Muoverci?"* ("*Come ci Muoviamo*"). "*Come ci Muoviamo*" is composed by two different web-questionnaires. The first (Part A) includes questions already well established in literature, which can ensure well-grounded comparison. The second one (Part B) is composed by new questions, derived from recent results from behavioural theories to overcome some gaps observed in previous researches by Gaborieau (2016) and Duboz (2018). Part A is composed by seven and Part B by two units, as described in Table 3.

Table 3: Web-questionnaire sections

Sections	Description and main questions (Part A)	main questions
1	***Mobility in a standard week***: trip purposes, the most important one, trip frequencies and used transport means for each trip purpose	4
2	***Diary of most important trip***: origin and destination, timetables, travelled distance, satisfaction	14
3	***Integrated mobility***: trip cost, willingness to pay for faster or more ecological travels, major reasons of transport mean choice, knowledge about other transport modes, car parking conditions, activity during the trip, aspire about PT, evaluation of other transport means use	11
4	***Mobility as a Service***: car sharing, fair group bought, carpooling, transport service pre-defined packages	8
5	***Attitudes and preferences***: attitude to go out from home, attitudes towards private car, GEB	3
6	***Availability towards research***: voluntary participation to focus group, second web-questionnaire and to know the results	3
7	***Personal data***: age, income, level of education, job, household size and composition, availability of car, seasonal PT ticket, bike and car sharing subscriptions	10
	Description and main questions (Part B)	
1	***Information about the most important trip***: how information about trip is collected, permanence in intermodal hub, service in intermodal hub, control of meteorological forecast, change of route	5

2	***Attitudes and preferences***: attitudes to environment and pollution, value of time, cost, security, safety, comfort, and technology	7

The two questionnaires have been administered in two waves to avoid a single too long questionnaire. The total number of questions is 65, 53 in Part A and 12 in Part B. The Part B is linked to the previous section by getting a personal link to access it by email, so that only who answers to Part A can continue with the second one by digit own e-mail address at the end of Part A. The key field to connect answers between Part A and Part B is the e-mail address of the respondents. The two questionnaires contain 785 variables – 365 categorical, 32 ordinal, 306 interval and 82 ratio types.

The General Ecological Behaviour (GEB) questionnaire (section 5 of Part A in Table 3) used in this research is based on two previous questionnaires GEB-40 and GEB-51 but includes only 26 items (GEB-26) reported in Table 4, resulting from deleting redundant and problematic items found in GEB-40 and GEB-51. The questionnaire has been designed to collect polytomous data based on a 6-point Likert scale where 1 was “completely disagree” and 6 “completely agree”. 11 items were added extra than GEB-40 in three categories for GEB-51 as reported in Table A1 in appendix A.

Table 4: Structure of GEB-26 questionnaire

No.	Item description	Code
	Category 1 – Pro-social behaviour	
1	Sometimes I give money to panhandlers	CS1
2	From time to time, I give money to charity	CS2
3	If an elderly or disabled person enters a crowded PT vehicle, I offer him/her my seat	CS3
4	If I were an employer, I would not hesitate to hire a person previously convicted of crime	CS4
5	Sometimes I ride public transport without paying a fare	CS6_REVC
	Category 2 – Ecological garbage handling	
6	I put dead batteries in the garbage	R1_REVC
7	I sort glass wastes for recycling	R5
	Category 3 – Water and power saving	
8	I turn off the heat at night	AE4
9	I wait until I have a full load before doing my laundry	AE5
10	In winter, I leave the windows wide open for long periods of time to let in fresh air	AE6_REVC
	Category 4 – Ecologically aware consumerism	

11	I use fabric softener with my laundry	CE1_REVC
12	I always look to buy vegetables from biological agriculture	CE6
13	Sometimes, I sell goods I don't use anymore	CE7
14	Sometimes, I buy second hands goods	CE8
15	Sometimes, I offer goods I don't use anymore	CE9
16	Sometimes, I rent for free to someone, goods I occasionally use	CE14
17	I eat less meat than years ago	CE15
	Category 5 – Garbage inhibition	
18	I re-use plastic bag from the groceries	RR1
19	I sometimes buy beverage in cans	RR2_REVC
	Category 6 – Environmental activism	
20	I often talk with friends about problems related to the environment	V1
21	I am a member of an environmental organization	V2
22	In the past, I have pointed out to someone his or her un-ecological behaviour	V3
23	I sometimes contribute financially to environmental organizations	V4
24	I boycott companies using OGM or pesticides	V5
	Category 7 – Transport	
25	Usually, I do not drive my automobile in the city	T1
26	I usually drive on freeways at speeds lower than 100km/h	T2

Note: _REVC is reverse coded, where items positively formulated as environmentally damaging were revers coded.

3.3 Survey administration and sample selection

The survey was administered to the population living in the Piedmont region, located in the North-West of Italy (yellow area in figure 2). The region capital is Torino, where most of the trips start and end or representative of collected survey data. The former Province of Turin is a province in the Piedmont region of Italy. Its capital is the city of Turin. The province existed until 31 December 2014, when it was replaced by the Metropolitan city of Turin.[11] From geographical point of view, it had an area of 6,830 km^2 (2,640 square meters), and a total population of 2,306,676 (30 June 2011). There were 316 communes in the province - the most of any province in Italy. Turin, the former regional capital of the province, and capital of the present-day Metropolitan City of Turin was the first national capital of unified Italy in 1861.[11]

[11] https://en.wikipedia.org/wiki/Province_of_Turin, accessed on September 20, 2021.

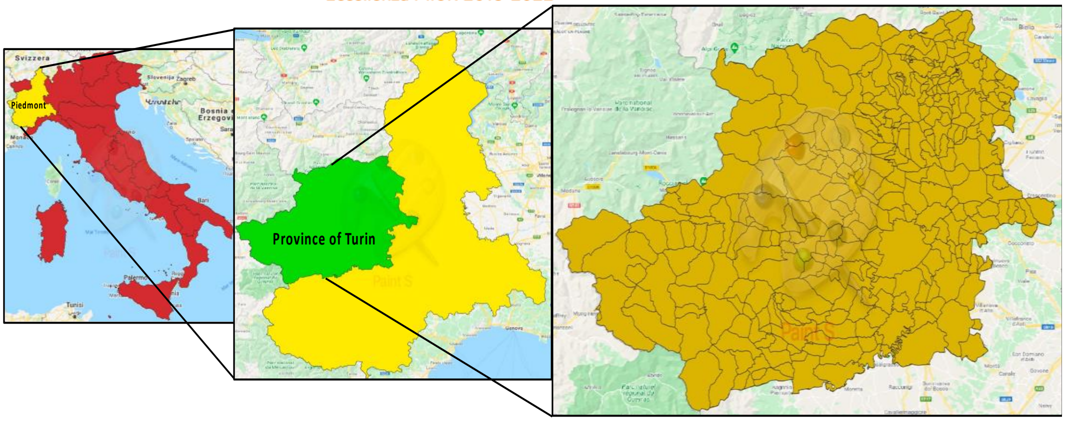


Figure 2: Study area Piedmont region (yellow) in Italy (red), province of Turin (green) with communes

The survey administration has been carried out with the method Computer Assisted Web Interviewing (CAWI). The two parts of the web-questionnaire are developed using the software Limesurvey, provided by Politecnico di Torino. The part A was made available on a dedicated website (www.comecimuoviamo.it) or people could accede to it thanks to a QR code included in a flyer. The survey was launched the 27th of October 2017 and closed the 24th of April 2018. Most data were collected in December and January. The survey *"Come Ci Muoviamo"* has been diffused to the population through a campaign managed by researchers. The survey also received the support from the local public bodies - *Regione Piemonte, Città di Torino,* main universities (*Politecnico di Torino* and *Università degli Studi di Torino*) and some transport operators which involved their contacts and customers. The main channels used to administer the survey were – email, flyers on the bus, link on Facebook page to customers of major bus PT operators, notice on web site to citizens of some municipalities (which accepted to support the survey), by formal notice to employees in Rail Infrastructure Managers, direct contact with major cultural and sport associations, newspaper with some articles and interviews of researchers, local radio, and twitter, including the survey in traffic bulletin. To this end, based on the snowball sampling plan, a sample of 4473 respondents was collected.

After data collection, the database has been built for the successive analyses, Part A and Part B have been merged to obtain a complete database. The database automatically generated from Limesurvey is not ready to be used for next analysis, because it includes some texts, which can be transformed in more suitable codes for the following examinations (e.g., “Yes/No” converted in “0 or 1”). For this reason, all answers of each variable are codified to make easier next steps. Thanks to the related research work carried out in the lab (Operti, 2019), the given data was already cleaned, which was very time consuming, but of utmost importance, provided in excel worksheets.

After collecting data and merging the database, following sections describes various analytical methodological steps for understanding travel behaviour in particular related to mode choice: firstly through a market segmentation to identify important factors across different groups of users and their level of sustainable behaviour; secondly, assessing GEB attitude measure and its impact on mode choice by identifying pro-environment activism as one of the factors in market segmentation; and, finally, mode choice modelling using Structural Equation Model (SEM) to correlate the identified important factors in market segmentation and Rasch measure of GEB attitude with stated mode choice.

3.4 Database construction

From the initial dataset of 4473 records and 785 features in total, 18 variables (see Table 5) were selected useful for understanding mobility patterns and the datatypes of all columns were checked i.e., datetime, integer, float so they can be set to proper datatype if they are not. The data types of selected 18 features is reported in Table B1 in appendix B.

Secondly, the dataset was checked manually, and the missing values were filled as much as possible. Table B2 in appendix B reports the number of missing values in selected feature. Going in depth into the dataset, it was found that the number of users who did not answered departure and arrival time choose a time slot of departure time. Six time slots were defined and presented in Table 5. There was not any direct method to fill in the time related missing values; the only way was to look manually each record, if they did not fill precise departure and arrival time, the corresponding time slots were seen to fill in the missing values. It means the departure time would be a random value among selected time slots. For instance, if the user chosen time slot 1 (departure time between 6h and 9h), the user’s departure time would be a random value from the vector [6, 7, 8]. In case a user selects two time slots, e.g., time slot 1 and 2, the user departure time value would be picked up from the vector [6, 7, 8, 9, 10, 12]. If the user selects more time slots, a random value would be chosen as departure time. The arrival time for the corresponding filled departure time records were filled by looking the travel duration feature, the travel duration was also calculated during the initial cleaning phase of the data using the origin and destination latitude/longitude coordinates. The same applies for the travel distance feature; the users who did not filled in the travelled distance, a travel distance slot was chosen for approximate distance. There were 6 travel distance slots defined in the survey, shown in Table 5.

Table 5: Six time and approximate travel distance slots

S.No.	Time slot	Distance slots
1	6h-9h	Maximum 10 km
2	9h-12h	Maximum 20 km
3	12h-14h	Maximum 30 km
4	14h-17h	Maximum 40 km
5	17h-20h	Maximum 50 km
6	20h-06h	Maximum 60 km

To fill in the values corresponding to the district and origin features, a python code was used to get the districts and origins using the latitude and longitude coordinates and the calculated values were cross-checked and verified using google maps. If some values did not match with the google maps results, the changes were done accordingly. A python library "reverse_geocoder" was used for this task. An example of this is shown in Table 6.

Table 6: Example of filling district and origin values

Input	Output
Latitude: '45.05057', Longitude: '8.26277'	[OrderedDict([('lat', '45.05057'), ('lon', '8.26277'), ('name', 'Moncalvo'), ('admin1', 'Piedmont'), ('admin2', 'Provincia di Asti'), ('cc', 'IT')])]

There was not any possible way to fill in the origin and destination code missing values, as well as the missing latitude and longitude coordinate values. After filling in all possible missing values, the dataset was checked to see which features still had missing values and how many. Table 7 gives an overview of the missing values. 1160 is the number of cells with missing values, while the number of records with missing values is 457. So, the final records useful for mobility pattern analysis are 4016, excluding 457 records.

Table 7: Missing values after filling some possible values

S.No.	Features	Missing values	Count
1	Respondent unique ID	False	0
2	Date of filling survey	False	0
3	District_Origin	False	0
4	Region_Origin	False	0
5	Latitude_Origin	False	0
6	Longitude_Origin	False	0
7	Code_Origin	True	244
8	Departure_Time	True	35
9	Arrival_Time	True	35
10	Travel_Duration	False	0
11	Travel_Distance	True	1
12	Travel_Mode	False	0
13	Latitude_Destination	True	181
14	Longitude_Destination	True	181
15	District_Destination	True	182
16	Region_Destination	True	140
17	Code_Destination	True	161
18	Travel_Purpose	False	0
Total	**18**	**18**	**1160**

107 features (reported in Table A2 in appendix A) out of total 785 related to attitudes and preferences were used mainly for the purpose of segmentation of users having similar behaviour by applying clustering. The socio-economic and mobility patterns related variables were also used for deeply understanding the clusters. For that, first the missing values were checked and remedied, followed by steps of statistical assumptions assessment and variable selection to prepare the data for segmentation.

3.5 Market segmentation

Segmentation approaches can range from throwing darts at the data to human judgment and to advanced cluster modelling (Horn and Huang, 2016). Rigorous analytic techniques (including factor analysis, discriminant analysis, k-means (Hartigan and Wong, 1979) and hierarchical clustering (Johnson, 1967), latent class segmentation (Bhatnagar and Ghose, 2004), and Factor Segmentation, are used to organize consumers into groups with similar attitudes, needs, and desires (Horn and Huang, 2016). Among the existing approaches, k-means clustering (Hartigan and Wong, 1979) technique is applied to get groups of similar behaviour of users in this study as explained in detail in the next section.

3.5.1 Statistical assumptions assessment and variable selection

During *statistical assumptions assessment*, first the normality was checked using Shapiro-Wilk test (Shapiro and Wilk, 2015), D'Agostino and Pearson's test (D'Agostino and Pearson, 1973), and Henze-Zirkler multivariate normality test (Henze and Zirkler, 1990). According to the result of normality checks, the dataset is not normally distributed. Hence, skewness and kurtosis is checked to identify the variables which are highly non-normally distributed. West *et al.,* (1995) suggests that skewness should be within the range of ±2; kurtosis values should be within range of ±7, and we considered this value.

During *variable selection* the variables which are not useful for differentiating clusters are removed. For final selection of variables, an iterative process of applying clustering (explained in section 3.5.2) and checking for different number of clusters starting from 3 to 6 clusters is followed. In iterative process of checking different number of clusters, the variables which have equal sample and within cluster means were removed. The variables with high skewness and kurtosis also belong to the variables excluded by an iterative clustering process and thus removed.

3.5.2 Cluster analysis

K-means is one of the most popular clustering methods. The basic idea is to give an initial but not optimal cluster, relocate each point to its new nearest centre, update the clustering centre by calculating the mean of the member points, and repeat the relocating-and-updating process until convergence criteria are satisfied (Mannor *et al.*, 2011). The advantage of this method is that it is fast, robust, and easier to use with large datasets with relative efficiency.

Before apply clustering, some assumptions are met to assess the cluster tendency of the data and to evaluate whether the data sets contain meaningful clusters or not. If yes, the number of clusters has to be defined; this process is defined "assessment of clustering tendency" or "feasibility of the clustering analysis". A big issue, in cluster analysis, is that clustering methods will return clusters even if the data does not contain any clusters (Adolfsson *et al.*, 2019), therefore it is important, firstly, to assess the cluster tendency. Two methods for evaluating the clustering tendency were used: i) statistical (Hopkins's statistic), and ii) metric based (Elbow, Silhouette score) method.

Hopkins statistic (H) (Lawson and Jurs, 1990) is used to assess the clustering tendency of a data set by measuring the probability that a given data set is generated by a uniform (no meaningful clusters) or non-uniform (contains meaningful clusters) data distribution. A value close to 1 shows that data is highly clustered, random data will tend to result in values around 0.5, and uniformly distributed data will tend to result in values close to 0.

Metrics based methods are used to find the optimal number of clusters to apply k-means clustering algorithm. Two methods, Elbow method and Silhouette score are used in this study. *Elbow method* (Marutho *et al.*, 2018) calculates the sum of intra-cluster distance between each point in the given cluster to its closest centroid. The method looks at the variance explained as a function of the number of clusters: one should choose several clusters so that adding another cluster does not allow a better modelling of the data. The second method is the *Silhouette score* (Rousseeuw, 1987), it uses the mean intra-cluster distance and the mean nearest-cluster distance for each sample to calculate the separation distance between the resulting clusters. A value of 0 indicates that the sample is on or very close to the decision boundary between two neighbouring clusters, negative values indicate that those samples might have been assigned to the wrong cluster, and higher Silhouette score relates to a model with better defined clusters.

After deciding the optimal number of clusters (k=6), the k-means clustering algorithm is applied on the selected dataset. Before applying clustering and to assess the cluster tendency, the dataset is standardized using MinMaxScaler function from sklearn python module. The obtained clusters are visualized using T-distributed Stochastic Neighbour Embedding (t-SNE) dimension reduction technique. t-SNE is a new technique that visualizes high-dimensional data by giving each datapoint a location in a two or three-dimensional map. It is much easier to optimize and produces significantly better visualizations by reducing the tendency to crowd points together in the center of the map (Van Der Maaten and Hinton, 2008). Furthermore, the number of records is reported for each cluster starting from 3 to 6 clusters. Python was used for clustering process.

3.5.3 Cluster validation statistics

The term cluster validation is used to design the procedure of evaluating the goodness of clustering algorithm results. This is important to avoid finding patterns in a random data, as well as in the situation where we compare two clustering algorithms. Generally, clustering validation statistics can be categorized into three classes (Brock *et al.*, 2008; Theodoridis and Konstantinos, 2009; Charrad *et al.*, 2014)). *Internal cluster validation* uses the internal information of the clustering process to evaluate the goodness of a clustering structure without reference to external information. *External cluster validation* consists in comparing the results of a cluster analysis to an externally known result, such as externally provided class labels. *Relative cluster validation* evaluates the clustering structure by varying different parameter values for the same algorithm. These approaches can also be used for determining the optimal number of clusters. Internal and relative cluster validation is used in this study.

3.5.4 Exploratory Factor Analysis (EFA)

After applying clustering to obtain the groups of similar users' behaviour, it was difficult to understand each cluster based on 82 variables. Hence, EFA is applied to understand the characteristics of each cluster. EFA belongs to multivariate statistical methods to identify the smallest number of hypothetical constructs that can parsimoniously explain the covariation observed among a set of measured variables (Tucker and MacCallum, 1997; Watkins, 2018). Before applying EFA, the requirements to perform EFA are checked as explained in the following sections.

3.5.4.1 Assumptions of EFA

First requirement to perform EFA is a linear correlation matrix (Ricolfi, (2002), obtained from a matrix CxV: column C equal to variables in the sample and row V equal to the users in the survey data. The variables have to be at least ordinal, but, in psychological research, it is common to use almost-ordinal variables. With the collected sample data, all variables used in the analysis satisfies these requirements.

Normality and Multicollinearity

To execute EFA, the variables must be normaly distributed, then a linear relationship between them can be expected (Piccolo, 2000). Firstly, Kolmogorov-Smirnov and Shapiro-Wilk tests are performed on data which are very sensitive to large samples: in that case they usually reject null hypothesis (Ruxton *et al.*, 2015). For this reason, kurtosis and skewness are also computed. If these two indices are, respectively, within the range of ±2 and ±7 (West *et al.*, 1995), the non-normality can be considered not too severe (Fabrigar *et al.*, 1999). If data does not respect this requirement, the EFA could still be performed: the minimum condition is that the relationship between variables and latent construct must be linear. Some degree of multicollinearity is desirable to apply EFA to identify interrelated sets of variables. In addition to the statistical bases for the correlations of the data matrix, there is also needed to ensure that the data matrix has sufficient correlations to justify the application of factor analysis. EFA requires a correlation matrix with absolute values greater than 0.3 (Albano and Molino, 2013). To ensure that performing EFA is profitable with own starting data, some diagnostic indices are calculated - Bartlett's sphericity test and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO measure).

Bartlett test of sphericity (Bartlett, 1950; Dziuban and Shirkey, 1974) is a statistical significance that the correlation matrix has significant correlations among at least some of the variables. However, increasing the sample size causes the Bartlett test to become more sensitive in detecting correlations among the variables. Bartlett's sphericity test assesses the hypothesis that correlation matrix is not an identity matrix. If this hypothesis is accepted, examined variables are correlated, so they are suitable to be analysed with EFA. For this reason, the test must provide small values of significance level (<0.05).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO measure) (Kaiser, 1970; Dziuban and Shirkey, 1974) is an index that represents the proportion of variance of examined variables that might be explained by the underlying factors. KMO measure can be calculated for all variables (and it provides information about whole database) or for each one, so the most suitable variables to be included in EFA can be selected. Following values of KMO measure (Table 8) are proposed by Howard (2016). With a huge number of variables, some authors suggest accepting just value greater than 0.70 (Norman and Streiner, 2014).

Table 8: KMO measures and threshold for Cronbach Alpha

KMO measure	Remark	Cronbach Alpha	Remark
0.00 through 0.50	Unacceptable – Bad	>0.9	Excellent
.50 through 0.60	Miserable – Bad	>0.8	Good
.60 through 0.70	Mediocre – Okay	>0.7	Acceptable
.70 through 0.80	Middling – Okay	>0.6	Questionable
.80 through 0.90	Meritorious – Good	>0.5	Poor
.90 through 1.00	Marvellous – Great	<0.5	Unacceptable

Sample size and variable/factor to observation ratio

The minimum dimension of sample for a reliable EFA is 200 (Guilford, 1957), but other authors state that smaller sample could be acceptable (Kline, 1994). For mathematic reasons, it's fundamental that there are more observations than variables, otherwise results will not be significant (Kline, 1994). The guidelines in literature about the proportion between variables and observations differ dramatically (Fabrigar *et al.*, 1999). Kline (1994) proposes a proportion of 1:2 (if factor structure is clear); Gorsuch (1983) suggests a ratio of 1:5; Everitt (1975b) and Nunnally (1978) recommend proportion of 1:10. Another guideline is about the proportion between factors and observations, which is more important than ratio between variables and observations (Arrindell and van der Ende, 1985). Among authors, there is a common agreement on the proportion between factors and observations equal to 1:20. All these rules are checked before performing EFA.

Variable selection

Variable selection is based on the inspection of computed *Anti Image Correlation Matrix* and *communality* of variables in the corresponding subset of samples. This matrix is composed by complementary to one of partial correlation coefficients. A partial correlation is the correlation that is unexplained when the effects of other variables are considered. The most valuable variables have small (<0.3) off-diagonal and high diagonal (>0.6) values (Norman and Streiner, 2014). All elements on the diagonal of this matrix should be greater than 0.5 if the sample is adequate according to Field (2000). The variables which have low values on the diagonal (<0.5) are left out from the EFA. According to Williams and Child (1974) communality below 0.2 should be removed.

Factor extraction method

Among the factor extraction methods, Unweighted Least-Squares Method (ULS) minimizes the sum of the squared differences between the observed and reproduced correlation matrices, ignoring the diagonals. Generalized Least-Squares Method (GLS) is similar to the previous one, but the correlations are weighted by the inverse of their uniqueness. Maximum-Likelihood Method (ML) computes parameter estimates that are most likely to have produced the observed correlation matrix. It requires that the sample has multivariate normal distribution. Principal Axis Factoring (PAF) is a method of extracting factors from the original correlation matrix, but initial estimates of the communalities are placed in the diagonal. These factor loadings are used to evaluate new communalities that substitute the previous communalities on the diagonal. Iterations continue until the changes in the communalities from one iteration to the next satisfy the convergence criterion for extraction. If the assumption of multivariate normality is severely violated, PAF can be applied (Fabrigar *et al.*, 1999). Using more than one method allows to measure reliability of factor structure. However, if the database is normally distributed, ML is better, if not PAF can be applied. If the number of factors is clear a priori, GLS or ULS methods are very efficient (Albano and Molino, 2013). We do not have clear factors a priori and the data is not normally distributed, therefore PAF is selected in this study.

Factor retention method

The resultant number of factors should not be benefitted by adding another factor, and the model should perform substantially worse if a factor is removed. For this reason, we need to be extremely careful in determining the factor retention decisions (Howard, 2016). The decision about how many factors have to extract should be relied on multiple criteria (Fabrigar *et al.*, 1999), including Kaiser criteria, Scree test, and Parallel analysis. *Kaiser criteria* compute the eigenvalues for the correlation matrix and determine how many of these eigenvalues are greater than 1 which is the number of factors to include in the model. A disadvantage of this procedure is that it is quite arbitrary and can leads to over factoring and sometimes under factoring (Fabrigar *et al.*, 1999). In *Scree test* the eigenvalues of the correlation matrix are plotted in descending order and factor number is identified with the drop in the eigenvalue's magnitude. It fits the examined correlation matrix, but it is too subjective, because there is no clear explanation of what is defined a substantial magnitude drop (Cattell and Jaspers, 1967). *Parallel analysis* identifies factor number through the comparison of eigenvalues computed from complete random data and ones calculated on real data (Horn, 1965; Humphreys and Montanelli, 1975). Each criteria have some advantages and drawback, so concurrent use of them could be the better approach and it is adopted in this research.

Factor rotation method

Once the number of factors has been chosen, the individual variable loadings need to be interpreted; however, the initial results are difficult to analyse (Fabrigar and Wegener, 2012). For this reason, we must rotate their EFA solutions. Several methods exist, and these fall into two categories: orthogonal and oblique.

Orthogonal rotations do not allow the resultant rotated factors to be correlated, which is often not preferable (Hinkin, 1995, 1998; Fabrigar *et al.*, 1999; Costello and Osborne, 2005) and include *quartimax* and *varimax* rotation. Varimax rotation seeks to increase the variances of the factor loadings, resulting in both large and small factor loadings. This is often preferable, as variables will (hopefully) clearly load or not load onto each factor. Alternatively, *oblique rotations* allow for the resultant factors to be correlated, causing authors to be preferable toward oblique rotations (Hinkin, 1995, 1998; Fabrigar *et al.*, 1999; Costello and Osborne, 2005) which include *promax* and *direct oblimin* rotation. Promax rotation begins by performing a varimax rotation, and then it allows the factors to correlate through raising the factor loadings to a specified power. Alternatively, direct oblimin rotations directly rotate to their final solution (Fabrigar and Wegener, 2012). To not underestimate the correlation among factors, an iterative approach of factor rotation methods applied. First direct oblimin rotation is applied to see if there is some correlation between factors >0.3. If correlation was not observed, orthogonal rotation was used in next run.

Factor structure evaluation

The choice of the most valuable factor structure is made considering three criteria. *Total explained variance*, where statistical quality is checked through the total explained variance accounted the by the final subset of selected variables within each cluster. *Cronbach Alpha* verifies the internal consistency of each factor. *Meaning and relevance of factors,* where the interpretation is carried out studying grade of simplicity of factor structure, factor over-determination, and how many makers (when a variable heavily loads just one factor) for each factor. The explained variance could be reported with sum of eigenvalues. The obtained values are compared with ones suggested in the literature, shown in Table 9 (Gliem and Gliem, 2003).

The statistical evaluation must be combined to an analysis of meaning and relevance of factor structure. The starting point is the interpretation of factors. This phase begins from those variables, the makers, who much load examined factor. In factor interpretation, the variable importance is defined studying their correlation with (loading on) factors. Some authors suggest measuring variable usefulness as reporting in Table 9 (Comrey and Lee, 1992).

Table 9: Variable correlation to factors and total explained variance

Correlation	Total Explained Variance	Evaluation
0.71	50%	Excellent
0.63	40%	Very good
0.55	30%	Good
0.45	20%	Sufficient
0.32	10%	Mediocre

In addition, there are two thumb rules to properly understand factor meaning (Albano & Molino, 2013): *factor over-determination*, when there are enough variables which show loading statistically different from zero. *Maker's presence*, where some variables heavily load only examined factor. A simple factor structure perfectly respects these rules and according to them a critical review of EFA structure is performed.

Factor scores computation

After the determination of the factor structure, it is necessary to estimate factor scores to represent respondents only through the latent constructs. There are two methods – refined and non-refined (Distefano *et al.*, 2009; Uluman and Dogan, 2016).

Refined methods include Regression scores, Bartlett scores and Anderson-Rubin scores. Scores from refined methods are linear combinations, based on the observed variables, which take into account what is shared between the factor and the item (shared variance) and what is not measured (unique variance) (Distefano *et al.*, 2009). The main advantage of this category is the production of factor scores which are highly correlated to a given factor, with unbiased estimation.

Non-Refined methods include sum scores by factor, sum scores above a cut-off value, sum scores standardized variables, weighted sum scores. These are very simple and efficient alternatives for researchers. They are defined as unsophisticated cumulative schemes (Grice, 2001). Non-refined methods have some advantages: firstly, their results do not strongly depend on used sample (Distefano *et al.*, 2009), secondly, they are very easy to perform.

Among the refined methods, Bartlett scores is chosen to compute the scores which was last step of EFA, because it maximizes correlation between factor scores and corresponding factor and minimize other correlations between factor score and other factors.

3.5.5 Profiling clusters

Finally, after EFA, the interpretation of clusters becomes easy with less variables (or factors) as compared to beginning just after clustering. This section interprets each cluster based on the following criteria:

- preferences and attitudinal variables excluded from clustering and EFA;
- socio demographic characteristics and mobility patterns considering the most important trip;
- factors emerged from EFA;

To describe clusters using extra variables not used in the cluster analysis and EFA, at first Kolmogorov-Smirnov and Shapiro-Wilk normality tests were performed to assess the data. Then, *Kruskal-Wallis (KW) nonparametric test* and *chi-square nonparametric test* are chosen to investigate eventual differences among the clusters. Mean/Median and standard deviation is also calculated for each variable used to describe the clusters. *KW test* is a nonparametric and does not make any assumptions about the data, where null hypothesis assumes that the samples (groups) come from identical populations if $p > 0.05$. Alternative hypothesis assumes that at least one of the samples (groups) comes from a different population than the others if $p < 0.05$ (McDonald, 2014). The test is appropriate when we have independent and dependent categorical ordinal variables for more than two independent groups with independent observations. Chi square is appropriate when the categorical variables in not ordinal but nominal. All assumptions are satisfied to apply these tests for the analysis.

3.6 Rasch model estimation for attitude measure

After observing pro-environment activism as one of important factors present in all clusters and identified in the literature, the people who behave in a more environment friendly way tend to be more sustainable. Therefore, a psychological model was selected to measure pro-environment attitude of respondent, using General Ecological Behaviour (GEB) questionnaire items to obtain a single measure. The estimation of general attitude towards the environment, based on the data collected by the GEB questionnaire, was analysed using Rasch Model for scale measurement (Rasch, 1961). Rasch analysis describes procedures that use a particular model with outstanding mathematical properties, developed by Georg Rasch (Rasch, 1961) for the analysis of data from tests and questionnaires in psychology, education, and other fields. The mathematical theory underlying Rasch models is a special case of Item Response Theory (IRT) and, more generally, a special case of a generalized linear model. Rasch analysis begins by ordering all possible response options to all items and all persons along a unitless logit-transformed continuum representing the levels of the latent construct (from very low to very high). It then statistically evaluates the hypothesis that people located higher on the continuum should show a higher likelihood of choosing response options that are also located higher on that same continuum scale (Wolins *et al.*, 1982). The statistical calculations employed by the Rasch model to locate and order persons and item difficulty is based on Guttmann Scaling (Pallant and Tennant, 2007). Rasch analysis can be applied to a variety of situations: the development of new rating scales, the analysis of the psychometric properties of existing scales, hypothesis testing of the structure of ordinal scales, constructing item banks and calculating change scores from ordinal scales (Pallant and Tennant, 2007). Rasch analysis can be used with both dichotomous and polytomous data sets via the dichotomous model or either of the polytomous models (Pallant and Tennant, 2007; Tennant and Conaghan, 2007). We used both dichotomous and polytomous model to compare the results of both scales as described in following sections.

For Rasch model analysis, the initial sample of 4473 records was resized to 4212 units excluding the persons whose destination was outside both Italy and the region. The 4212 records have been used in Rasch model estimation. The residential locations are classified in three areas, urban (metropolitan area of Torino), suburban (municipalities around Torino-first belt) and rural (rest of the territory-second belt). The Piedmont Territorial Demographic Observatory identifies a "first" and a "second" belt of municipalities surrounding Torino.[12] Most respondents come from urban area and the distribution of the three residential locations is: 2154 (51.14%) urban, 740 (17.57%) suburban, and 1318 (31.29%) rural.

3.6.1 Dichotomous Rasch Model (DRM)

Dichotomous Rasch model (DRM) (Rasch, 1961) is the simplest model in the Rasch family of models (Wright *et al.*, 2004). It was designed for use with ordinal data that are scored in two categories. The DRM uses sum scores from these ordinal responses to calculate interval-level estimates that represent person locations and

[12]https://web.archive.org/web/20140727134854/http://www.demos.piemonte.it/site/images/stories/caricafile/territori/E_area_metropolitana.pdf, accessed on July 15, 2021.

item locations on a linear scale that represents the latent variable (the log-odds or "logit" scale). The difference between person and item locations can be used to calculate the probability for a correct or positive response (x = 1), rather than an incorrect or negative response (x = 0). The equation for the DRM is expressed in equation (1):

$$B_n - D_i = \ln(P_{ni}/1 - P_{ni}) \qquad (1)$$

where:

B_n = ability of a specific person n;
D_i = difficulty of a specific item i;
P_{ni} = probability of person n correctly answering item i;
$1 - P_{ni}$ = probability of person n not correctly answering item i;
ln = "log-odds units" (logits), which is a natural logarithm.

The DRM specifies the probability P that the person n with ability B_n succeeds on item i of difficulty D_i.

The key Rasch model requirements suggested by Wind and Hua (2021) are unidimensionality, local independence, persons-invariant item estimates/person parameter separability, and item-invariant person estimates/item parameter separability. Evidence that data approximate these requirements provides support for the meaningful interpretation and use of item and person estimates on the logit scale as indicators of item and person locations on the latent variable (Wind and Hua, 2021).

3.6.2 Polytomous Rasch model

The *Polytomous Rasch model* is a generalization of the DRM developed for polytomous data (data with ≥2 ordinal categories) (Wind and Hua, 2021). It was derived by Andrich (1978), subsequent to derivations by Rasch (1961) and Andersen (1977). The two most widely used polytomous Rasch models are Rating Scale Model (RSM) (Andrich, 1978) and Partial Credit Model (PCM) (Masters, 1982). RSM is used when all items have same number of response categories, while PCM is used with different categories among items. We have same categories for all GEB items, therefore, RSM (Andrich, 1978) was applied. Below, we present the RSM as described by Planinic *et al.,* (2019). The probability of a person n endorsing category j over previous category *(j-1)* or being observed in category j of item i can be expressed in a Rasch–Andrich RSM as in equation (2).

$$log\left(\frac{P_{nij}}{P_{ni(j-1)}}\right) = B_n - D_i - F_j \qquad (2)$$

where:

- P_{nij} is the probability of observing category j for person n on item i;
- F_j is the Rasch–Andrich threshold (step calibration) or the point on the latent variable where the probability of person n being observed in category j of item i equals the probability of the same person being observed in category $(j–1)$;
- B_n is the ability of person n;
- D_i is the difficulty of item i.

The assumptions of RSM are same as DRM, furthermore there are rating scale guidelines suggested by Linacre (1999, 2002) to validate the polytomous scale of the survey questionnaire, which include:

1. 10 observations in each rating scale category;
2. regular observation distribution;
3. average measures advance monotonically with category;
4. the outfit MeaN-SQuare (MNSQ) is less than 2;
5. orderly series of step calibrations that advance in monotonic way;
6. ratings imply measures, and measures imply ratings;
7. step difficulties advance by at least 1.4 logits;
8. step difficulties advance by less than 5.0 logits.

The detailed description of these guidelines can be found in Linacre (2002).

3.6.3 Rasch measure and model fit estimation

Winsteps Rasch Analysis program version 4.8.0 was used for the parameter estimation for both Dichotomous Rasch Model (DRM) and Rating Scale Model (RSM). Winsteps implements two methods of estimating Rasch parameters from ordered qualitative observations: Joint Maximum Likelihood Estimation (JMLE) also known as UCON (Unconditional maximum likelihood estimation) (Wright and Panchapakesan, 1969) and PROX (Normal Approximation Algorithm) devised by Cohen (1979). Rasch model fits are used to examine the unidimensionality of the latent trait to measure attitude towards GEB. Unidimensionality is evaluated using: 1) point-biserial correlation (Brann *et al.*, 2021); 2) fit statistics; 3) Principal

Component Analysis of Residuals (PCAR) (Linacre, 2009); and 4) local independence.

Point-biserial correlation: point-biserial correlation is a useful diagnostic indicator of data miscoding or item mis-keying: negative or zero values indicate items or persons with response strings that contradict the variable. Positive values are less informative than INlier pattern sensitive FIT statistics (INFIT) and OUTlier sensitive FIT statistics (OUTFIT) statistics.[12] Li *et al.*, (2018) suggests that point-measure correlation larger than 0.3 indicate that items are measuring the same construct.

Fit statistics: Rasch analysis provides fit statistics to test assumptions of fundamental measurements. Once identified, persons and items that misfit can then be examined qualitatively to determine the causes of the problems. Problems may include items with confusing wording or items that assess a construct that is different from the principal construct being measured. Understanding poor fit can guide decisions about improving or dropping items (McCreary *et al.*, 2013). The Rasch model provides two indicators of misfit: INFIT is sensitive to unexpected responses to items near the person's ability level and OUTFIT considers differences between observed and expected responses regardless of how far away the item endorsability is from the person's ability (Tennant and Conaghan, 2007). MNSQ (MeaN-SQuare) is a chi-square calculation for the outfit and infit statistics. The ZSTD (Z-STanDardized) provides a *t*-test statistic measuring the probability of the MNSQ calculation occurring by chance. Since the ZSTD value is based on the MNSQ and in accordance with advice from Linacre (2012), we firstly examine the MNSQ for evaluating fit. If the MNSQ value lies within an acceptable range of fit, we ignore the ZSTD value as suggested by Boone *et al.*, (2014). According to Linacre (2012) guidelines, INFIT and OUTFIT mean-square fit statistics >2 represents distorted items, 1.5-2 represents unproductive items, 0.5-1.5 represents productive items and, <0.5 represents less productive but not degrading items for measurement. Typically, we identify respondents with ZSTD values of outside range ±2, as worthy of further investigation. For the detailed explanation and mathematical formulation of point-biserial correlation refer to Linacre (2008), while INFIT, OUTFIT, and ZSTD can be found in Gaborieau and Pronello (2021).

[12] https://www.winsteps.com/winman/ptbiserial.htm, accessed on November 10, 2020.

***Principle Component Analysis of Residuals (PCAR)*:** unidimensionality was checked through Principal Component Analysis (PCA) in Winsteps. Unidimensionality will hold if the first extracted factor explains a much higher amount of the total variance than that explained by the secondary dimensions. As mentioned before, multiple methods for assessing unidimensionality exist, including the data-model fit statistics. However, studies indicated that these statistics lack the sensitivity required to detect multidimensionality. Hence, it is logical to use PCA on the raw data and residuals, in addition to checking the data-model fit. For determining the unidimensionality of questions in the PCA method, Reckase (1979) suggested that the following criteria are good if : a) amount of variance explained by measures is >20%; b) unexplained variance of the eigenvalue for the first contrast is <3 and unexplained variance accounted by first contrast is <5%.

***Local independence*:** Item Response Theory (IRT) models assume local independence, meaning that after the contribution of the latent trait(s) to the data is removed, all that is left is random and normally distributed noise. Unidimensionality and local independence are related because, by definition, a data set is unidimensional when item responses are locally independent based on a single latent variable (Fayers, 2004; McDonald, 1981). Residuals are those parts of the data not explained by the Rasch model. High correlation of residuals for two items (or persons) indicates that they may not be locally independent, either because they duplicate some feature of each other or because they both incorporate some other shared dimension (Yen, 1984, 1993). In practical terms, a correlation of 0.4 shows a low dependency while the correlation needs to be around 0.7 to be concerned about dependency.[13]

Besides these, Rasch model assumptions include assessing reliability and separation of measures (persons and item reliability, person and item separation), Differential Item Functioning (DIF), evaluation of item difficulty by presenting on a Write map to evaluate construct validity (Lunz, 2010), and checking overlapping of items using Item Characteristic Curve (ICC) plots.

***Reliability and Separation of measures*:** reliability refers to the percentage of observed responses that are reproducible, which is estimated for both persons and items (Bond and Fox, 2003). Reliability ranges from 0 to 1. The closer the reliability

[13] https://www.winsteps.com/winman/table23_99.htm, accessed on November 10, 2020.

is to 1, the less the variability of the measurement can be attributed to measurement error (Stelmack *et al.*, 2004). The reliability value of >0.8 is highly acceptable, 0.6-0.8 is also acceptable, and <0.6 is not acceptable (Bond and Fox, 2003). Person and item separation indexes are used for describing the reliability of the test in Rasch analysis. A larger separation index means that the measurement function level can be distinguished more strongly by the test. The criteria of the person separation index were as follows: (a) 1.5 represents an acceptable level of separation, (b) 2 represent a good level of separation according to Miller and Dishon (2006) and 3 represents an excellent level of separation as reported by Duncan *et al.*, (2003). Separation can range from 0 to infinite, thus, there is no ceiling to this index and a higher value is better than a lower value.

Differential Item Functioning (DIF)**:** DIF procedures are used to determine whether the individual items on a test function in the same way for two or more groups of examinees (Scheuneman and Bleistein, 1989). Among the two DIF methods – Mantel-Haenszel (MH) and Rasch-Welch implemented by Winsteps – MH (Mantel and Haenszel, 1959) test for dichotomies and Mantel test for polytomies is used in this study (MH test is referred as Mantel for polytomies). The MH test is non-parametric and one of the most popular methods to detect DIF (Birch, 1964; Holland and Thayer, 1988). The detailed formulation of MH chi-square test statistic can be found in Li (2015) and Mantel and Haenszel (1959). DIF statistical significance is influenced by the size of DIF effect and classification groups. Scott *et al.,* (2009) suggests minimum of 200 respondents per group is good to ensure adequate performance. The sample used in this research satisfies each group size for DIF detection. Items are flagged as DIF when the MH probability value is ≤0.05 and then the DIF size is assessed according the criteria suggested by Zwick *et al.*, (1999). Moderate to large DIF when size CUMLOR (Cumulative Log-Odds Ratio) is ≥0.64, slight to moderate DIF when size CUMLOR is ≥0.43, and negligible when size CUMLOR is <0.43. We investigated DIF by three criteria: 1) gender; 2) residential location; and 3) four classified age groups.

3.7 Mode choice modelling using Structural Equation Model (SEM)

After having identified important factors (present in all clusters) using market segmentation to understand the mode choice and having investigated how people can be attracted towards sustainable modes, Rasch model was applied to obtain a single measure of pro-environment attitude. The reason was that pro-environment activism factor was present in all clusters, assuming that more environmentally friendly users tend to use sustainable modes. Finally, it is important to statistically validate the main psychological determinants behind mode choice. Therefore, Structural Equation Model (SEM) is used to test the relationship between antecedent constructs (identified in market segmentation and Rasch model estimation), variables, and modal choice. The various steps of methodology adapted in this research are explained in the next sections.

3.7.1 Variable selection and construction

This section describes the preprocessing steps for mode choice modelling using SEM. As first step, the variable selection is performed through an iterative process of using variables in the model building. Table 10 reports the final subset of variables selected. The initial list of variables used in the model testing are reported in Table A3 in appendix A.

Table 10: Variables used in mode choice model

No.	Variables*	Independent variables	Scale
	Section 1 - Satisfaction about the most imp trip (Part A)		
1	SatSpeed	Fast	1-Not at all to 6-very (6-point Likert scale)
2	SatFlexibile	Flexible	
3	SatReliable	Affordable and (constant) compared to the duration of the journey	
	Section 2 - Determinants of mode choice (Part A)		
4	UseLesDelay	Seem to have less delay	1-CD to 6-CA (6-point Likert scale)
	Section 4 - Attitudes towards travelling (Part A)		
5	LikDiscNewPlace	I like to move around looking for new places	1-CD to 6-CA (6-point Likert scale)
6	LikDareTravl	I prefer adventurous travel	
7	LikRechUnknDest	I'm willing to move to achieve unknown destinations	
8	LikTravlAltrntiv	I like to experiment with different travel alternatives to reach the same destination	
	Section 6 – Car travel attitude (Part B)		
9	AFF	I like to drive	NA, 1-CD to 6-CA (6-point Likert scale)
	Section7 – Personal details (Part B)		

10	Residential location (Home)	Where do you live?	Trinomial (Urban, Suburban, Rural)
11	Perceived Accessibility (PAC)	PT/bike/bike sharing/walk is available for most important trip?	Binomial (Yes/No)
		Dependent variables (Part A)	
12	ModBin	Travel mode used during most important trip	Binomial (Private and PT&Soft)
13	ModTrin		Trinomial (Private, PT, Soft)

Note: CD is completely disagree, CA is completely agree.
** The detailed description of variables is reported in Table A2 in appendix A.*

Among independent variables reported in Table 10, variables from 1 to 9 are directly observed from respondents. Classification of variable residential location in urban, suburban, and rural is described in section 3.6. Perceived Accessibility (PAC) states if Public Transport (PT)/bike/bike sharing/walk is available for most frequent trip as an alternative to car. It was constructed as binomial variable with Yes/No choice after cross-checking other details of respondents related to most frequent trip and mobility in a standard week. Other details include cross checking of travel modes used for different travel purposes: if they used other travel modes different than the one used in the most frequent trip: which was the other mode specified; if they have or not other travel alternatives; if they have PT/bike sharing subscriptions, and number of cars in their household. All these other details help to conclude whether PT/bike/bike sharing/walk is available for respondents during the most frequent trip, without considering that they use them or not.

For the construction of dependent variables, some pre-processing is required for trip chain mode choice. Most of the respondents use the trip chain as mode choice during the most important trip. Out of 4212 records selected in Rasch model estimation, two users mentioned “other” as mode choice out of 11 modes in the survey. Hence, those were excluded as not useful for model analysis. Thus, 4210 records were then used in mode choice model analysis. The mode distribution of final selected sample (4210 records) is given in figure 3. Hence, firstly, the pre-processing and understanding of trip chain is performed in detail to select the dominated mode among all those used during the most important trip.

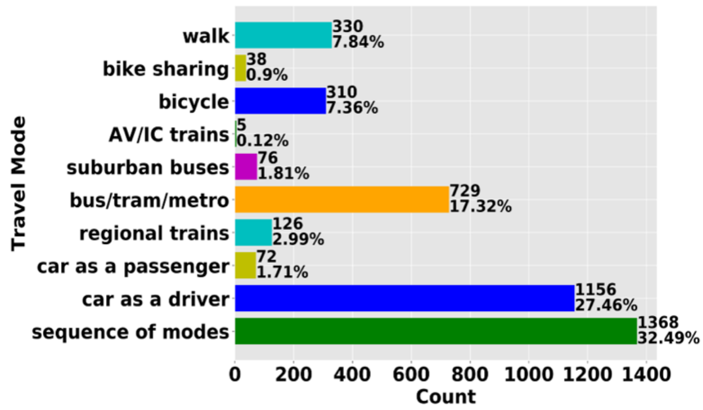


Figure 3: Mode distribution of 4210 selected records

3.7.1.1 Dependent variables

Observed dependent behaviours included in the models took two forms, all based on self-reported behaviours:

- one *binomial model choice* for the most frequent trip, labelled "ModBin", providing two modes:
  (1) "Private", for people using car as driver, car as passenger and car sharing;
  (2) "PT and Soft" for people using PT (bus/tram/train/metro) and soft modes;
- one *trinomial model choice* for the most frequent trip, labelled "ModTrin", providing three modes:
  (1) "Private", for people using car as driver, car as passenger and car sharing;
  (2) "PT" for people using PT;
  (3) "Soft", for people riding a bicycle or walking for their most frequent trip.

Finally, 13 variables were used in SEM model (11 independent variables, 2 dependent variables). The selection of final subset of variables is made by an iterative process of applying each step of methodology explained in the next section. Among total 4210 records, variable AFF has 255 missing values (as Not Applicable). Hence, 255 records were then excluded without any imputation to avoid the bias and 3955 were finally selected for model analysis.

3.7.2 Analysis and modelling

A five-stage procedure is used. IBM SPSS statistical tool version 23 for Exploratory Factor Analysis (EFA), and AMOS (Analysis of a Moment Structure) version 23 for Confirmatory Factor analysis (CFA) and SEM analysis were used. This section describes all the steps adopted in this study for mode choice modelling using SEM.

Step 1: Defining individual constructs

Based on the extensive literature reviewed, this study used SEM model to test the relationship between antecedent constructs, variables, and modal choice. Subsequently, based on the findings available in the literature and adopting an iterative process of testing constructs in existing behavioural theories, EFA was used to obtain reliable latent psycho-social constructs. All steps of performing EFA are explained in market segmentation section.

Step 2: Developing the overall measurement model

The constructs obtained in the first step were then used to develop measurement model (CFA) by drawing a path diagram. In path diagrams, ovals or circles represent latent variables, and rectangles or squares represent observed variables. CFA is a statistical technique used to verify the factor structure or the latent construct of a set of observed variables (Kismiantini *et al.*, 2014).

Step 3: Designing a study to produce empirical results

This step aims to assess the adequacy of sample size, select the appropriate estimation method and missing data approach. The observed or measured variables have traditionally been restricted to metric data (interval or ordinal) (Hair *et al.*, 2010). We have ordinal data, thus this condition is satisfied. Regarding sample size, according to Hair *et al.,* (2010), minimum sample size requirement is 100 for the models containing five or fewer constructs, each with more than three items and with high item communalities (0.6 or higher). In addition to these characteristics of the model being estimated, sample size should be increased, when data deviates from multivariate normality, using sample-intensive estimation techniques (e.g., ADF) and/or (3) missing data exceeds 10 percent. As suggested by Hair *et al,.* (2010), pairwise deletion of missing cases (all-available approach) is a good alternative for handling missing data when the amount of missing data is less than 10 percent and the sample size is ≥ 250. We have very large sample size >250 (4210) with 0.37% missing values; however, those values are not missing because they express the choice of respondents to the item as “Not Applicable”, so pairwise deletion of missing cases was used to avoid any manipulation and bias.

In AMOS, the built-in test for normality involves the calculation of Mardia’s coefficient, which is a multivariate measure of kurtosis. AMOS provides this coefficient and a corresponding “critical value” which can be interpreted as a significance test (a critical value of 1.96 corresponds to a *p*-value of 0.05). If Mardia's coefficient is significant (critical ratio is >1.96), the data may not be normally distributed. However, this significance test on its own is not a practical assessment of normality, especially in SEM. This is because these kinds of tests are highly sensitive to sample size, with larger sample sizes being more likely to produce significant (non-normal) results. According to that, it is recommended that the significance tests are used together with descriptive statistics, namely the kurtosis values for individual variables (Rosenblad, 2009). Kurtosis values >3 may indicate that a variable is not normally distributed (Westfall and Henning, 2013). As suggested by Hair *et al.,* (2010), our data is not multivariate normally distributed, hence, Asymptotically Distribution Free (ADF) estimation method was selected, due to its insensitivity to non-normality of the data, as its requirement of large sample sizes is also satisfied in the study.

Step 4: Assessing measurement model (CFA) validity

Measurement model validity depends on establishing acceptable levels of goodness-of-fit for the measurement model and finding specific evidence of construct validity.

Goodness of fit (GOF): according to Hair *et al.,* (2010), using three to four fit indices provides adequate evidence of model fit. However, we should report at least one incremental index (Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Normed Fit Index (NFI)) and one absolute index (Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA)), one goodness of fit index (GFI, CFI, TLI, etc.), one badness of fit index (RMSEA, Standardized Root Mean Squared Residual (SRMR), etc.), in addition to the chi-square (χ^2) value and the associated degree of freedom (df), because using a single Goodness of fit (GOF) index, even with a relatively high cut-off value, is no better than simply using the χ^2 GOF test alone (Marsh *et al.*, 2004). Thus, reporting the χ^2 value and df, the CFI or TLI, and the RMSEA will usually provide sufficient unique information to evaluate a model. Regarding the cutoff values of these indices, Hair *et al.,* (2010) suggest that, with number of observed variables <12 in the model and sample size >250, small χ^2 value with corresponding insignificant *p* value (>0.05), CFI or TLI of 0.95 or better, RMSEA of 0.07 with CFI of 0.97 or higher are good indicators of the acceptable model fit.

Construct validity: construct validity is made up of three components - Convergent validity, Reliability, and Discriminant validity. *Convergent validity* states that items that are indicators of a specific construct should converge or share a high proportion of common variance; this is assessed using factor loadings and Average Variance Extracted (AVE). According to Hair *et al.,* (2010), standardised loading estimates should be 0.5 or higher, and ideally 0.7 or higher. AVE of 0.5 or higher is a good rule of thumb suggesting adequate convergence. An AVE of less than 0.5 indicates that, on average, more error remains in the items than variance explained by the latent factor structure imposed on the measure. An AVE measure should be computed for each latent construct in a measurement model.

Reliability is assessed using Cronbach Alpha reliability test using SPSS statistics tool and Construct Reliability is computed as reported in Hair *et al.,* (2010). Reliability estimates of 0.7 or higher suggests good reliability, between 0.6 and 0.7 may be acceptable, provided that other indicators of a model's construct validity are good. High construct reliability indicates that internal consistency exists, meaning that the measures all consistently represent the same latent construct.

Discriminant validity is the extent to which a construct is truly distinct from other constructs and provides evidence that a construct is unique and captures some phenomena other measures do not. A more rigorous test is to compare the AVE values for any two constructs with the square of the correlation estimate between these two constructs (Fornell and Larcker, 1981). The AVE should be greater than the squared correlation estimate.

Step 5: Specifying the structural model and assessing validity

It involves specifying the structural model by assigning relationships from one construct to another based on the proposed model (figure 4) using path diagram. To understand determinant factors in the mode choice behaviour of users and following the findings in literature, we propose the hypotheses first assessing the direct effect of selected independent variables/constructs on modal choice and then mediation effects. Mode Pleasure (MP) and Travel Pleasure (TP) are exogenous constructs in the model.

Direct effects

H_1: Mode Pleasure (MP) has a significant impact on Perceived Accessibility (PAC).
H_2: Mode Pleasure (MP) has a significant impact on modal choice.
H_3: Mode Pleasure (MP) has a significant impact on I like to drive (AFF).
H_4: Travel Pleasure (TP) has a significant impact on modal choice.
H_5: Travel Pleasure (TP) has a significant impact on I like to drive (AFF).
H_6: Perceived Accessibility (PAC) has a significant impact on modal choice.

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

H_7: I like to drive (AFF) has a significant impact on modal choice.
H_8: Residential location (Home) has a significant impact on modal choice.

Mediation effects

Mediation analysis was performed to assess the mediating role of observed variables (PAC, Home, AFF) on modal choice. Four hypotheses are proposed to assess the mediation analysis as following:

H_9: PAC mediates the relationship between MP and modal choice.
H_{10}: AFF mediates the relationship between MP and modal choice.
H_{11}: AFF mediates the relationship between TP and modal choice.
H_{12}: Home mediates the relationship between PAC and modal choice.

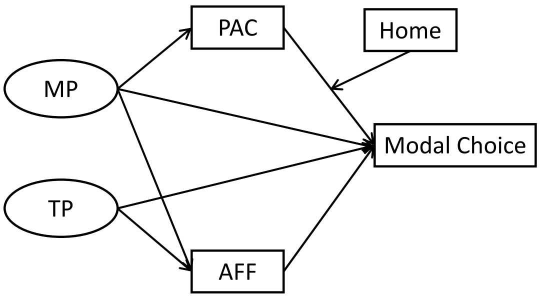


Figure 4: Proposed mode choice model

After specifying the relationships among the variables/factors based on the proposed hypotheses, the SEM model is then estimated and assessed using the same criteria used in the measurement model validity. A recent review of handling categorical and other non-normal variables in SEM (Kupek, 2005, 2006) recommends Asymptotically Distribution Free (ADF) method (Browne, 1984) with larger sample size, which is used for ModTrin. Extremely non-normal variables such as binary may be difficult to handle using ADF method with sufficient precision according to Kupek (2006). Therefore, Maximum Likelihood Estimation (MLE) with bootstrapping is used for large sample size and non-normal binary dependent variable ModBin. Along with observing the overall model fit, particular emphasis was placed on the estimated parameters for the structural relationships, to provide empirical evidence to the hypothesized relationships depicted in the SEM model.

Chapter 4

Results

This chapter describes the results obtained in this study. After the results of case study of mobility apps, a brief description of sample is presented showing the socio-economic attributes and mobility patterns. Following sections present the results of market segmentation using cluster analysis, followed by Exploratory Factor Analysis (EFA) to identify the important factors present in all cluster and to understand how people can be addressed towards more sustainable modes. Then, results of Rasch model analysis are presented to assess the General Ecological Behaviour (GEB) of users, to understand if it influences the mode choice. To this end, a single measure of pro-environmental attitude has been defined and the pro-environment activism was found as one of the factors present in all clusters in market segmentation. Finally, the results of mode choice modelling using Structural Equation Model (SEM) are presented to identify the main psychological determinants behind the mode choice.

4.1 Case study of mobility apps

Around 100 smartphone apps, Software Development Kits (SDKs), and platforms, related to transport sector, were found but only 81 suited the criteria defined in the methodology. In the next subsections the results of the classification are reported followed by the SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis. The various apps developed overall the world are depicted in figure 5 (some apps are used in more than one country; thus, the number of depicted apps is greater than 81) that shows they are mainly concentrated in Europe and North America while a few are in Australia, Singapore, and Africa. In Europe, The Netherlands is the most active country in developing and using apps.

A total of 81 apps, retrieved from the literature and on the websites of the companies, universities, and research centres have been found and analysed, observing that they are mainly focused on travel data collection with three different objectives: 1) Travel Data Collection and Analysis (TDCA); 2) Travel Surveys (TS); and 3) Promote Sustainable Mobility (PSM). Table 11 reports the classification of the apps/SDKs/Platforms (alphabetically ordered) according to the objectives. The most numerous categories refer to TDCA with 41 apps, followed by PSM (30 apps) and TS (20 apps). The apps developed to TDCA, aiming at understanding the travel behaviour of people, actively collect acceleration data as well as spatial and temporal data, further analysed to understand the mobility patterns. 6 out of the 41 apps are common to the group related to TS purpose. This last category provides applications detecting speed, location, and departure and arrival times automatically, storing all the data when individuals participate to a TS. Indeed, along with automatic travel data collection, survey questionnaires are used when users have to manually enter their mobility information. The PSM apps are the answer of technology to contribute to tackle one of the primary concerns for urban areas in the 21st century, which is sustainability in using resources and in maintaining environmentally conscious approaches to urban development (Gebresselassie and Sanchez, 2018). To this end, these apps use the same type of algorithms and trip visualisation as the previous ones, but their aim is to influence travel behaviour, trying to promote sustainable travel choices and to reduce environmental impacts.

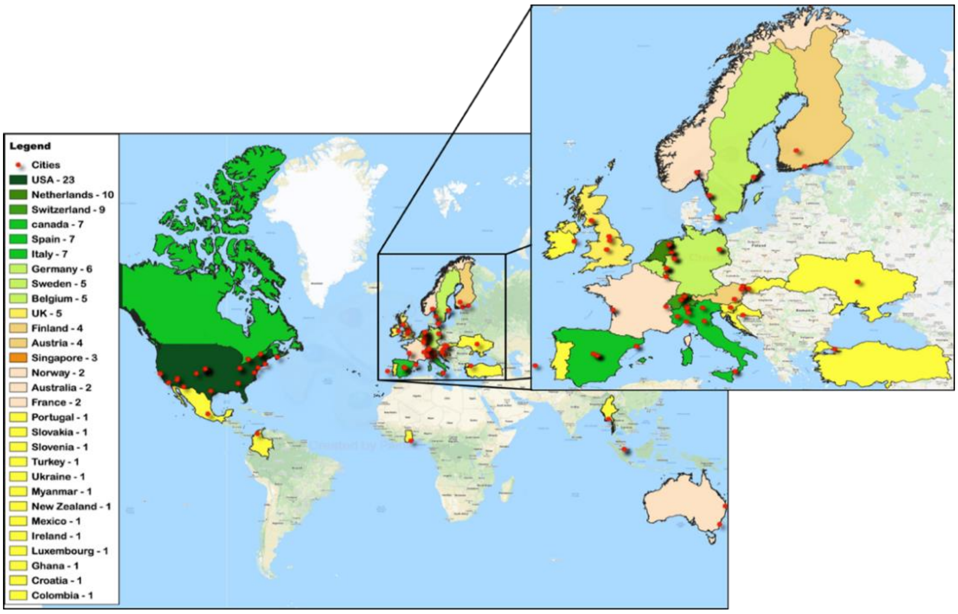


Figure 5: Smartphone apps developed in the world: number of apps per each country by highlighting in European countries and cities (red stars)

Table 11: Apps/SDKs/platforms classification based on purpose of development

Category	Purpose	Classification in alphabetical order
Apps	**TDCA**	AggieTrack[14] , CITYing (Shin *et al.*, 2015), CityLogger[15] , Commute Warrior[16] , CONNECT (Vlassenroot *et al.*, 2015), DataMobile (Patterson and Fitzsimmons, 2016), Dynamica (*18*), E-Mission (Shankari *et al.*, 2018), e-mobiliTI (Cellina *et al.*, 2013), GoEco Tracker (Cellina *et al.*, 2016), Guide2Wear Tracker[17], HDYCopilot (Fernandes *et al.*, 2015), IBB CepTrafik (Dilek and Ayozen, 2016), i-Log App (Maddalena *et al.*, 2019), InnoZ tracker [18], LAPSMobile[19], MEILI(Prelipcean *et al.*, 2018), Metropia (Zhu *et al.*, 2013), Mobilita Dinamica [20], MobilitApp (Puglisi *et al.*, 2016), Modalyzer[21], Moje poti[22], MOVE (Vlassenroot *et al.*, 2015), MoveSmarter (Geurs *et al.*, 2015), MTL Trajet (Fallah-Shorshani *et al.*, 2018), MyMoby[23], My Places Diary(Weber *et al.*, 2014), PinMe (Mosenia *et al.*, 2018), Predict.io Demo[24], Routes, RouteScout[25], Sense.DAT[26], Sesamo[27], SmartMo (Berger and Platzer, 2015), Studio Mobilita[28], TapLog, TRAC-IT[29], TravelWatcher (Teeuw *et al.*, 2012), Tripzoom

[14] http://fr.4androidapps.org/developer/lenss-tamu/aggietrack-download-8698.html, accessed on April 22, 2019.
[15] https://tts2.ca/app/our-app-city-logger/, accessed on June 06, 2019.
[16] http://transportation.ce.gatech.edu/commutewarrior, accessed on April 26, 2019.
[17] https://play.google.com/store/apps/details?id=de.innoz.innoztracker.guide2wear, accessed on April 8, 2019.
[18] https://play.google.com/store/apps/details?id=de.innoz.innoztracker, accessed on April 7, 2019.
[19] https://play.google.com/store/apps/details?id=ca.itinerum.lapsmobile, accessed on May 24, 2019.
[20] https://my-moby.com/#!/, accessed on June 7, 2019.
[21] *www.modalyzer.com*, accessed on May 27, 2019.
[22] https://www.itf-oecd.org/sites/default/files/docs/passenger-mobility-app-slovenia.pdf, accessed on June 3, 2019.
[23] https://play.google.com/store/apps/details?id=it.toniciminds.yangonbus&hl=en, accessed on May 1, 2019.
[24] https://www.predict.io/, accessed on April 4, 2019.
[25] https://apps.apple.com/app/routescout/id624140294?ign-mpt=uo%3D4, accessed on April 15, 2019.
[26] http://archief.dat.nl/en/products/sensedat/, accessed on May 28, 2019.
[27] http://sesamo.nl/, accessed on April 21, 2019.
[28] https://studio-mobilita.ch/eng/page/apps?project=public, accessed on June 2, 2019.
[29] https://www.locationaware.usf.edu/ongoing-research/projects/trac-it/, accessed on April 12, 2019.

		(Broll *et al.*, 2012), UnCrowdTPG (Gustarini *et al.*, 2014), Wander (Rieser-Schüssler and Axhausen, 2014), Woorti (Cornet *et al.*, 2019)
	TS	AggieTrack, ATLAS II, Boulder Travel Survey[30], CityLogger, DailyTravel[31], DataMobile, farMove, Fort Collins Travel Survey[32], Future Mobility Sensing (Carrion *et al.*, 2014), GPS-ATD (Yen *et al.*, 2012), Itinerum (Patterson *et al.*, 2019), Mobile Market Monitor[33], rMove[34], RouteScout, Sesamo, SmartMo, T: TravelSurvey[35], TRavelVU[36],Wander Nosa[37], X-ING[38]
	PSM	Bellidea(Cellina *et al.*, 2018), Better Points[39], CicloGreen[40], CO2GO (Manzoni *et al.*, 2011), Commute Greener, GoEco! (Cellina *et al.*, 2016), GreenOwl, Green Travel choice, Guide2Wear Tracker, InnoZ tracker, LetsGoTessValley[41], MatkaHupi (Jylhä *et al.*, 2013), Metropia, MoveMore (Helle *et al.*, 2018), MoveUs[42], Peacox[43], PEIR (Mun *et al.*, 2009), Positive Drive[44], Quantified

[30] https://appadvice.com/app/boulder-travel-survey/1277832197, accessed on April 20, 2019.
[31] https://dailytravelapp.com/, accessed on April 16, 2019.
[32] https://appadvice.com/app/fort-collins-travel-survey/1225449302, accessed on April 29, 2019.
[33] https://www.mobilemarketmonitor.com/, accessed on May 27, 2019.
[34] https://rmove.rsginc.com/, accessed on April 10, 2019.
[35] https://digital.library.unt.edu/ark:/67531/metadc700116/, accessed on June 30, 2019.
[36] https://www.travelvu.se/, accessed on April 23, 2019.
[37] https://appadvice.com/app/wander-noosa/1145229490, accessed on April 23, 2019.
[38] https://appadvice.com/app/x-ing/1450587308, accessed on April 25, 2019.
[39] https://www.bellamossa.it/, accessed on June 3, 2019.
[40] https://www.ciclogreen.com/, accessed on June 29, 2019.
[41] http://www.letsgoteesvalley.co.uk/, accessed on March 30, 2019.
[42] http://www.moveus-project.eu/, accessed on June 21, 2019.
[43] http://www.project-peacox.eu/, accessed on June 1, 2019.
[44] https://www.energiekbreda.nl/duurzame-mobiliteit/fietsen-in-breda/positive-drive-app, accessed on April 17, 2019.

		Traveller (Jariyasunant *et al.*, 2012), Routecoach[45], SBBMyWay[46], SETA Tracking[47], SMART[48], SUPERHUB (Gabrielli *et al.*, 2013), TRAKiT[49], Tripzoom, UbiActive (Fan *et al.*, 2012), UbiGreen Transportation Display (Froehlich *et al.*, 2009), Zwitch[50]
Platforms	**TDCA**	Google Timeline[51], INRIX[52], Metropia Total Mobility, MOVESMART, MODE[53], WhereIsMyTransport[54]
	PSM	Metropia Total Mobility
SDKs	**TDCA**	MOPRIM, MOTIONTAG[55], Predict.io, Sentiance[56]

[45] http://www.routecoach.be/, accessed on April 18, 2019.
[46] https://www.sbb.ch/de/fahrplan/mobile-fahrplaene/mobile-apps/myway.html, accessed on March 29, 2019.
[47] http://setamobility.weebly.com/seta-app.html, accessed on June 3, 2019.
[48] https://www.smartintwente.nl/, accessed on April 22, 2019.
[49] https://trakitapp.ca/, accessed on June 2, 2019.
[50] https://www.zwitch.eu/, accessed on June 5, 2019.
[51] https://support.google.com/maps/answer/6258979?co=GENIE.Platform%3DDesktop&hl=en, accessed on April 9, 2019.
[52] http://inrix.com/products/ai-traffic/, accessed on April 16, 2019.
[53] https://www.ait.ac.at/en/solutions/sensing-travel-behavior/mode/, accessed on May 4, 2019.
[54] https://www.whereismytransport.com/, accessed on April 11, 2019.
[55] https://motion-tag.com/en/mobility/, accessed on May 2, 2019.
[56] https://www.sentiance.com/, accessed on May 1, 2019.

In Table 12, some common issues as well as differences among the categories of applications do appear. Apps in colour reveal that TDCA apps are those most easily including the characteristics needed for performing TS or to PSM. Instead, no apps fulfil both purposes of surveys and sustainability. This is because PSM apps are thought to bring on changes of travel behaviour through an increase of awareness about personal mobility patterns and proposals to use soft modes. Alternatively, a pure data collection has a mechanistic scope that can become strategic when supporting transport planners thanks to a deeper knowledge of people mobility patterns.

Thus, the main purpose of the development of the apps strongly influences their design as well as their user interface but also the accuracy of reported behavioural change. The information released to user has to be precise when reporting the time and distance travelled with the different modes, to allow the comparison among the different choices; furthermore, to lure travellers to continue to use the app, it must be reliable and ensure a good user experience. Such elements imply a development more geared to the user and, sometimes, a wider set of options and features suiting user needs. Such consideration is confirmed looking at Table 12, where the apps are classified according to their features. Among the applications fulfilling more objectives, there are a few including a high number of characteristics and, hence, are more useful both to planners and users alike. Further in detail, the apps ticking most boxes - out of the 33 (TDCA), 7 (TS) and 16 (PSM) features - are Tripzoom and E-mission. Tripzoom includes 12 features: 5 of TDCA and 7 of PSM. E-mission has all 13 features of TDCA. The other apps presenting more characteristics, out of the 33 related to TDCA are: Woorti (11); e-mobiliTI (9); MobilitApp (9); AggieTrack (8). Instead, GoEco! and Bellidea includes features from both TDCA (respectively, 5 and 6) and PSM (respectively 6 and 4). The few apps focused on TS include the basic features common to TDCA, as location tracking, mode detection and purpose. Some of them require an interaction with the user to check the information and revise responses if necessary (FM Sensing and SmartMo). All the 81 apps were studied in detail to understand which methods (sensors, API and techniques) have been used to develop the features; to this end, a form was designed, providing all the information useful to meet the objective of the research: the developer, funding organizations, lapse of operation, location, number of users, features and methods used to design it, accuracy of data, battery consumption, problems and future work. This analysis showed that a lot of information about technical specifications were missing. The reason why might be their unwillingness

Table 12: Classification of apps based on features

Purpose		Data typology	Features	Applications
TDC	TDCA	Automatic Tracking/ Recording	Route Tracking	ATLAS II, Bellidea, Better Points, CO2GO, DataMobile, E-Mission, e-mobiliTI, GoEco, GoEco Tracker, Green Travel Choice, Guide2Wear-Tracker, InnoZtracker, Itinerum, MMM survey, MobilitApp, Modalyzer, MODE, MojePoti, MOTIONTAG, MTL Trajet, MyMoby, Positive Drive, Routecoach, Seasamo, Sense.DAT, Sentiance, SMART, SmartMo, TRAKiT, TravelSurvey, TravelWatcher, UbiGreen Transportation Display, Wander Nosa, Woorti, Zwitch
			Location Tracking	CITYing, Commute Warrior, CONNECT, DataMobile, i-Log, MOVE, MoveMore, My Places Diary, PEIR, PinMe, Woorti, Studio Mobilita, TapLog, Tripzoom, UnCrowdTPG, Wander
			Trip Distance	AggieTrack, Bellidea, CicloGreen, CITYing, CO2GO, Commute Warrior, E-Mission, GoEco, GoEco Tracker, Green Travel Choice, InnoZ tracker, Modalyzer, MODE, MoveMore, MoveSmarter, MTL Trajet, Positive Drive, Quantified Traveller, Sense.DAT, SETA Tracking, SmartMo, TapLog, TRAKiT, TravelVU, TravelWatcher, UbiActive, Woorti, Zwitch
			Trip Duration	AggieTrack, ATLAS II, Bellidea, CITYing, CO2GO, Commute Greener, Commute Warrior, Dynamica, E-Mission, FM Sensing, GoEco, GoEco Tracker, Guide2Wear-Tracker, IBBCepTrafik, InnoZ tracker, Metropia, Mobilita Dinamica, Modalyzer, MoveMore, MoveSmarter, MyMoby, Quantified Traveller, Sense.DAT, Sesamo, SMART, SmartMo, TapLog, TRavelVU, TravelWatcher, UbiActive, Wander, Woorti, Zwitch
			Stay duration at	Mobilita Dinamica, My Places Diary
			Stop detection	e-mobiliTI, FM Sensing, TapLog, UnCrowdTPG

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

		Speed calculation	AggieTrack, Bellidea, CicloGreen, Dynamica, TapLog, IBB CepTrafik, TRavelVU, TravelWatcher,
		Travel Cost	Sense.DAT, TapLog, Tripzoom
	Inferred Information	Mode detection	AggieTrack, Bellidea, CITYing, CO2GO, CONNECT, Dynamica, E-Mission, e-mobiliTI, FM Sensing, GoEco, GoEco Tracker, Green Travel Choice, Guide2Wear-Tracker, i-Log, MatkaHupi, MEILI, MobilitApp, Mobilita Dynamica, MODE, MMM Survey, Modalyzer, MOTIONTAG, MOVE, MoveSmarter, MTL Trajet, My Places Diary, MyMoby, Peacox, PEIR, PinMe, Positive Drive, Predict.io Demo, Quantified Traveller, SBB MyWay, Sense.DAT, Sentiance, Sesamo, SETA Tracking, SMART, TapLog, TRAC-IT, TRAKiT, TRavelVU, TravelWatcher, Tripzoom, UbiActive, Wander, Zwitch
		Trip Purpose	AggieTrack, CITYing, CONNECT, Dynamica, E-Mission, e-mobiliTI, GoEco Tracker, MEILI, Modalyzer, MODE, MMM Survey, MOTIONTAG, MOVE, MoveSmarter, MTL Trajet, My Places Diary, Peacox, Sense.DAT, Sesamo, SmartMo, TRAC-IT, TRAKiT, TravelWatcher, Wander, Woorti
	Network Information	Traffic Information	Commute Greener, IBB CepTrafik, MobilitApp, MyMoby, Peacox, SMART, SUPERHUB, TRAC-IT, Tripzoom, UnCrowdTPG
		Accident Detection	HDYCopilot, Metropia, MobilitApp, MoveUs, Sentiance, SUPERHUB
		Weather Conditions	IBB CepTrafik, MoveSmarter, MoveUs, Peacox, Sense.DAT
		Real time Chat	Mobilita Dinemica
	Visualization	Map Visualization	CO2GO, DataMobile, E-Mission, Guide2Wear-Tracker, IBB CepTrafik, Mobilita Dinemica, MobilitApp, MoveSmarter, MyMoby, My Places Diary, Predict.io Demo, TapLog, TRavelVU, TravelWatcher, SmartMo, Wander
	Suggestions	Alternative route solutions	IBB CepTrafik, SMART, Woorti
		Edit/Correct Option	e-mobiliTI, InnoZ tracker, MMM Survey, Modalyzer, My Places Diary, Sense.DAT, SmartMo, TRavelVU,

	User Validation	Bellidea, CONNECT, E-Mission, GoEco Tracker,
Personal/ Useful Information	Travel experience metrics (e.g. mood)	Sense.DAT, Woorti
	UserSatisfaction/ Feedback	e-mobiliTI, i-Log App, SUPERHUB, Woorti
	Socio Demographic Information	AggieTrack, i-Log App, MTL Trajet
Environmental Impact	Carbon footprint/ CO_2 emission	CITYing, e-mobiliTI, InnoZ tracker, MobilitApp, Modalyzer, Woorti
	Calories burned	E-Mission, MobilitApp, Sense.DAT, Woorti
	CO_2 saved	MobilitApp, Sense.DAT
	Step Counter	E-Mission, MobilitApp
	Energy Consumptions	e-mobiliTI
Other functions	Web interface	E-Mission, Itinerum, MMM Survey, MOVE, PEIR, Studio Mobilita, SUPERHUB, TRAKiT
	Backend integration	AggieTrack, CITYing, DataMobile, Dynamica, E-Mission, e-mobiliTI, GoEco, IBB CepTrafik, i-Log, Modalyzer, MODE, Moje poti, MoveSmarter, MOVE, Predict.io Demo, Studio Mobilita, TRAC-IT, TRAKiT, Tripzoom, UnCrowdTPG
	Travel Statistics	AggieTrack, Dynamica, Mobilita Dinemica, MyMoby, Sense.DAT, Studio Mobilita, Woorti
	Calendar View	Commute Warrior, Dynamica, Mobilita Dinemica,
	Survey Questionnaire	Better Points, CONNECT, UbiActive
	Setting goals	E-Mission
	Community sharing	E-Mission

	Data typology	Features	Applications
TS	Trip Information	Origin/Destination	DataMobile, FM Sensing, GPS-ATD, Itinerum, rMove, SmartMo, TravelSurvey, TravelVU
		Trip Mode	DataMobile, FM Sensing, GPS-ATD, Itinerum, rMove, SmartMo, TravelSurvey, TravelVU
		Trip Purpose	DataMobile, FM Sensing, Itinerum, rMove, SmartMo, TRavelVU
	Other functions	Correction/Edit option	FM Sensing, SmartMo
		Socio Demographic information	DataMobile, Itinerum, MTL Trajet, TravelSurvey, TravelVU
		Vehicle information	TravelSurvey
		Household information	TravelSurvey
Purpose	**Data typology**	**Features**	**Applications**
PSM	Environmental Impacts	CO_2 emission	Bellidea, CO2GO, GoEco, Green Travel Choice, Guide2Wear-Tracker, MatkaHupi, Peacox, PEIR, Quantified Traveller, SBB MyWay, SUPERHUB, TRAKiT, UbiGreen Transportation Display
		Saved CO_2	Better Points, CicloGreen, Commute Greener, Metropia, Positive Drive, Routecoach
		Calories burned	CicloGreen, CO2GO, Commute Greener, Positive Drive, Quantified Traveller, Routecoach, SETA Tracking, TRAKiT, Tripzoom, UbiActive
		Step Counter	MoveMore
		Pollution exposure	Peacox
		Money saved	CicloGreen, Commute Greener, Positive Drive, Routecoach

Other functions	Eco friendly travel suggestions	Commute Greener, GoEco, Peacox, SMART, Tripzoom
	Energy Consumption	Bellidea, GoEco
	individual and group challenges	Bellidea, CicloGreen, Commute Greener, GoEco, MatkaHupi, MoveMore, SMART, Tripzoom
	Interactive gamification	Better Points, GoEco, Positive Drive, SUPERHUB, Tripzoom
	Rewards and awards (trophies and badges)	Bellidea, Better Points, CicloGreen, Commute Greener, GoEco, MatkaHupi, Metropia, Positive Drive, SBB MyWay, SMART, SUPERHUB, Tripzoom, Zwitct
	Fast food exposure	PEIR
	Self-report trip survey	UbiActive
	Self-report psychological experience survey	UbiActive
	Eco Goal setting	SUPERHUB, Tripzoom
	Travel behaviour comparison	Positive Drive, SBB MyWay, Tripzoom

to disclose too much information, potentially loosing competitive advantage in the development. Thus, out of the above 81 applications, only 24, providing a sufficient number of details, were considered to assess their usefulness for researchers and practitioners; those will be the basis for the SWOT analysis, whose results are presented in the next section. It is observed that the most used sensors, transversal to all the apps, are the GPS and the accelerometer while APIs are used in several cases to improve the accuracy together with some algorithms (mainly classifiers) for mode and purpose detection. The information about the accuracy is not known for all the features; looking at mode detection, the best results are recorded by E-Mission that shows a wide interval of accuracy (60-95%), while MTL Trajet shows good performances for route tracking (81%) and purpose (71%). While the origin and destination of trips is something easier to detect thanks to the GPS, the route tracking is a bit more complex. Indeed, more sensors as WiFi or GSM are needed, jointly to APIs as Google direction, Moves (now discontinued) and algorithms as geofencing and random forest. The tools used are those referring to data analytics and statistical software, together with machine learning. The combination of more methods, sensors, APIs, and algorithms help to obtain higher accuracy, but require more calculations leading to battery drain. This last issue is of utmost importance for the user, even more when the use of the app is spontaneous (as for PSM). Thus, finding the best trade-off between battery duration and accuracy of the information provided to the user is a big challenge, considering that, nowadays, most of the apps show a medium to high consumption.

SWOT Analysis

The results of SWOT analysis are reported as following according to the criteria defined in the methodology section.

Strengths and Weaknesses

Table 13 reports strengths and weaknesses of the 24 selected apps (see methodology). The apps have the great advantage to collect information in a continuous way and in a very detailed manner, allowing to have an accurate footprint of the different legs of a trip with their space-time information, also for long periods (for all the apps not related to TS, limited to the duration of the survey). However, the GPS, in certain places as well as at indoor locations, does not perform very well, reducing the accuracy of data. Another big concern refers to the accuracy of mode and purpose detection – amongst the most difficult tasks. A good trip detection requires the combined use of sensors, APIs and algorithms that demand extra computing power with an important impact on batteries. However, there exists no app, at present, accurate enough to allow foregoing current TS. Nevertheless, apps allow to incorporate online questionnaires, creating synergies between the automatic (passive) tracking and the active intervention of user when confirming the collected information and filling in the socio-economic information. However, the active and attentive participation to a survey is not guaranteed if the app is not well performing. Concerning the PSM apps, the challenge of involving users is much greater as the low number of users shows. They are usually those involved in a specific project or test and their number is limited to 50–100 persons who remain involved only if incentives are provided. This small sample thwarts both the cost reduction and the usefulness in terms of data collection as well as of behavioural change. Unfortunately, there is very little knowledge concerning methods that can be used to engage a large enough sample of respondents and to lure them to download and (if necessary) to interact with the app/web interface (Clark *et al.*, 2017). The problem is that such apps have been conceived for data collection purposes, thus benefitting planners or scientists, not to attract the favour of the public as a lot of Google services do. The new methods have big potential for a continuous monitoring while reducing the costs and the information burden on respondents. Certain methods also have the potential to improve the quality and quantity of collected data (Clark *et al.*, 2017) even though the apps developed so far still reveal inconsistences, missing or incomplete data and low accuracy in properly detecting the mobility patterns (notably mode and purpose), creating dissatisfaction in the users who often complain about the low quality of user experience. Finally, an insufficient knowledge and the need for cooperation between transport and computer science experts are issues to be considered to improve the current quality of the apps (Anda *et al.*, 2017), notably in terms of user experience.

Opportunities and Threats

Table 14 reports opportunities and threats of the 24 apps analysed. Currently, the worst threat is the battery drainage, and the increase of accuracy could even worsen this aspect. Most of the smartphone apps have not been fully evaluated in terms of their accuracy in travel data collection. Different smartphones have different operating systems and/or versions and such differences could result in different accuracy for the same application. If these apps would become reliable and, hence, extensively used, they could provide huge benefits both to planners and users, and to the society at large. Arguably, a deeper knowledge of own mobility patterns can provide awareness about the time spent travelling, the cost paid, and the emissions produced (Whipple *et al.*, 2009). Thus, awareness programs that focus on individual travellers' decisions to make smarter travel choices can improve transport efficiency, thence enhance human habitat, and create living environments greener and healthier. Furthermore, educating travellers about the dangers of unsafe driving/walking behaviour could have significant safety benefits to all

Table 13: Strengths and Weaknesses

Strengths	Weaknesses
<u>1. Data</u> **a. Availability** (no strengths) **b. Quality** 1. Relationship between activity and space-time information (all apps) 2. Better understanding of travel behaviour in different conditions and time periods (e.g., seasons, different days) 3. Automatic data collection + online questionnaires (3 out of the 81 apps) 4. Minimization of under-reported trips 5. Decrease of response and recall bias, burden, and fatigue (all apps) 6. Decrease of survey nonresponse rate (all apps) 7. Surveys can last several days or long periods (all apps) 8. High quality and quantity positioning data (e.g., SmartMo) 9. Increase of efficiency and reliability in data collection 10. Security, confidentiality and anonymity of data using automatic encryption and authorised access (SmartMo, Future Mobility Sensing, Wander, MTL Trajet, Bellidea) 11. Compliance with the GDPR, using a unique identifier (i-Log) 12. Record of the complete trip chain (MEILI) 13. Detection of all transport modes during a trip chain	**<u>1. Data</u>** **a. Availability** 1. Unstandardised formats and incompleteness of available environmental data affect the effectiveness of apps (e.g., Peacox) 2. Lack of enough user data for training (Peacox, i-Log) 3. Lack of enough technical details about features development for further research and benchmark in almost all the 24 apps **b. Quality** 1. Detection of inconsistencies, missing data, disambiguation, validation errors, data gaps (30% data cannot be used to draw any conclusions: SmartMo, Future Mobility Sensing, i-Log, Wander, MOVE. 16% of overall trips identified as missing and 5% of missing trips were associated with a metro trip: Wander, PinMe) 2. Incorrect trip segmentation (i-Log, MTL Trajet, Predict.io Demo, 60 % users reported at least one wrong trip detection in MEILI, missing trip detections are beyond 10% in MoveSmarter, 14% of all trips are not complete in SmartMo, Predict.io Demo) 3. Underreporting of trips (MoveSmarter) 4. Data samples are not representative enough (MoveSmarter, SmartMo) 5. Not enough data to train/model algorithms for automated analysis (i-Log)
2. <u>Technical characteristics</u> 1. Automatic and coordinated data collection (all the apps) 2. Timeliness and punctuality (all apps) 3. Wireless synchronization (MobilitApp, My places diary, MoveSmarter, SmsrtMo, FM Sensing, i-Log, DataMobile,	**2. <u>Technical characteristics</u>** 1. Smartphone's GPS is less precise than the GPS of a dedicated device; accuracy is reduced when participants travel indoors (My Places diary, FM Sensing, MTL Trajet, GoEco, GoEco tracker) 2. Low quality of positioning detection due to poor WiFi (My Places Diary)

UnCrowdTPG, Predict.io Demo have WiFi Sensor) 4. Second-by-second detailed information (i.e., speed, acceleration) (MobilitApp, MEILI, MoveSmarter, FM Sensing, i-Log, CO2GO, CITYing, HDYCopilot, UnCrowdTPG, Dynamica, Peacox, GoEco, 5. Strong support for automated data analysis (all the apps) 6. More functionalities together (SmartMo, DataMobile for both TDCA+TS purpose) 7. Less burden on respondents by avoiding manual data entry (all apps) 8. Possibility of long survey duration with reduced costs (all the apps) 9. Paperless participation reduces environmental impact (all apps) 10. Mode detection accuracy (77% MonilitApp (avg. success rate is 1.5 times higher than API of google), 54% MEILI, 97% Wander, 82.14% CO2GO, 82.051% CITYing, 86% Dynamica, 80% UnCrowdTPG, 87% MTL Trajet, 80% GoEco! And GoEco Tracker, 60-95% E-Mission, 89.6% Bellidea, 91% PEIR, 50% Predict.io Demo) 11. Purpose inference (87.1% My Places Diary, 50% MEILI, >95% Dynamica, 71% MTL Trajet, 80-85% Peacox) 12. Stop detection (97% MEILI, 95.5% Future Mobility Sensing, 80% UnCrowdTPG) 13. Trip chain detection (79% MEILI); Trip validation rate (80%-DataMobile); Transit itinerary detection (81%-MTL Trajet); Trip leg detection (70% MEILI)	3. OS dependency/availability of apps could decrease their use (MobilitApp, My Places Diary, i-Log, CITYing, HDYCopilot, UnCrowdTPG, Dynamica, MOVE is available for Android only) 4. Heatmap does not seem to work (E-Mission) 5. Many apps have only one functionality (MobilitApp, My Places Diary, MEILI, MoveSmarter, i-Log, Wander, CITYing, HDYCopilot, UnCrowdTPG, Dynamica, MTL Trajet, GoEco Tracker, E-Mission, MOVE, PinMe, Predict.io Demo for TDCA; Future Mobility Sensing for TS; and, CO2GO, Peacox, GoEco!, Bellidea, PEIR only for PSM purpose) 6. Unavailability of sufficient resources to store, process, and analyse the collected travel data (MobilitApp) 7. Sometimes not distinguishing among motorized transport modes (MobilitApp, Myplaces Diary, GoEco!, E-Mission) 8. No feasible solution for purpose inference (MEILI) 9. Missing trip detection (>10% MoveSmarter, 14%-Smart-Mo, 16% DataMobile) 10. Wrong trip detection (60% users reported at least one wrong trip detection in MEILI) 11. Not always straightforward to identify the actual transit itinerary (MTL Trajet) 12. GPS location accuracy is reduced when participants travel indoors (My Places diary, FM Sensing, MTL Trajet, GoEco, GoEco tracker, MOVE) 13. Accuracy is not reported in some apps (HDY Copilot, MOVE) 14. Calories counter is not precise in all cases (E-Mission)
<u>3. Design & User Interface</u> 1. 50% of users are satisfied with detection of departure and arrival; 22% are satisfied with mode detection in MoveSmarter; in SmartMo 81% evaluate it very good and good, 16% satisfactory, and 3% sufficient. Nobody considered usability not adequate	**<u>3. Design & User Interface</u>** 1. In MoveSmarter, dissatisfaction with departure and arrival detection (21%), with mode detection (49%), with battery consumption (50%) 2. Low participation rate (<100 in MEILI, Wander; >100 in MobilitApp, My Places Diary, SmartMo, GoEco, GoEco Tracker, Bellidea; >500 in

2. Participation rate is high in one app only (>10,000 in MTL Trajet) 3. Privacy is ensured in some of the apps and compliant with the national and international laws (MobilitApp, MEILI, MoveSmarter, Peacox) 4. User have control on their own data (i-Log)	MoveSmarter, DataMobile; >1000 in Future Mobility Sensing, i-Log, UnCrowdTPG, E-Mission, information is N/A for CO2GO, CITYing, HDYCopilot, Mobilità Dynamica, Peacox, MOVE, PinMe, PEIR, Predict.io Demo) 3. User needs to install an App on his/her smartphone 4. Report socio-economic information is perceived as long and difficult 5. Unexpected errors prompt users to stop using the system (MEILI) 6. Lack of a functional incentive did not keep the users motivated enough to annotate their trips through the whole period (MEILI, SmartMo) 7. Lack of focus on user experience improvement and easiness to use (MEILI) 8. Difficulties in finding a balance between mandatory and optional questions

Table 14: Opportunities and Threats

Opportunities	**Threats**
<u>**1. Data**</u> **a. Availability** 1. Availability and openness of data with complete documentation could support further research in mobility app development 2. Potential of extensions using open data, APIs etc. **b. Quality** 1. Continuous and large quantity of data can be achieved by using more powerful techniques (MobilitApp, SmartMo, DataMobile, GoEco!, E-Mission) 2. Travel data could be linked with people's actual experiences 3. Integrated use of other smartphone sensors to increase data collection speed and accuracy (MobilitApp, MEILI, MoveSmarter, SmartMo, MOVE, PEIR) 4. Inclusion of information of the household could allow to make further socio demographic analysis (DataMobile)	<u>**1. Data**</u> **a. Availability** 1. Companies, advertisers, cyber-criminals and in some situation federal agencies may be interested in the data or may change smartphone settings and take contact and other information without user permission (all apps) 2. Apps can collect all sorts of data and transmit it to the app-developer and/or sell it to third-party advertisers **b. Quality** 1. Data collection heavily consumes the smartphone's battery, and the dead battery may affect the data quality and quantity (all apps)

5. Alternative recruitment methods can be used to collect more data (in all apps) 6. Implement methods to reduce storage requirements (Dynamica, E-Mission) 7. Enlarge the duration of tracking period (GoEco!)	
2. Technical characteristics 1. Allowing use of new/efficient methods for data analysis/processing as machine learning, data mining, artificial intelligence techniques (SmartMo, MobilitApp, MEILI, MoveSmarter, Future Mobility Sensing, Wnader, Dynamica, My Places Diary, i-Log, MTL Trajet, GoEco!, e-Mission, CITYing) 2. Evaluation of algorithmic correctness and integration of more complex algorithms for error analysis (My Places Diary, SmartMo) 3. Independency from other APIs could strengthen the app development and working in continuous way (Bellidea) 4. Develop app version for other operating systems to support and use the app (MobilitApp, Dynamica, i-Log, CO2GO, CITying, HDYCopilot, UnCrowdTPG, MOVE for iOS/another) 5. Finding possible insights in the variability in mobility (MoveSmarter) 6. Consider more context information in the back-end algorithms such as network and timetable data of public transport (MoveSmarter, SmartMo, FM Sensing, i-Log, Dynamica, GoEco tracker) 7. Improve smartphone energy performance/reduce battery consumptions thanks to more efficient methods (MobilitApp, MEILI, MoveSmarter, SmartMo, Wander, MTL Trajet, Dynamica) 8. Dashboard and server preparation for deployement and compilation of the apps to greater extent of users (MobilitApp, MEILI, E-Mission) 9. Inclusion of more features and user criteria (i.e., E-call in MobilitApp for accident detection and Wander; cleanliness, noise level, security in UnCrowdTPG; personal calendars, in-app questionnaires, or weather data,	**2. Technical characteristics** 1. Battery consumption problems (high in MobilitApp, MEILI, Future Mobility Sensing, Wander, MTL Trajet, MOVE, GoEco! and low in i-Log, DataMobile, CITYing, My Places Diary and 2% in Predict.io Demo, in others information N/A for comments) 2. Trade-off between measurement accuracy and battery consumptions (in MoveSmarter, Future Mobility Sensing location accuracy is reduced when smartphone runs out of battery), 3. Dependency of apps on other app's APIs may stop the whole working of the app (i.e., Bellidea functionality stopped due to absence of Moves API) 4. Availability of apps on different OS are out of control (GoEco!) 5. Apps may also be infected with malware (malicious software that can pose a threat to your smartphone) 6. Privacy and Security Issues (for My Places Diary, DataMobile, CO2GO, CITYing, HDYCopilot, Dynamica, GoEco, GoEco tracker, E-Mission, MOVE, PinMe, PEIR and Predict.io Demo information is not available regarding privacy) 7. High battery consumptions and dead battery may affect the accuracy of spatial data collected which consequently affects the analytical results quality

and improve on the immediacy of eco-feedback in GoEco Tracker) 10. Focus on scalability, stability, performance, and usability (PEIR) 11. Improve: mode detection accuracy (SmartMo, MobilitApp, My Places diary, MoveSmarter, i-Log, Fututre Mobility Sensing, CO2GO, Dynamica, MOVE, PEIR, CITYing); purpose detection accuracy (My Places Diary, SmartMo, MOVE, CITYing); stop detection algorithm accuracy using ML/new techniques (MobilitApp, Future Mobility Sensing); trip detection accuracy (MoveSmarter, MOVE); position detection accuracy by considering alternative information to GPS (MobilitApp, MEILI, MoveSmarter, SmartMo, MOVE, PEIR)	
3. Design and Users Interface 1. Enhance data privacy and security (Dynamica, GoEco Tracker, E-Mission) 2. Educate people about their travel impacts on environment 3. Make people aware about the travel costs to save money and time 4. Make people closer to new technologies to reduce the digital divide (all apps) 5. Make app more attractive for users adding gamification elements and considering user feedback (MobilitApp, SmartMo, Future Mobility Sensing, Dynamica) 6. Compilation and deployement of the mobility collector apps to users (MEILI) 7. Integration of backend system to allow user self-monitoring (SmartMo) 8. Improvement in travel statistics (daily, weekly, monthly, etc.) can attract more users (Dynamica) and visualisation of mobility footprint	**3. Design and Users Interface** 1. Low engagement of people/users (MEILI >50; Wander >62; MobilitApp, My Places Diary, SmartMo, Bellidea have >100 users; MoveSmarter, DataMobile, GoEco, GoEco tracker have >100 and <1000 users; FM Sensing, i-Log, UnCrowdTPG, E-Mission have >1000 users; MTL Trajet have maximum 10,000) 2. Road users' distraction can cause accidents 3. Smartphone has not been carried out for all activities (smartphone forgotten) 4. Not everyone has access to a smartphone

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

road users. However, the other side of the coin refers to the massive use of such apps through users' interactions with applications – manually, visually, and cognitively – that could divert their attention from the primary task of driving, biking, or walking.

Transport authorities can benefit from applications by showing accurate travel information to the users. Another option is collaboration among transport authorities, application developers and research institutes; actually, information should be made available to stakeholders through open data or agreements between public administration and private actors. Requirements with regard to the documentation of, for example, data cleaning and processing algorithms may be important in ensuring quality (Clark *et al.*, 2017). Many questions remain about the representativeness of the new methods; further research is needed to clarify how meaningful data have to be collected. This is a key issue, because if a representative sample of population was not reached, data, even if of higher quality and less expensive to collect, will not be usable (Clark *et al.*, 2017). It is also unclear whether all the apps meet the requirements in terms of managing personal data, as the regulations governing the management of such data vary from one country to another. Thus, the asymmetries should be eliminated as the apps developed in Europe must comply with the provisions of the General Data Protection Regulation, that it is not the case of extra-EU apps. The results of this case study have been published in a paper in "Advances in Intelligent Systems and Computing" [Pronello, C., Kumawat, P., (2021) Smartphone Applications Developed to Collect Mobility Data: A Review and SWOT Analysis. DOI:10.1007/978-3-030-55187-2_35. Pp.449-467. In Advances in Intelligent Systems and Computing – ISSN:2194-5357 vol. 1251].

By summarising, as there exists no app, at present, accurate enough to allow foregoing current TS, it is not possible to use apps for data collection for the purpose of this research. Moreover, the apps data can be useful for spatial analysis but not enough for psychological model analysis mainly using attitudes and preferences. Therefore, we decided to collect data from TS in innovative way by web questionnaire. The following section presents results of the sample collected from the survey, data analysis, and modelling.

4.2 Sample description

This section gives a brief description of socio-economic attributes and mobility patterns of the sample.

4.2.1 Socio-economic descriptive

Table 15 shows the socio-economic characteristics of the sample. The sample is composed by 2277 (50.91%) females, 2139 (47.82%) males, and 8 (0.18%) belonging to other gender groups with 49 (1.09%) missing information. Concerning age distribution, 6 age groups were created. The sample distribution for these selected groups is as follows: 40 (0.89%) respondents from 1 to 17 years old, 1544 (34.52%) from 18 to 25 years old, 1081 (24.17%) from 26 to 40 years old, 1516 (33.89%) from 41 to 60 years old, 239 (5.34%) with more than 60, and 53 (1.18%) did not answer. In the sample there is slight female majority with 139 more females comparing to males. The sample is almost equally distributed among the youngest (18-25 years old) and older (41-60 years old) users and dominated by young respondents (18-40 years).

4315 (96.47%) users have not any handicap, 109 (2.44%) have some handicap, and 49 (1.10%) did not answer. Regarding driving license, the majority of respondents, 4177 (93.38%), have the driving license while only 241 (5.39%) do not have the driving license; 55 (1.23%) persons did not answer. Most of the sample population own a driving license, and this is evident as the second dominant mode of transport used by the respondents is car as a driver followed by trip chain.

Majority of respondents, 1909 (42.68%), are employees followed by students 1851 (41.38%). The sample is dominated by employees and student's population. The third and fourth largest group of respondents are, respectively, self-employed (198, 4.43%) and teachers (177, 3.96%). The largest household (HH) size is 4 with 1379 (30.83%) persons, followed by 3, 2, 1, and >4 persons, respectively with 1155 (25.8%), 947 (21.17%), 547 (12.23%), 393 (8.79%); 53 (1.18%) did not answer.

The majority of respondents, 1465 (32.75%) households (HH), have 2 children, followed by 0, 1, 3, >3 children, respectively 1402 (31.34%), 1170 (26.16%), 319 (7.13%), 65 (1.45); 52 (1.16%) did not answer. Among all sample respondents, the majority (2929, 65.48%) have no children under 14 years old, 488 (10.91%) have 1 child under 14 years followed, by, respectively, 2, and 3 with 223 (4.99%), and 33 (0.74%); 799 (17.86%) did not answer.

The income is formed by 13 categories. The biggest category includes 781 persons (17.46%) with an income >10,000 €/month. The second largest income group (571, 12.77%) is in the range 2501-3000 €/month, then followed by 1501-2000 €/month (514, 11.31%), 2001-2500 €/month (512, 11.45%), 1001-1500 €/month (506, 11.31%), 3001-3500 €/month (304, 6.8%), and 4001-4500 €/month (250, 5.59%); 236 (5.28%) did not answer.

2118 respondents (47.35%) own a high school diploma, followed by five-year degree (1079, 24.12%), bachelor's degree (739, 16.52%), PhD (238, 5.32%), and secondary school (172, 3.85%).

Table 15: Socio economic and demographic characteristics

Feature	Categories	Count	%
Gender	Male	2139	47.39
	Female	2277	50.91
	Other	8	0.18
	No answer	49	1.09
Age (years)	1-17	40	0.89
	18-25	1544	34.52
	26-40	1081	24.17
	41-60	1516	33.89
	60+	239	5.34
	No answer	53	1.18
Handicap	Yes	109	2.44
	No	4315	96.47
	No answer	49	1.10
Driving license	Yes	4177	93.38
	No	241	5.39
	No answer	55	1.23
Occupation	Looking for a job	81	1.81
	Unemployed	24	0.54
	Retired	49	1.1
	Student	1851	41.38
	Housewife	5	0.11
	Worker	48	1.07
	Employee	1909	42.68
	Manager	79	1.77
	Teacher	177	3.96
	Self-employed	198	4.43
	Other	4	0.09
	No answer	48	1.07
Household composition	1	547	12.23
	2	947	21.17
	3	1154	25.8
	4	1379	30.83
	>4	393	8.79
	No answer	53	1.18
Children in household distribution	0	1402	31.34
	1	1170	26.16
	2	1465	32.75
	3	319	7.13
	>3	65	1.45

	No answer	52	1.16
Children under 14 in household distribution	0	2929	65.48
	1	488	10.91
	2	223	4.99
	3	33	0.74
	4	1	0.02
	No answer	799	17.86
Income distribution	1001-1500	506	11.31
	1501-2000	514	11.49
	2001-2500	512	11.45
	2501-3000	571	12.77
	3001-3500	451	10.08
	3501-4000	304	6.8
	4001-4500	250	5.59
	5001-6000	163	3.64
	6001-7000	66	1.48
	7001-8000	56	1.25
	8001-9000	35	0.78
	9001-10000	28	0.63
	>10000	781	17.46
	No answer	236	5.28

Observing Table 16, 43.39% of respondents (1941) own two cars that is the largest number of owned cars by households (HH), followed by, 1 (1411, 31.54%), 3 (648, 14.49%), 0 (275, 6.15%) and >3 cars (134, 3%); 36 did not answer. The highest number of respondents, 2926 (65.41%), owns a car with more than 4 years old, followed by cars with 1 (408, 9.12%), 4 (286, 6.39%), 2 (278, 6.22%), and 3 years old (262, 5.86%); 485 (10.85%) did not answer. The first largest car price is in the range of 10,001-15,000 € with 1282 (28.66%) respondents, followed by 5,001-10,000 (1024, 22.89%), 15,001-20,000 (625, 13.97%), 1,001-5,000 (596, 13.32%), and >20,000 € (457, 10.22%). The most used fuel is gasoline with 1867 (41.74%) respondents, followed by diesel (1374, 30.72%), LPG-Benz (669, 14.96%), methane (167, 3.73%); only 63 respondents (1.41%) use hybrid cars.

Table 16: Car characteristics and distribution in household

Feature	Categories	Count	%
Number of cars in households	0	275	6.15
	1	1411	31.54
	2	1941	43.39
	3	648	14.49
	>3	162	3.62
	No answer	36	0.8
Car age distribution (years)	1	408	9.12
	2	278	6.22

	3	262	5.86
	4	286	6.39
	>4	2926	65.41
	No answer	313	7
Car price composition	1001-5000	596	13.32
	5001-10000	1024	22.89
	10001-15000	1282	28.66
	15001-20000	625	13.97
	>20000	457	10.22
	No answer	485	10.85
Fuel used in cars	Gasoline	1867	41.74
	Diesel	1374	30.72
	LPG-Benz	669	14.96
	Methane	167	3.73
	Hybrid	63	1.41
	Electric energy	4	0.09
	Other	18	0.4
	No answer	311	6.95

The largest number of respondents (more than half of the sample population) do not have any kind of transport subscriptions (category "No subscriptions" in Table 17). Then, the second highest category is related to annual subscription (1062, 23.74%), followed by annual bike sharing subscriptions (508, 11.36%). Concerning monthly subscriptions, 444 (9.93) users have got an urban PT subscription, followed by 333 (7.44%) with suburban PT and 330 (7.38%) with train subscription. Other categories of subscriptions are used by less users. Regarding carsharing subscriptions, most of respondents, 3594 (80.35%) do not use car sharing services. Almost 20% (827, 18.49%) respondents enrolled to car sharing services, 3594 (80.35%) did not enroll and 52 (1.16%) did not answer.

Table 17: Transport subscriptions

	Bike sharing	**Urban PT**	**Suburban PT**	**Suburban PT with O/D rates**	**Train**
Categories	**Count (%)**	**Count (%)**	**Count (%)**	**Count (%)**	**Count (%)**
No subscriptions	3847 (86)	2429 (54.3)	3653 (81.67)	4242 (94.84)	3740 (83.61)
5-day weekly	4 (0.09)	47 (1.05)	16 (0.36)	3 (0.07)	8 (0.18)
Weekly	1 (0.02)	61 (1.36)	39 (0.87)	9 (0.2)	36 (0.8)
Monthly	11 (0.25)	444 (9.93)	333 (7.44)	59 (1.32)	330 (7.38)
3 months	3 (0.07)	6 (0.13)	7 (0.16)	4 (0.09)	1 (0.02)
10 months	16 (0.36)	243 (5.43)	62 (1.39)	26 (0.58)	32 (0.72)
Annual	508 (11.36)	1062 (23.74)	267 (5.97)	45 (1.01)	179 (4)
Other	27 (0.6)	126 (2.82)	42 (0.94)	28 (0.63)	91 (2.03)
No answer	56 (1.25)	55 (1.23)	54 (1.21)	57 (1.27)	56 (1.25)

4.2.2 Mobility patterns

This section presents the results of mobility pattern analysis of the sample to understand its daily mobility habits: how, when where and why people move. To this end, at first the weekday trip characteristics (travel duration, distance, purpose, mode etc.) distribution is presented, followed by trips' spatial distribution and visualisation.

As shown in figure 6, the minimum travel duration in the sample is 1.16 minutes and the maximum duration is 900 minutes, which might be trips for long distance or outside the study area; the 25th percentile of duration is under 20 minutes, and the 75th percentile of duration is within 60 minutes. Thus, most of the trips last around one hour with an average duration of 46.42 minutes.

The average travel distance is 19.02 km, with minimum distance of 0.03 km and maximum distance of 400 km which could be related to long trips, outside Piedmont (figure 7). The 75th percentile of trips is under 25 km.

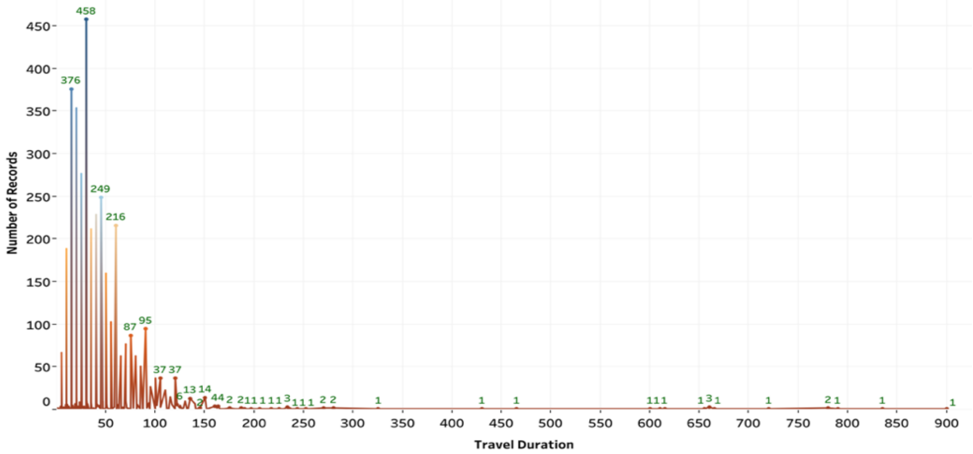


Figure 6: Distribution of travel duration (minutes)

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

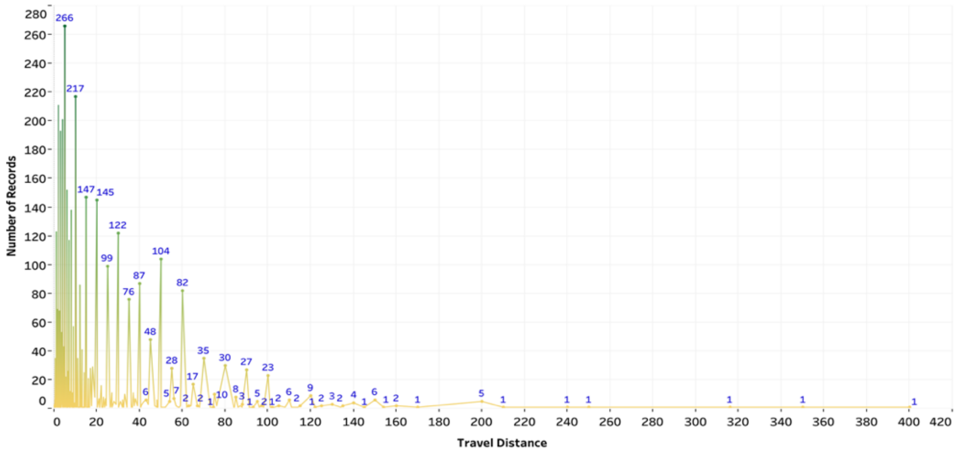


Figure 7: Distribution of travel distance (km)

The analysis of the distribution of travel mode (Table 18) shows that trip chain is the most used mode (32%), followed by car as a driver (28%), Public Transport (PT) (22.2%) and soft modes, walking and cycling (16.5%).

Table 18: Summary of travel mode distribution

No.	Aggregation	Modes	Counts	%
1	**Trip chain**	Trip chain	1288	32.07
2	**Private vehicle**	Car as Driver	1096	27.29
3		Car as Passenger	66	1.64
Total	**2**	**2**	**1162**	**28.93**
4	**Public Transport (PT)**	Regional Trains	105	2.61
5		Bus/Tram/Metro	712	17.73
6		Bus Extra-urban	72	1.79
7		AV/IC Trains	5	0.12
Total	**4**	**4**	**894**	**22.26**
8	**Car sharing**	Car Sharing	3	0.07
9	**Soft modes**	Bicycle	305	7.59
10		Bike Sharing	37	0.92
11		Walk	324	8.07
Total	**3**	**3**	**666**	**16.58**
12	**Other**	Other	3	0.07
Total=12			**4016**	**100**

The distribution of travel purpose is summarized in Table 93. 97% of trips refer to systematic mobility with the purpose of Home-Work, Work and, Home-School/University; only 6% of trips are non-systematic mobility for free time, pickup someone, other reasons, etc.

Table 19: Summary of travel purpose

No.	Mobility-type	Purpose	Trip Counts	%
1	Systematic mobility	Home-Work	2210	55.03
2		Work	55	1.37
3		Home-School/University	1509	37.57
sub-total	**3**	**3**	**3774**	**93.97**
4	Non-Systematic mobility	Expenses or/Bureaucratic Commissions	55	1.37
5		Free Time	85	2.12
6		Pick up/accompany someone	72	1.79
7		other reason	30	0.75
sub-total	**4**	**4**	**241**	**6.03**
Total	**7**	**7**	**4016**	**100**

The hierarchical zoning is adopted in this study to understand how people are travelling. The distribution of origins and destinations of the weekday trips is visualised, firstly, referring to large zones as the regions (Table 20 and figure 8). Then, a more detailed visualisation refers to zones inside the region, the provinces (Table 21 and figure 9).

Table 20: Origins and destinations distribution in Italian regions

No.	Regions	Origin-count	%	Destination-count	%
1	Piemonte	3961	98.63	3970	98.85
2	Lombardia	31	0.77	29	0.72
3	Liguria	6	0.15	7	0.17
4	Aosta Valley	5	0.12	1	0.02
5	Veneto	3	0.07	2	0.05
6	Lazio	2	0.05	2	0.05
7	Emilia-Romagna	2	0.05	1	0.02
8	Friuli-Venezia Giulia	1	0.02	-	-
9	Marche	1	0.02	-	-
10	Trentino-Alto Adige	1	0.02	1	0.02
11	Puglia	1	0.02	1	0.02
12	Toscana	1	0.02	1	0.02
13	Umbria	1	0.02	1	0.02
Total	**Italy**	**4016**	**100**	**4016**	**100**

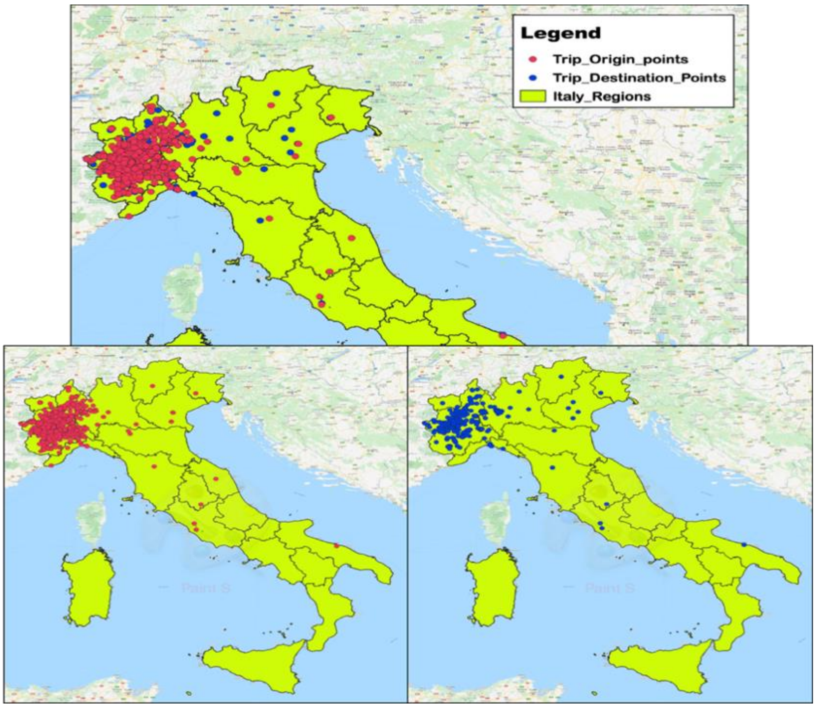


Figure 8: Spatial distribution of origins and destinations in Italian regions

The study area is Piedmont region, with focus on the Province of Turin, where most of respondents live and travel. In total, the origins are in 13 out of 20 Italian regions. The distribution of trips in provinces are reported in Table 21 and visualised in figure 9.

Table 21: Origins and destinations distribution in provinces of Piedmont

No.	Province	Origin-count	%	Destination-count	%
1	Torino	3422	86.39	3616	91.24
2	Cuneo	178	4.49	73	1.84
3	Alessandria	96	2.42	87	2.19
4	Vercelli	83	2.09	62	1.56
5	Asti	83	2.09	23	0.58
6	Novara	56	1.41	79	1.99
7	Biella	32	0.81	16	0.40
8	Verbano-Cusio-Ossola	11	0.28	7	0.18
11	**Italy**	**3961**	**100%**	**3963**	**100%**

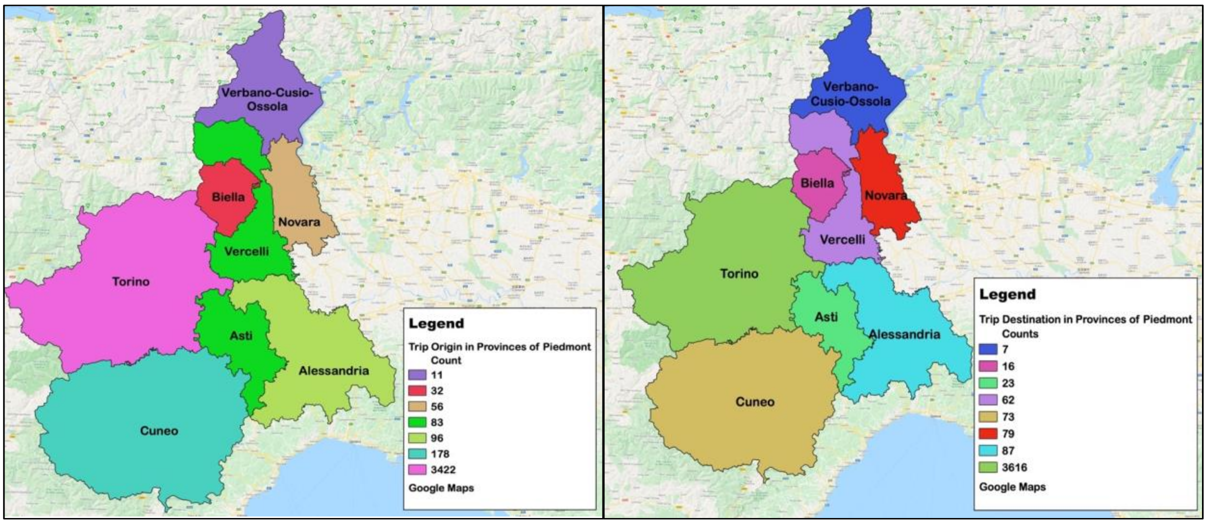


Figure 9: Spatial distribution of origins and destinations in provinces of Piedmont

Figure 10 shows the distribution of origins and destinations inside the province of Turin. In figures from 11 to 13, the distribution of origins and destinations refers to the zoning based on IMQ zones (figure 11), commune zones (figure 12), and finally, to census zones (figure 13). The zoning comparison is made to select the best granularity of zones for final trips visualisation to minimize the error. Thus, census zones were selected to understand mobility patterns in detail. Observing the distribution of origins and destinations over territory, according to above defined hierarchical criteria of study area - 4016 origin and destination points are in Italy; 3961 origin and 3970 destination points are in Piedmont; 3422 origin and 3616 destination points are in Turin province; and 55 origin and 46 destination points are in other regions of Italy.

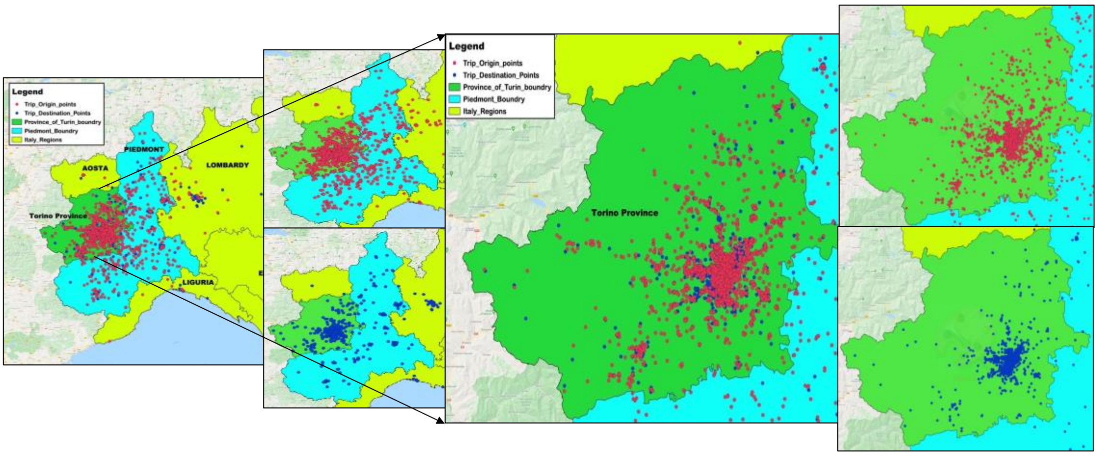


Figure 10: Spatial distribution of origins and destinations in Province of Turin, in Piedmont region

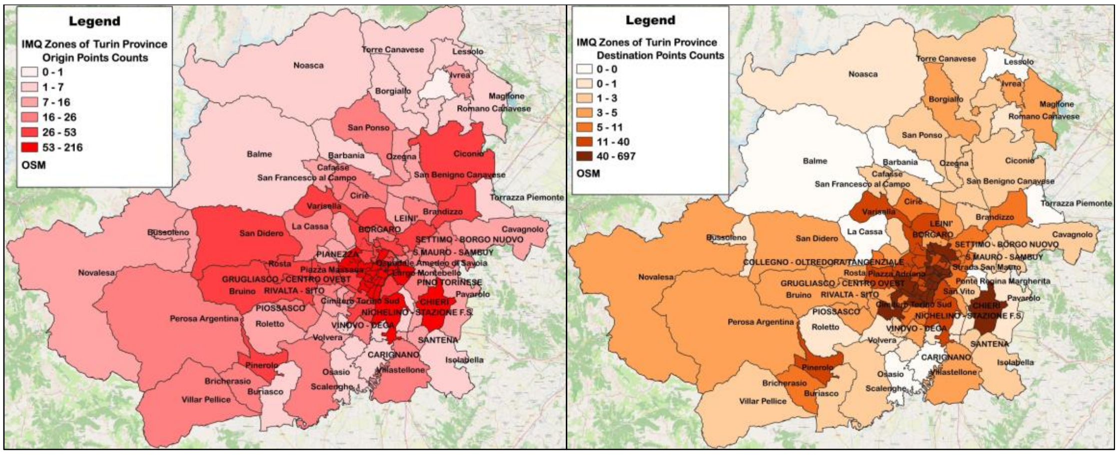


Figure 11: Origins and destinations distribution in IMQ zones of province of Turin

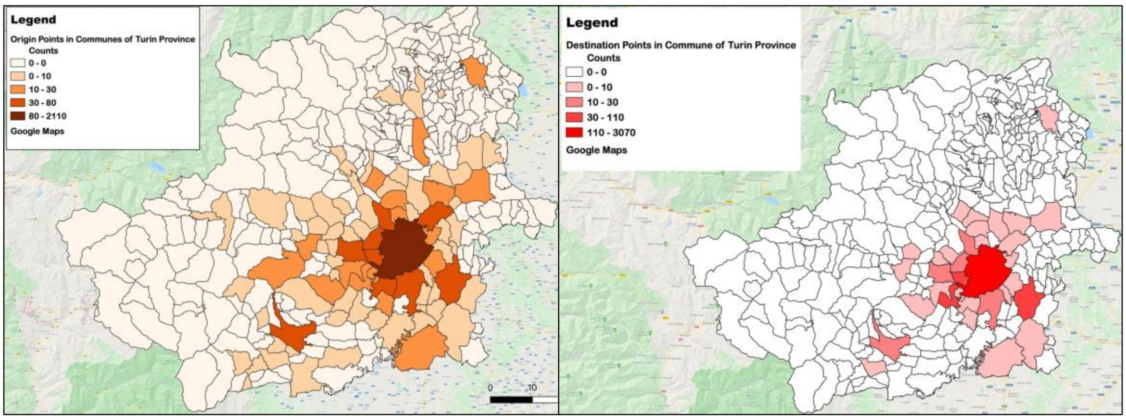


Figure 12: Origins and destinations distribution in commune zones of province of Turin

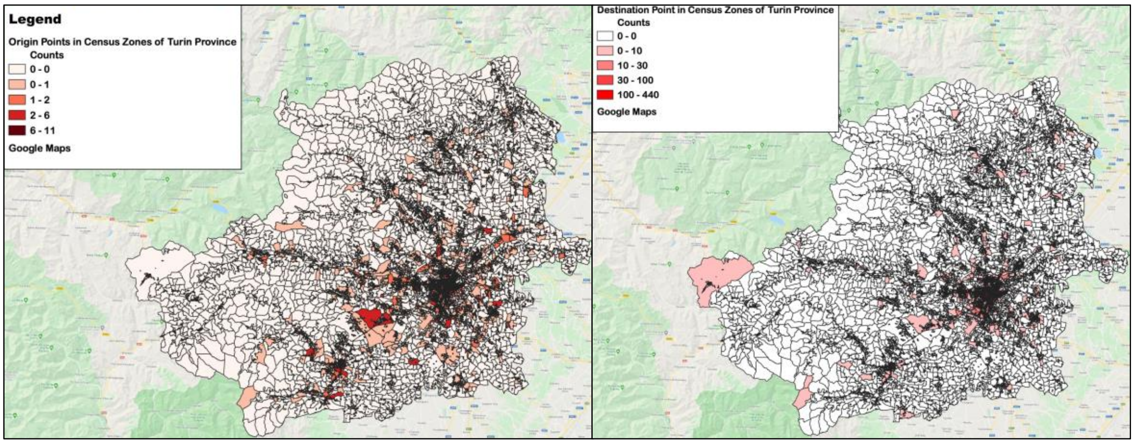
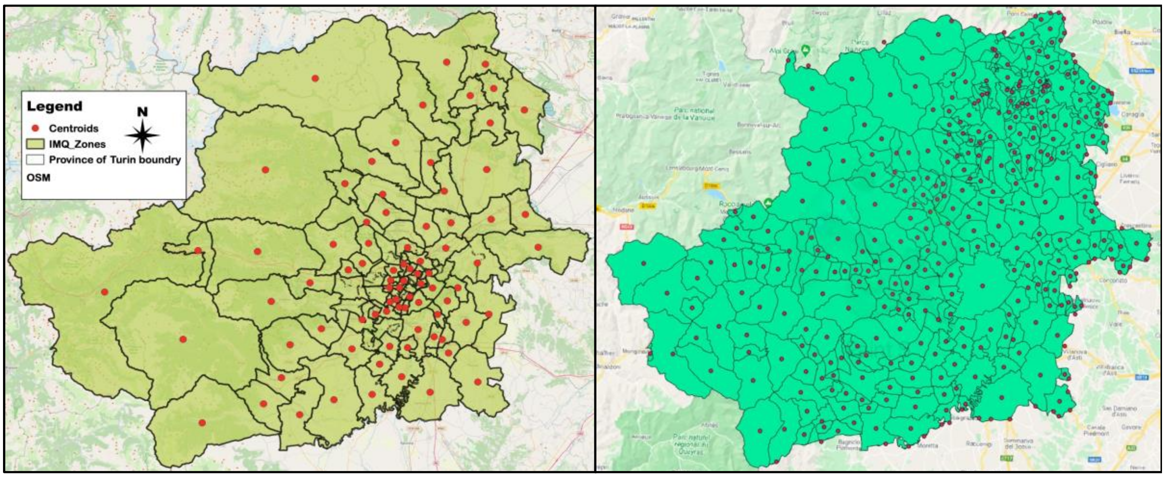


Figure 13: Origins and destinations distribution in census zones of Turin province

Figure 14a shows the centroids located in IMQ zones while figure 14b shows the centroids of commune zones and figure 15 in census zones.



(a) (b)

Figure 14: Turin Province (a) IMQ zones centroids (b) commune zones centroids

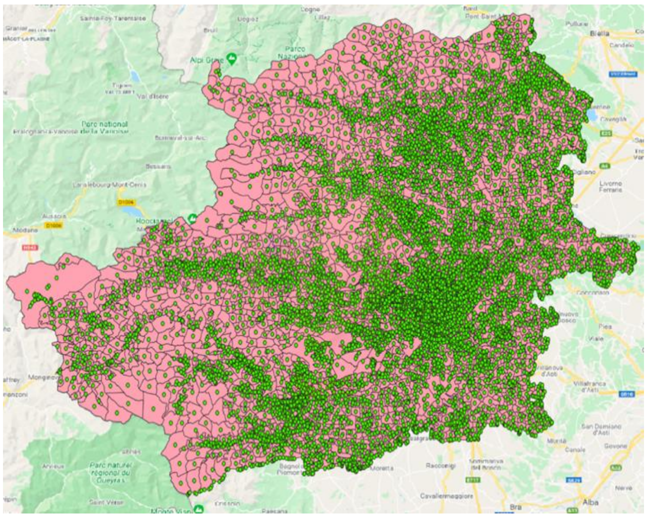


Figure 15: Turin Province census level zones centroids

To visualise the trips (weekday) through origin-destination lines in Province of Turin, the zones were assigned to each trip using hierarchical search. After having coupled the destinations to the origins, the analysis was made on an hourly basis to match the trip distribution by time of the day to the corresponding zones. To visualize the trips on map a line connecting the centroids of the origin and destination is shown. The visualisation was made, at first, for the 24 hours (figure 16) and then, for the peak hours (figures 17, 18 and 19). The figures show how most of the respondents travel to the city of Turin and surrounding areas.

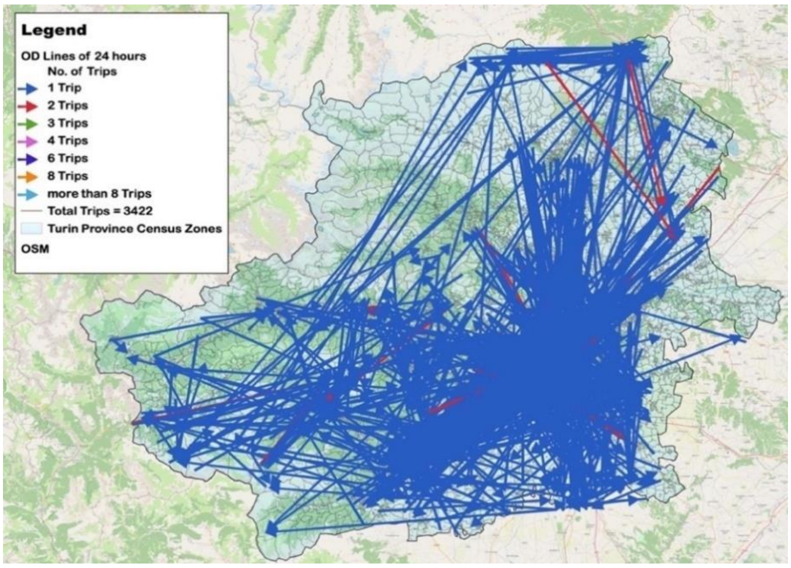


Figure 16: Visualisation of trips of 24 hours

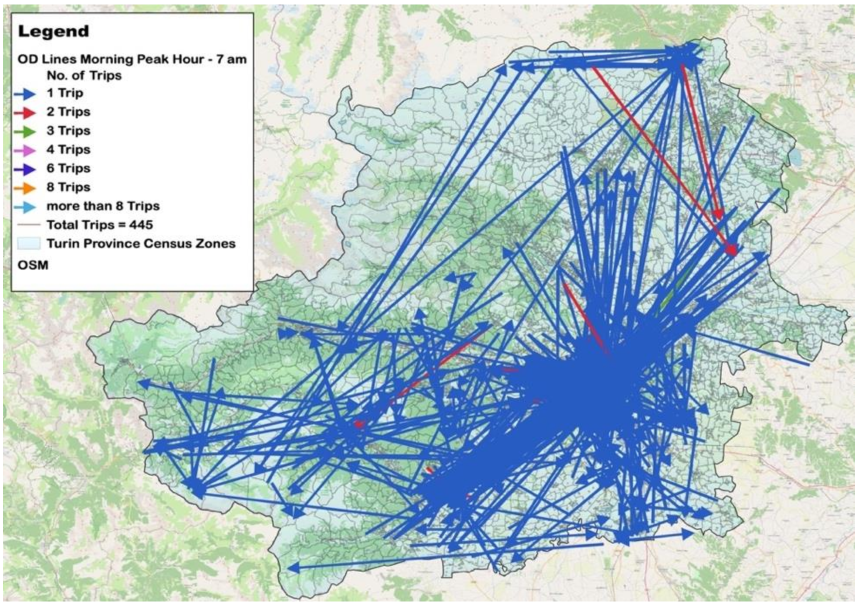


Figure 17: Visualisation of trips at morning peak hour 7:00 am

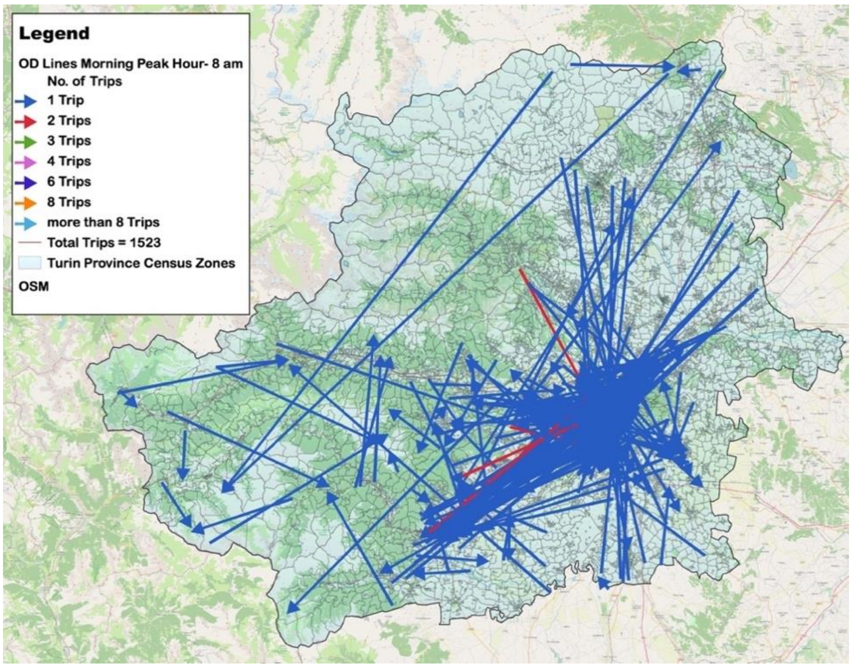


Figure 18: Visualisation of trips at morning peak hour 8:00 am

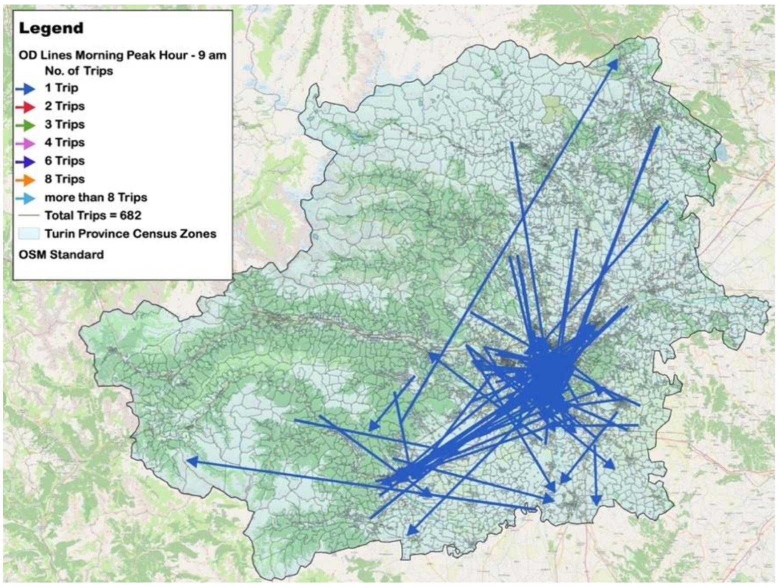


Figure 19: Visualisation of trips at morning peak hour 9:00 am

Then the distribution of trips by purpose was done, as shown in Table 22. Half of the trips (55.31%) refer to Home-Work purpose, followed by 37.90% for Home-School/University.

Table 22: Trips distribution by purpose in province of Turin

No.	Purpose	No. of Trips	%
1	Home-Work	1843	55.31
2	Work	34	1.02
3	Home-School/University	1263	37.90
4	Expenses or/Bureaucratic Commissions	52	1.56
5	Free Time	68	2.04
6	Pick up/Accompany Someone	56	1.68
7	Other Reason	16	0.48
Total	**7 purposes**	**3332**	**100**

Trips are sometimes classified according to peak and off-peak period; the proportion of journeys by different purposes usually greatly varies with time of the day. Thus, figure 20 reports the trip distribution (by origin) by hour of the day showing the peak morning hour at 8 am, followed by 9 and 7 am, while other hours can be considered off-peak.

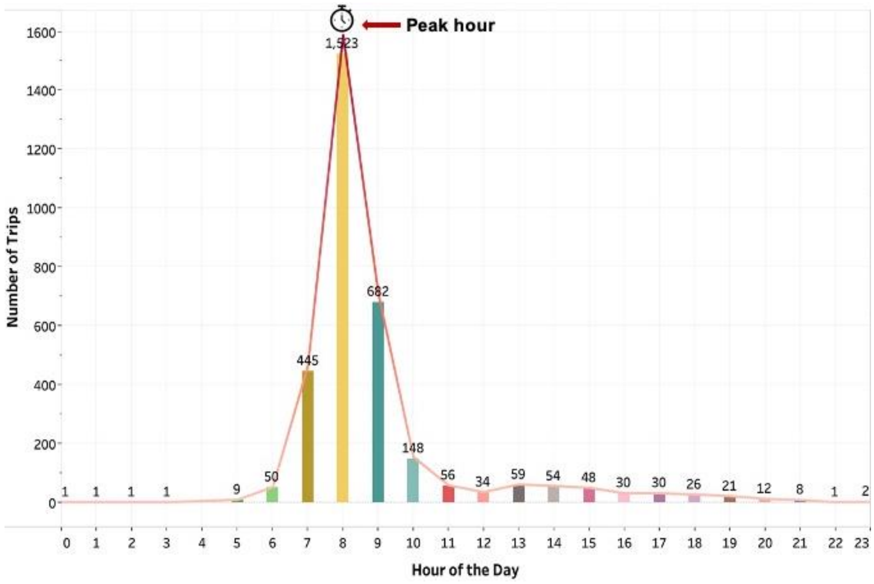


Figure 20: Weekday trips origin counts by hour of the day

Figure 21a shows that most of the Home-Work trips are done in the morning peak hours, from 6 to 9 am. Likewise, most of the trips occur in the morning peak hours also for the Work purpose (figure 21b).

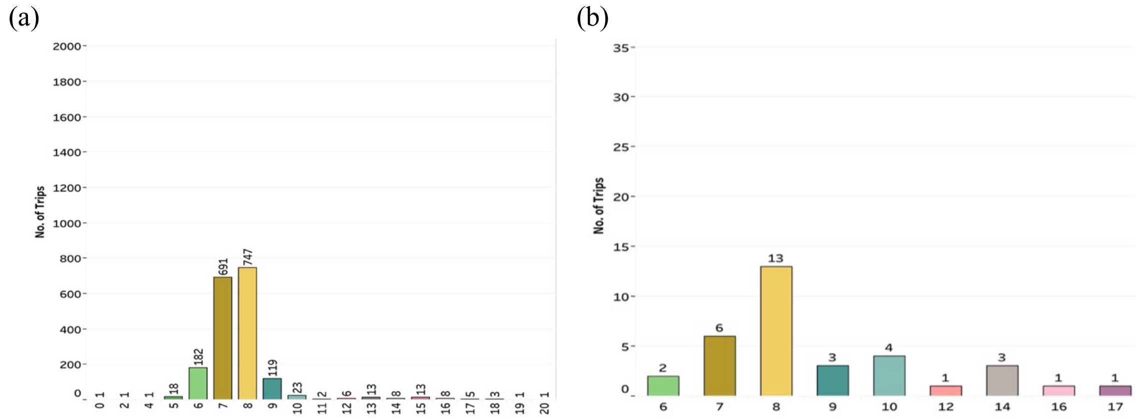


Figure 21: Trips by hour of the day of (a) Home-Work and (b) Work purpose

A similar pattern is observed for the home-school/university, mainly generated in the morning peak hours (figure 22a). Most of shopping or/bureaucratic trips (figure 22b) occur in the morning peak hours, while some trips occur in the afternoon from 3 to 6 pm.

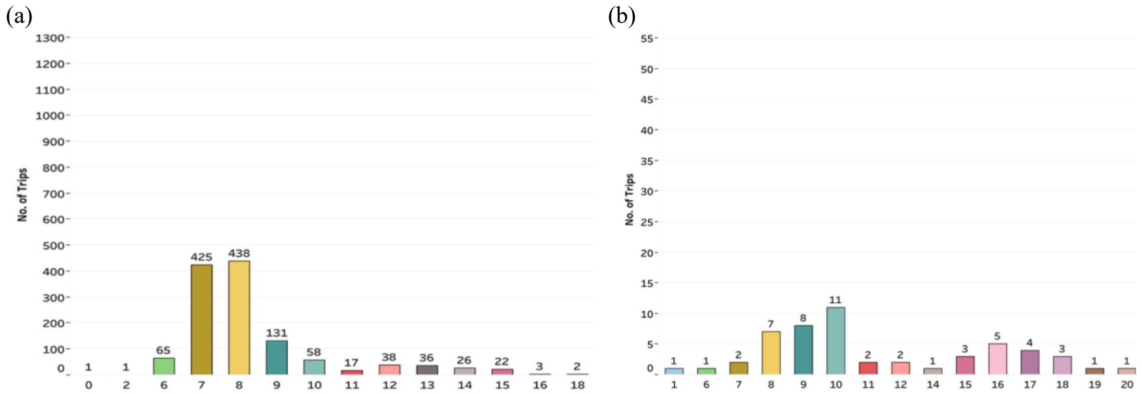


Figure 22: Trips by hour of the day (a) Home-School/University and (b) Expensesor/Bureaucratic Commissions purpose

As depicted in figure 23a, the free time trips mainly occur in the evening, from 5 to 8 pm. Trips referring the pick-up/accompany someone (figure 23b) are present both in the morning and the afternoon, related to drop/pick up children to schools or accompany someone.

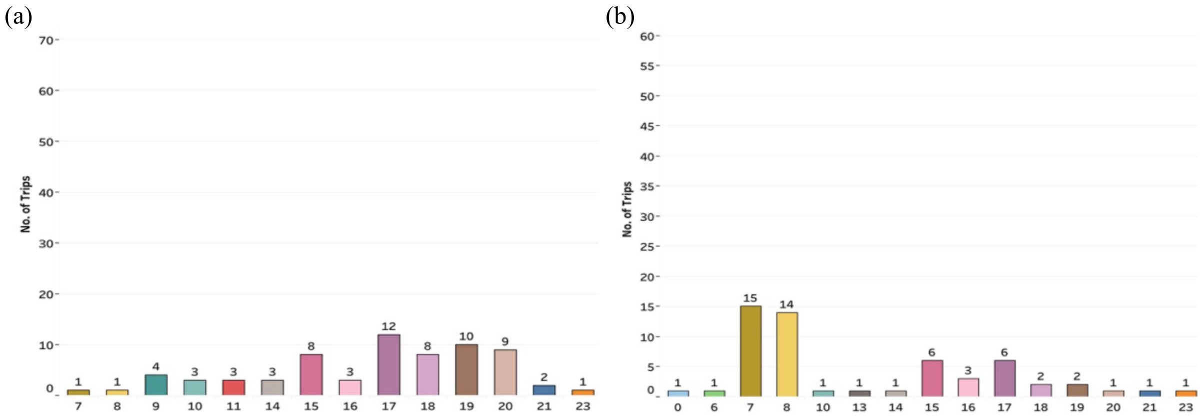


Figure 23: Trips by hour of the day for (a) free time and (b) Pick-up/Accompany Someone purpose

Very few trips are recorded for other purposes, being the sample composed mainly by workers and students; the peaks can be observed in the afternoon, at 3 and 5 pm, and in the morning, at 9 am (figure 24).

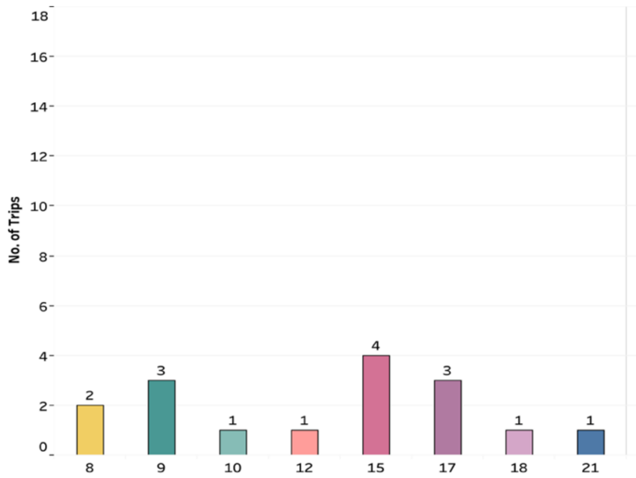


Figure 24: Other purposes trips by hour of the day

4.3 Market segmentation

In the next sections the results of the market segmentation are reported. Firstly, the variables selection process on which the cluster analysis has been made is presented, and, consequently, the latent factors allowing to interpret the defined market segments. The cluster analysis allows identifying six travellers' psychographic profiles analysed through the latent factors from Exploratory Factor Analysis (EFA). The resulting clusters are quite informative and policy relevant, highlighting the importance of attitudinal items.

4.3.1 Variable selection

The initially selected 107 features (reported in Table A2 in appendix A) were used for data examination of missing values, normality checks, and final variable selection. Starting with initial data (4473 rows and 107 variables) some rows have missing values, that could affect the obtained results. Hence, variables with too many missing values were removed, by excluding 11 variables instead of losing the data. The missing data removal decreased the number of variables, resulting in 4473 rows and 96 variables. Table B3 in appendix B shows the count of missing values for the 11 variables. As a result of the normality tests mentioned in the methodology section, the dataset is not normally distributed (*p* values <0.05). Multiple methods help to get robustness of normality checks on the data, thus multiple methods were applied. Seven variables are highly skewed, as reported in Table 23. Four variables with high kurtosis values also belongs to the seven skewed variables.

Table 23: Highly skewed and kurtosis variables

No.	Variables*	Skewness	Kurtosis
1	WatchMovie	4.87	25.74
2	TalkStranger	2.95	11.09
3	TravelWithoutTickets	2.25	4.35
4	NotCareWaste	2.11	3.23
5	Recycling	-3.11	9.42
6	ReuseShopBag	-2.78	7.72
7	EnvOrganActivities	2.03	3.70

* *The detailed description of variables is reported in Table A2 in appendix A.*

However, the issue of normality is not relevant to clustering and, at the expense of making up some data, 99.9999% of Likert-type scales do not look normal. Indeed, if all the variables were normal, this would have suggested that clustering was perhaps not even relevant. Therefore, at this stage, no variables were excluded, based on skewness and kurtosis; instead, those variables will be removed in an iterative process of variable selection by applying clustering and identifying undifferentiated variables.

For the final selection of variables, an iterative process with a different number of clusters, starting from 3 to 6, is adopted. The optimal number of clusters, at first, was 4 and 5, to investigate the variables based on the statistics reported in the next section. Thus, 3 and 6 clusters were not checked in this step. In the iterative process of checking a different number of clusters, 14 variables with equal sample and within cluster median were removed. The removed variables, the within clusters and sample median, standard deviation and number of clusters are reported in Table B4, in appendix B. Seven variables (Table 23) with high skewness beyond ±7 and kurtosis beyond ±2 also belongs to these aforementioned 14 variables, thus excluded for further clustering. The final subset of variables selected are 82 (96 – 14), used for clustering (highlighted in red colour in Table A2 in appendix A). All the steps used in clustering and in the iterative process of variable selection are explained hereafter.

4.3.2 Cluster analysis

As explained in the methodology, k-means algorithm is used for clustering. Before clustering and assessment of its tendency, the *Hopkins's statistical test* was made, giving a score (H) of 0.4614 (<0.5), showing that the data is random. Among *metrics-based methods*, by applying *elbow method* (figure 25a), when k=6, the marginal gain for intra-cluster distance starts dropping, which can be confirmed in the Table 24. Thus, k=6 is the optimal number of clusters, also validated by Silhouette score. For k=6 the Silhouette score happens to be the 6th highest among all the cluster number after that it starts to decrease (figure 25b and Table 24); therefore, k=6 to was selected to cluster the data.

Figure 26 shows the visualisation from 3 to 6 clusters, using T-distributed Stochastic Neighbour Embedding (t-SNE). We can see the little overlap of observations in 3 to 5 clusters, and clusters are not equally distributed. For k=6, clusters are almost equally and well separated, even with the high dimensional dataset of 82 variables. Thus, this visualisation validates the right number of chosen clusters. The number of records per cluster is shown in Table 25.

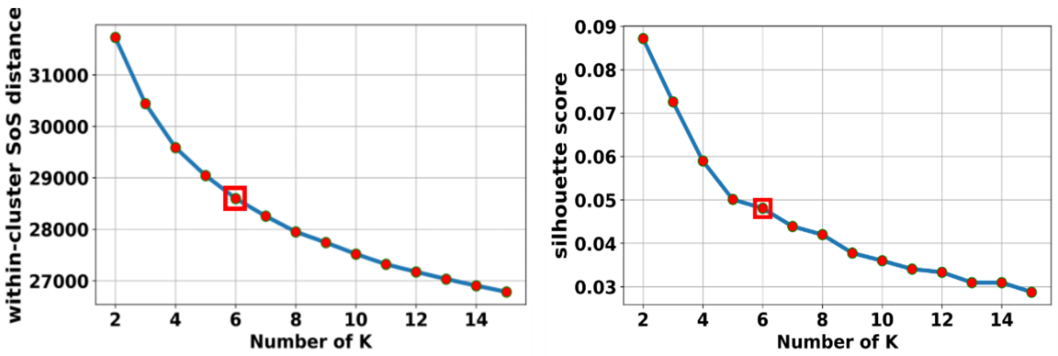


Figure 25: Optimal k using (a) elbow method (SoS is Sum of Squares) and (b) Silhouette score

Table 24: Optimal value of k using total within-cluster SoS distance and silhouette score

Clusters (k)	SoS distance	Silhouette score	Davies-Bouldin score	Calinski-Harabasz score
2	31731.17	0.087	3.109	449.39
3	30445.52	0.072	3.353	328.51
4	29589.59	0.058	3.535	268.38
5	29045.44	0.050	3.726	225.94
6	28599.79	0.048	3.709	197.45
7	28255.93	0.043	3.726	175.56
8	27951.29	0.042	3.706	159.04
9	27742.82	0.038	3.879	144.37
10	27519.49	0.036	3.856	133.36

Table 25: Number of records from 3 to 6 clusters solution

	Number of records			
Clusters	**k=3**	**k=4**	**k=5**	**k=6**
1	1144	1127	956	751
2	1483	1001	904	696
3	1846	952	1050	796
4		1393	682	811
5			881	724
6				695

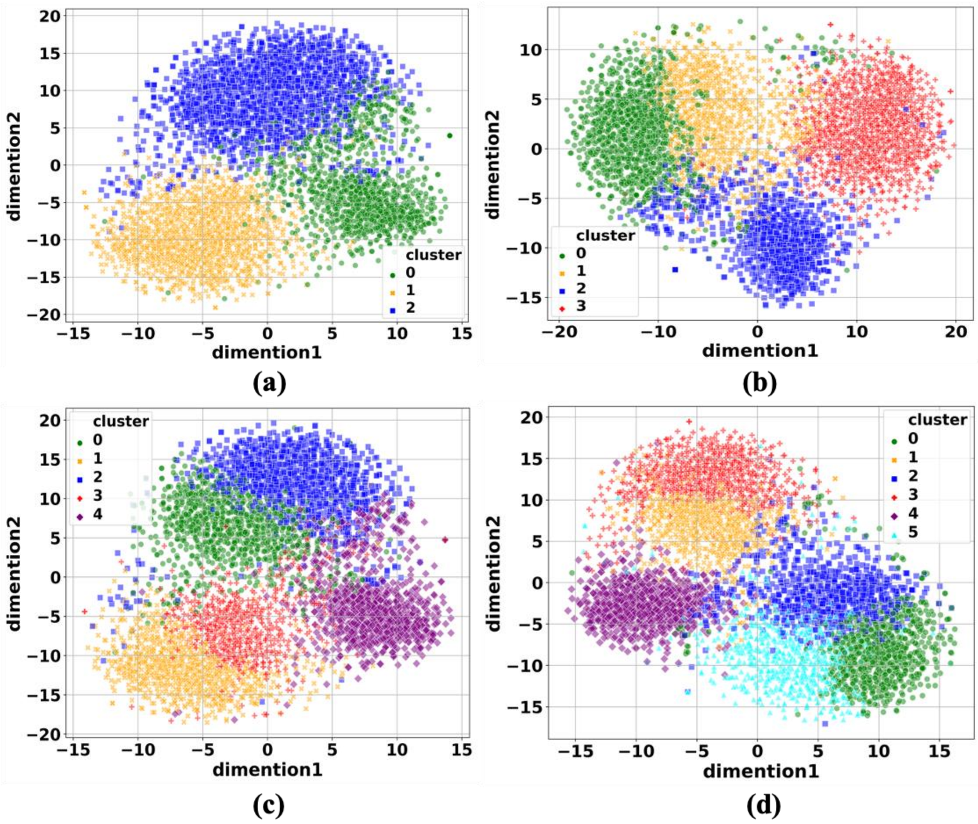


Figure 26: Visualisation of clusters from 3 to 6, using t-SNE

4.3.3 Cluster validation statistics

As explained in the methodology section, two kind of measures – internal and relative measures – are used to validate the clusters. As internal validation measures, *Silhouette score* for various number of clusters is reported in Table 24 which is also used to select the optimal number of clusters (6) for this study. In figure 27a we can see that 6 is the right number of clusters because the value of *Davies-Bouldin index* is increasing for values greater than 6; this validates our cluster stability, also confirmed from Table 24. For values greater than 6, the *Calinski-Harabasz index* score is decreasing significantly (figure 27b), that is not good and can be confirmed from the Table 24, confirming 6 as the right number of clusters.

Relative cluster validation is already done in the clustering step of choosing optimal value of clusters by applying Elbow method and Silhouette score. t-SNE (Van Der Maaten and Hinton, 2008) results can also be used as external cluster validation which confirms the right number of cluster selection. Hierarchical clustering is also used for the validation using ward linkage method (figure 28) that clearly confirms that 6 is the right choice of clusters.

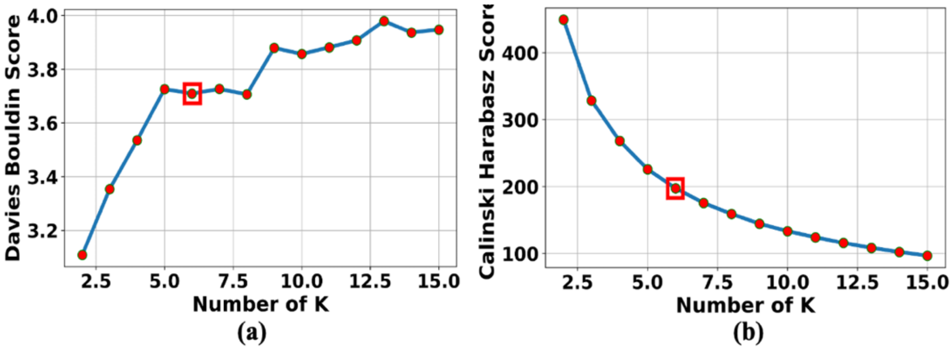


Figure 27: Cluster validation using (a) Davies-Bouldin and (b) Calinski-Harabasz index

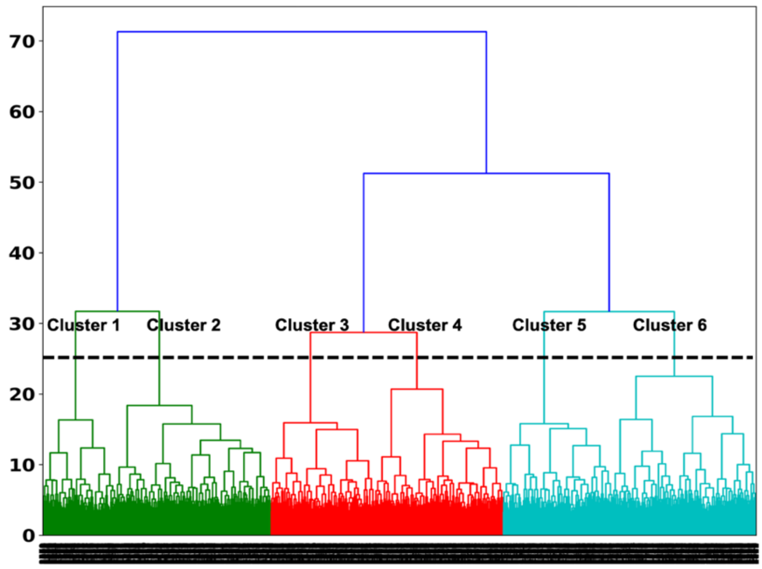


Figure 28: Hierarchical clustering dendrogram using ward linkage

4.3.4 Exploratory Factor Analysis (EFA)

After the definition and validation of clusters, EFA was used to describe the groups by measuring the correlated variables into small number of factors for easy interpretation of each cluster. The results of each step of the methodology to perform EFA is described in the next section.

4.3.4.1 Assumptions of EFA

The results of each step of the assumptions checked before applying EFA are reported for each cluster.

Normality and Multicollinearity

As resulted from Kolmogorov Smirnov and Shapiro Wilk test, the null hypothesis is rejected by obtaining *p* value <0.05, which means the dataset in all clusters are not normally distributed. The highly skewed and kurtosis variables are reported in Table 26 for each cluster which were excluded before applying EFA. Cluster 6 does not have highly skewed and kurtosis variable.

Table 26: Variables with high skewness and kurtosis in clusters

Cluster	Variables*	Skewness	Kurtosis
Cluster 1 (2 variables)	PT_MoreFreq	-2.2	-
	PT_OnTime	-2.81	8.82
Cluster 2 (7 variables)	UseFast	-2.34	-
	UseWhyFelFre	-2.54	-
	Work	9.90	-
	Read	7.41	-
	SocialNetwrk	3.55	-
	Chatting	2.38	-
	JoinGAS	2.42	-
Cluster 3 (2 variables)	AV_WatchMovie	2.76	8.01
	JoinGAS	2.09	-
Cluster 4 (4 variables)	Work	16.35	282.26
	Read	16.71	331.59
	SocialNetwrk	3.68	14.11
	Chatting	2.61	7.34
Cluster 5 (8 variables)	SatCheap	3.87	17.07
	SatEco	4.34	19.76
	UseLeastPolutnt	-2.39	-
	UseWhyLike	2.11	-
	Work	15.18	262.35
	Read	10.02	107.22
	SocialNetwrk	10.38	128.68
	Chatting	7.25	58.480
Cluster 6	-	-	-

* *The detailed description of variables is reported in Table A2 in appendix A.*

We observe some absolute values >0.3 in correlation matrix for all clusters, which justifies the application of EFA. Bartlett test of sphericity accepts the hypothesis that correlation matrix is not an identity matrix for each cluster with significant acceptable *p* value (<0.05) and acceptable mediocre Kaiser-Meyer-Olkin (KMO) test results for each cluster are reported in Table 27. Hair *et al.,* (2010) suggests accepting a value >0.5 for KMO.

Table 27: Bartlett and KMO test results for 6 clusters

Cluster	Bartlett test (*p* value)	Remark	KMO test	Remark
1	0.000	significant	0.710	Middling – ok
2	0.000	significant	0.701	Middling – ok
3	0.000	significant	0.723	Middling – ok
4	0.000	significant	0.701	Middling – ok
5	0.000	significant	0.702	Middling – ok
6	0.000	significant	0.672	Mediocre – ok

Sample size and variable/factor to observation ratio

Before performing the analysis, the adequate sample size and the ratio of variables/factors to observations are checked; results fall in acceptable range of values (Table 28), according to methodology.

Table 28: Adequate sample size, variables/factors to observations ratio

	Sample size	Variables: Observations	Factors: Observations	Remark
Requirement→ **Cluster ↓**	**>200**	**<1:10(<0.10)**	**<1:20(<0.05)**	
1	751	21:751(0.03)	7:751 (0.009)	satisfied
2	696	30:696 (0.04)	10:696 (0.04)	satisfied
3	796	27:796 (0.05)	8:796 (0.01)	satisfied
4	811	27:811 (0.03)	9:811 (0.01)	satisfied
5	724	30:724 (0.04)	9:724 (0.01)	satisfied
6	695	20:695 (0.03)	7:695 (0.01)	satisfied

Variable selection

In addition to assessing previous assumptions, the variables with values less than 0.5 on the diagonal of Anti Image Correlation Matrix and with low communality <0.2 are rejected in the first run before applying EFA, because they are not profited in factor solution. To reach a final subset of variables for each cluster, an iterative process was made on the variables remained after the first selection. The objective is to improve the factor solution. This goal is completed through three actions: a) exclusion of variables with lowest communalities; b) deletion of variables strongly correlated to two or more factors; and c) rejection of factors which do not have makers or variables heavily loading just one factor. In this way, the analysis produces a simpler factor structure. After this process, the final subset of variables retained in EFA for each cluster are, respectively, 21, 30, 27, 27, 30 and 20.

Factor retention method

To select the number of factors, three criteria are applied in synergy: Kaiser criteria, Scree test, and Parallel analysis. Based on *Scree test*, the eigen values (factors) >1 is selected for each cluster and assessed using scree plot (figure 29). Eigen values from *Kaiser criteria* and *parallel analysis* are assessed for selecting final number of factors together with scree plots. The number of factors agreed until the eigenvalues of *Kaiser criteria* >1 and greater than the eigen value from parallel analysis (coloured red in Table 29). The final number of factors retained for each cluster are, respectively, 7, 10, 8, 9, 9 and 7.

Table 29: Eigenvalues from EFA and Parallel analysis for clusters

	EFA eigenvalues for clusters						Parallel analysis eigenvalues for clusters					
Factors	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
1	3.50	3.56	3.54	3.60	3.66	3.09	1.36	1.45	1.39	1.39	1.45	1.37
2	2.34	3.08	2.92	2.59	2.69	2.20	1.29	1.39	1.34	1.33	1.38	1.29
3	2.27	2.56	2.75	2.47	2.37	1.99	1.24	1.34	1.29	1.29	1.33	1.25
4	1.78	2.14	2.24	2.01	2.28	1.81	1.21	1.30	1.26	1.25	1.29	1.21
5	1.55	1.97	1.89	1.67	2.16	1.62	1.18	1.27	1.23	1.22	1.26	1.17
6	1.26	1.74	1.42	1.64	1.99	1.37	1.14	1.23	1.19	1.19	1.23	1.14
7	1.16	1.56	1.33	1.39	1.66	1.27	1.12	1.21	1.17	1.16	1.20	1.11
8	0.91	1.38	1.18	1.33	1.31	0.91	1.09	1.18	1.14	1.13	1.18	1.08
9	0.77	1.21	0.95	1.16	1.28	0.71	1.06	1.15	1.12	1.11	1.15	1.05
10	0.67	1.17	0.89	0.90	0.93	0.66	1.04	1.13	1.09	1.09	1.13	1.03
11	0.61	0.88	0.80	0.82	0.82	0.61	1.01	1.11	1.07	1.06	1.10	0.99
12	0.57	0.79	0.69	0.60	0.76	0.54	0.99	1.09	1.05	1.04	1.08	0.98

Factor extraction and rotation method

As explained in the methodology, Principal Axis Factoring (PAF) is selected being suitable in case of violation of normal distribution in the data, according to Fabrigar *et al.,* (1999) for factor extraction. For the *factor rotation*, different methods based on the sample data for each cluster are chosen separately. In the first run, PAF with non-orthogonal rotation method, direct oblimin, was chosen to assess the factor correlation matrix to validate the rotation method. If some absolute values are >0.32 in factor correlation matrix, then the oblimin rotation or promax is retained, concluding that factors are correlated. Otherwise, orthogonal method varimax or quartimax is selected, whichever is best to reach a simple factor loading structure.

Factor structure evaluation and score calculation

The final obtained factor structures for each cluster are reported in Tables from 30 to 35, where almost all the variables show very high correlation onto the factors they load, being between good and excellent, according to Comrey and Lee (1992).

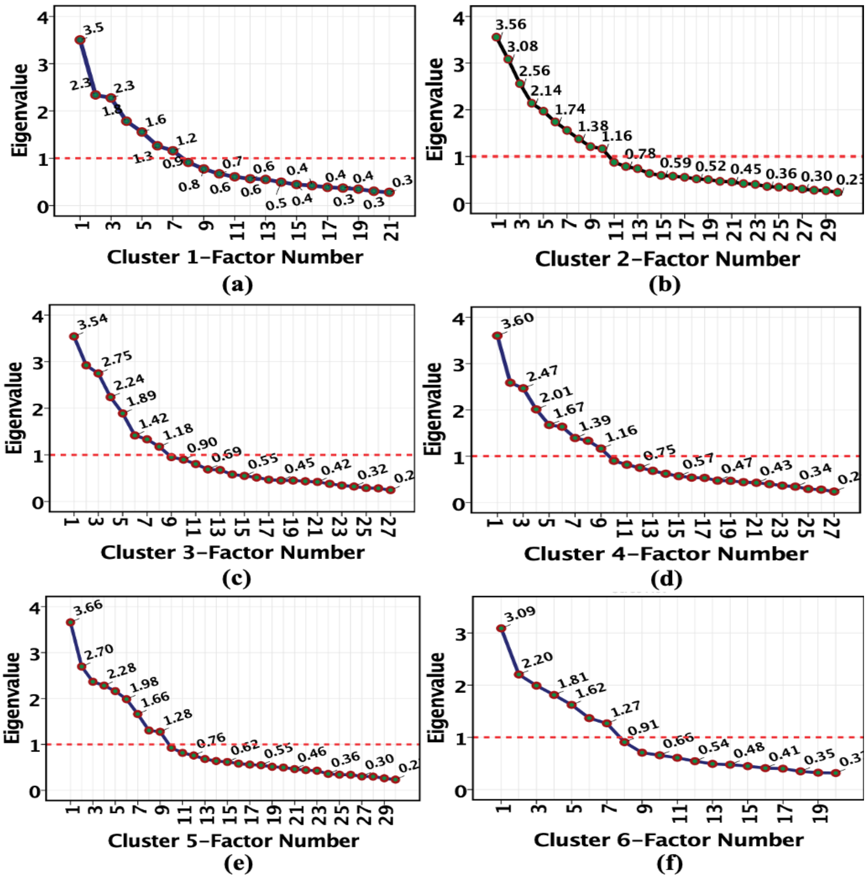


Figure 29: Scree plots for 6 clusters

Table 30: Rotated factor loadings for cluster 1

	Factors						
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**
LikDareTravl	.87	-.03	.05	-.08	-.02	-.01	-.03
LikRechUnknDest	.83	-.00	.01	-.02	.02	-.04	.03
LikDiscNewPlace	.75	.05	.00	.02	.03	.02	.04
LikTravlAltrntiv	.59	-.03	-.04	.08	-.03	.01	-.05
PT_MoreClean	.04	.88	.01	.02	.05	-.00	-.04
PT_MoreSecurity	-.02	.70	-.00	-.04	.02	-.04	.03
PT_MoreComfort	-.04	.63	-.00	-.00	-.09	.06	.01
AV_SocialNetwrk	-.02	-.01	.74	-.04	.04	.04	.03

AV_Chatting	-.04	-.02	.73	-.04	.02	.03	.00
AV_Relax	.01	.02	.54	.11	-.07	-.02	-.01
AV_WatchMovie	.08	.02	.53	.01	-.02	-.06	-.03
SupportEnvOrganisation	-.04	-.05	.02	.67	.04	-.06	-.06
NoOGMProducts	-.09	.01	.06	.65	.02	-.05	-.03
ChatProEnvironment	.13	.01	-.06	.56	-.03	.06	.04
ProEnvBehaviour	.07	.00	.02	.44	-.03	.09	.09
SatLikeMode	.01	-.02	-.03	.00	.79	.00	-.01
UseWhyLike	-.00	.01	.00	.02	.79	.01	.01
SatSafe	.01	-.05	-.04	-.05	.01	.80	-.03
UseLesAcident	-.03	.06	.03	.05	.00	.67	.01
GiveOutOld	-.02	.05	-.03	.01	.03	-.01	.76
LendItems	.00	-.06	.03	-.01	-.03	-.01	.74

Note: PAF with Promax rotation is used.
** The detailed description of variables is reported in Table A2 in appendix A.*

Table 31: Rotated factor loadings for cluster 2

	Factor									
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
LikRechUnknDest	.90	.00	-.01	.04	.07	.04	.01	.02	-.05	.06
LikDiscNewPlace	.75	.00	.05	.05	.04	.04	.07	.04	.02	.05
LikDareTravl	.75	.02	-.05	.02	.04	.12	-.07	.06	.06	.02
LikTravlAltrntiv	.61	.01	.00	-.04	-.05	-.02	.06	.02	.03	.02
UseLesAcident	.02	.77	.03	.00	.09	.05	.05	.03	-.01	-.09
UseLeastPolutnt	-.01	.72	.09	-.05	-.06	.08	.04	.11	.04	-.06
UseCheap	-.04	.60	.09	-.09	-.05	.03	-.03	.09	.05	-.04
SatSafe	.07	.54	-.07	.05	.23	-.02	-.00	.04	-.01	-.03
PT_MoreClean	-.02	.01	.86	-.01	-.00	.03	.02	.07	.01	.00
PT_MoreSecurity	-.03	.05	.76	-.04	.01	-.01	.12	.04	.01	.02
PT_MoreComfort	.04	.06	.64	-.01	.03	-.01	-.04	.06	.02	-.01
AV_Chatting	.01	-.07	-.04	.95	.02	.09	-.16	.07	.02	.06
AV_Call	-.00	-.02	.02	.63	-.02	.08	-.02	.04	.13	.04
AV_SocialNetwrk	.04	-.01	-.05	.54	.01	.09	-.15	.06	-.00	.20
SatComfort	.02	-.03	.06	-.05	.81	.07	.01	.12	.04	.08
SatReliable	-.02	.21	.01	-.03	.71	.02	.05	.12	-.04	-.04
SatFlexibile	.05	.00	-.02	.06	.57	.03	.05	-.01	-.01	-.03
Landscape	.08	.06	-.01	.07	-.06	.69	.04	.07	.18	-.05
Think	.00	.05	.01	.15	.05	.67	-.04	.04	-.05	.07
Relax	.09	.02	.00	.03	.14	.61	-.06	.13	.12	.14
ChatProEnvironment	.05	.04	.09	-.07	.02	.03	.70	-.02	.00	-.00
SupportEnvOrganisation	.03	.02	-.06	-.07	.04	-.06	.53	.04	-.06	-.04
ProEnvBehaviour	.03	-.01	.04	.02	.01	.05	.52	-.01	-.05	.03
NoOGMProducts	-.04	-.01	.01	-.18	.01	-.09	.49	.05	-.01	-.07
UseWhyLike	.07	.21	.10	.09	.06	.16	.07	.79	-.02	.04
SatLikeMode	.07	.12	.09	.09	.17	.11	.02	.77	.02	.05
AV_TalkFriend	.01	.00	.04	.19	.02	.05	-.08	.06	.81	.11

TalkFriend	.06	.05	.01	-.01	-.02	.16	-.08	-.05	.67	.00
AV_ListenMusic	.03	-.03	-.01	.15	-.03	.10	-.04	.03	.13	.73
ListenMusic	.10	-.19	.03	.12	.01	.10	-.04	.04	-.02	.69

Note: PAF with Varimax rotation is used.
** The detailed description of variables is reported in Table A2 in appendix A.*

Table 32: Rotated factor loadings for cluster 3

	Factor							
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
UseWhyFelFre	.77	-.01	.07	-.07	.01	.03	.05	-.06
UseLesDelay	.67	-.02	.10	-.22	.05	-.05	-.01	.01
UseFast	.63	.03	.08	-.08	-.05	.12	.03	.01
UseWhyLike	.63	.01	-.06	.26	-.01	-.03	-.03	-.01
SatLikeMode	.53	.00	-.13	.22	-.05	-.05	-.02	.03
SatComfort	.39	-.03	-.19	.02	.05	-.03	-.10	.04
LikRechUnknDest	-.01	.88	.00	-.01	-.03	.02	-.01	-.01
LikDiscNewPlace	.00	.79	.11	.03	.01	-.05	.04	-.07
LikDareTravl	-.01	.74	-.05	-.02	-.06	.03	-.03	.06
LikTravlAltrntiv	.02	.61	-.08	-.04	.11	.01	-.04	.05
PT_MoreClean	.04	-.01	.88	.01	.02	.01	-.03	.06
PT_MoreSecurity	.05	-.02	.75	.03	.00	-.02	-.02	-.03
PT_MoreComfort	-.04	-.01	.75	.04	-.02	.00	-.01	.00
UseLesAcident	-.09	.00	.07	.78	.07	.04	-.05	-.01
UseLeastPolutnt	.12	.02	.03	.59	.02	-.05	.08	.05
SatSafe	-.09	-.04	.00	.56	.02	.07	-.04	.03
UseCheap	.00	.00	.01	.55	-.08	-.00	.03	-.06
SupportEnvOrganisation	-.01	-.03	-.03	-.04	.69	-.04	-.09	-.03
ChatProEnvironment	.02	.03	-.02	-.00	.68	.03	.05	-.01
NoOGMProducts	-.07	.03	.06	.08	.56	-.09	.01	-.04
ProEnvBehaviour	.05	.01	-.01	-.00	.54	.12	.12	.05
SocialNetwrk	.07	.01	.02	-.03	-.00	.87	-.01	-.04
Chatting	-.04	-.01	-.04	.09	.01	.74	.00	.02
GiveOutOld	-.01	.00	-.02	.03	-.03	-.03	.95	-.05
LendItems	.01	-.04	-.04	-.04	.09	.02	.52	.12
CarPooling_Driver	-.00	.00	.02	-.01	-.01	-.01	-.00	.82
CarPooling_Pax	-.01	.03	.02	.02	-.02	-.01	.06	.59

Note: PAF with Promax rotation is used.
** The detailed description of variables is reported in Table A2 in appendix A.*

Table 33: Rotated factor loadings for cluster 4

	Factor								
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
LikRechUnknDest	.87	-.01	-.00	-.01	-.03	-.03	.01	-.00	-.00
LikDiscNewPlace	.79	-.00	-.02	.01	.01	-.06	.00	-.02	.00
LikDareTravl	.71	-.03	.02	.03	-.01	.08	.02	.01	-.04

LikTravlAltrntiv	.55	.05	.02	-.05	.05	.04	-.05	.04	.05
PT_MoreClean	.00	.90	.02	.01	-.05	.04	-.04	-.04	-.01
PT_MoreSecurity	-.01	.72	-.05	.07	.03	-.03	-.02	.02	-.03
PT_MoreComfort	.02	.69	-.01	-.00	.05	-.04	.02	.01	.01
PT_OnTime	-.00	.46	.04	-.05	-.08	.03	.03	.01	.05
Landscape	-.03	-.02	.95	-.11	.01	.00	-.06	.03	.02
Think	.03	-.02	.52	-.03	-.07	-.05	.07	-.13	.02
AV_Landscape	.02	.11	.45	-.06	.07	.06	.19	.08	-.02
Relax	.01	-.06	.43	.22	-.03	.01	-.03	.04	-.03
UseContctLndscp	.00	.04	.42	.34	.03	-.01	-.05	.04	-.02
UseWhyLike	-.02	.01	-.04	.91	.021	.01	.03	.01	-.02
SatLikeMode	-.00	.01	.03	.81	-.02	-.01	.00	-.03	.05
ChatProEnvironment	-.03	.01	-.03	-.04	.71	.04	.06	-.01	-.06
SupportEnvOrganisation	-.02	-.06	-.04	.00	.55	-.01	-.04	.01	.07
ProEnvBehaviour	.07	-.04	.00	.12	.55	.01	.01	.01	-.00
NoOGMProducts	.01	.02	.05	-.07	.52	-.05	-.06	-.04	.01
CarPooling_Driver	.02	-.02	-.00	.02	-.02	.80	.00	-.00	-.01
CarPooling_Pax	.00	.03	-.01	-.03	.01	.78	-.02	-.03	.02
AV_Call	.01	.05	.04	-.03	.04	-.05	.75	-.05	.02
AV_Chatting	-.03	-.07	.01	.07	-.06	.03	.75	-.02	-.01
AV_TalkFriend	.00	.03	-.07	-.04	-.02	-.01	.10	.91	.01
TalkFriend	.01	-.04	.06	.02	-.01	-.02	-.16	.58	-.00
LendItems	-.00	-.04	-.01	.04	.00	.05	.01	.06	.75
GiveOutOld	.01	.06	.01	-.01	.01	-.04	.01	-.06	.71

Note: PAF with Promax rotation is used.
* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 34: Rotated factor loadings for cluster 5

	Factor								
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
LikRechUnknDest	.89	-.04	-.01	.00	-.04	.02	-.00	-.03	-.01
LikDareTravl	.80	-.08	.01	-.05	.03	-.01	-.06	.07	.00
LikDiscNewPlace	.76	.05	-.08	.07	.01	.03	.08	-.03	.01
LikTravlAltrntiv	.61	.09	.05	.01	-.02	-.06	.00	-.01	.02
ChatProEnvironment	.04	.73	.04	-.03	.09	-.01	-.04	-.03	-.06
NoOGMProducts	.02	.66	-.03	.01	-.10	.00	-.01	.05	-.06
SupportEnvOrganisation	-.06	.56	-.04	-.05	-.04	.08	.01	.02	.07
EatLessMeat	-.05	.55	-.09	.05	.01	-.04	.04	.01	.02
ProEnvBehaviour	.06	.46	.01	-.05	.05	-.08	.03	-.01	.08
UseFast	-.03	.01	.73	.03	.01	-.03	-.02	-.00	-.03
UseLesDelay	.02	.01	.68	.04	.02	.03	.02	-.08	.11
SatSpeed	-.03	-.07	.66	.01	-.01	-.12	-.02	.08	.01
UseWhyFelFre	.02	-.03	.55	.02	-.01	.04	.14	-.02	.01
PT_MoreClean	-.00	-.00	.07	.91	-.02	.01	-.02	.02	-.01
PT_MoreSecurity	-.02	-.01	-.01	.73	.04	-.01	-.02	-.00	.00
PT_MoreComfort	.04	-.03	.03	.65	.00	.04	-.01	.03	-.03

AV_Chatting	.02	-.04	.02	-.05	.97	.02	.01	-.00	-.00
AV_Call	.01	.09	-.01	.05	.63	-.01	-.04	.00	.06
AV_SocialNetwrk	-.05	-.05	-.00	.03	.59	-.02	.03	.02	-.08
UseLesAcident	-.03	.02	-.13	.12	.02	.81	.04	-.07	.05
SatSafe	-.01	-.09	-.16	.01	-.01	.66	.04	.05	.05
UseLesAgreson	.04	.05	.29	-.02	-.01	.53	-.07	-.04	-.08
SatSecure	.01	.03	.22	-.18	-.03	.49	-.07	.11	-.07
Landscape	.02	.02	.04	.02	-.02	-.03	.73	.01	-.04
Think	-.03	.03	-.02	-.01	.06	.04	.63	.01	.04
Relax	.02	-.03	.08	-.06	-.04	.01	.63	.01	-.03
CarPooling_Pax	.02	.06	-.03	.02	.03	.04	.01	.81	-.00
CarPooling_Driver	-.01	-.02	.02	.03	-.01	-.03	.01	.75	.03
LendItems	.02	-.07	.02	-.08	-.02	.02	-.02	.03	.92
GiveOutOld	-.02	.16	.06	.07	-.00	-.01	-.00	-.02	.62

Note: PAF with Promax rotation is used.
** The detailed description of variables is reported in Table A2 in appendix A.*

Table 35: Rotated factor loadings for cluster 6

	Factor						
Variables*	**1**	**2**	**3**	**4**	**5**	**6**	**7**
LikRechUnknDest	.86	-.06	-.05	-.08	-.05	.01	-.00
LikDareTravl	.75	-.01	.06	.05	-.04	.02	-.05
LikDiscNewPlace	.69	.09	.04	-.02	.03	-.01	-.01
LikTravlAltrntiv	.52	.02	-.04	.09	.10	-.03	.09
PT_MoreClean	-.03	.82	.03	.00	-.02	-.04	-.02
PT_MoreSecurity	.01	.77	-.05	.02	.01	.02	-.00
PT_MoreComfort	.06	.60	.01	-.03	-.01	.04	.03
ChatProEnvironment	.04	-.03	.65	.01	.01	-.02	-.03
SupportEnvOrganisation	-.06	.01	.63	-.03	.01	.01	.07
NoOGMProducts	-.02	.03	.52	-.01	-.02	-.05	-.02
ProEnvBehaviour	.06	-.03	.50	.06	.01	.07	-.01
CarPooling_Driver	.00	-.04	-.03	.75	-.05	.01	-.05
CarPooling_Pax	.02	.05	-.02	.72	.06	-.02	-.01
JoinGAS	-.01	-.02	.09	.49	-.03	.01	.07
UseWhyLike	.01	.01	.04	-.02	.86	-.01	.01
SatLikeMode	.01	-.03	-.03	.00	.76	.01	-.02
AV_Chatting	-.02	.01	.04	.03	.01	.78	-.01
AV_SocialNetwrk	.01	.01	-.04	-.04	-.01	.73	.01
LendItems	.03	-.02	-.06	.05	.00	.00	.85
GiveOutOld	-.01	.03	.08	-.05	-.02	-.00	.65

Note: PAF with Promax rotation is used.
** The detailed description of variables is reported in Table A2 in appendix A.*

Finally, the factor structure is evaluated based on the complementary aspects of *total explained variance, Cronbach Alpha* and *meaning and relevance of factors*. Table 36 reports

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

the total variance explained in EFA for each cluster sample and subset of selected variables. The gradual reduction of variables allows to increase the percentage of the variance. Obtained factor solution satisfies the threshold for each cluster (Table 36). Cronbach Alpha is reported in Tables 37-42 (see column Cronbach Alpha) for each factor solution for each cluster. All Cronbach Alpha values are acceptable. As mentioned in the methodology, Bartlett score method is chosen for factor score calculation for further factor visualisation and cluster explanation.

Table 36: Total explained variance by clusters

Cluster	Total explained variance
1	50.58%
2	53.41%
3	50.63%
4	51.84%
5	51.30%
6	51.66%

Interpretation of factors

Interpretation of the obtained factor solution is made to better explain the meaning and relevance of each factor and to assign a name to the factors based on the variables loading it. The Tables 37-42 represent the variables loading each factor and their corresponding names, to better understand the typology of respondents belonging to each cluster.

Table 37: Factor interpretation for cluster 1

Variables*	Loads	Cronbach Alpha	Factor (F)
LikDareTravl	0.87	0.837	F1: Travel pleasure
LikRechUnknDest	0.83		
LikDiscNewPlace	0.75		
LikTravlAltrntiv	0.59		
PT_MoreClean	0.88	0.774	F2: Improvement of onboard service quality
PT_MoreSecurity	0.70		
PT_MoreComfort	0.63		
AV_SocialNetwrk	0.74	0.716	F3: Activities on AV
AV_Chatting	0.73		
AV_Relax	0.54		
AV_WatchMovie	0.53		
SupportEnvOrganisation	0.67	0.656	F4: Pro-environment activism
NoOGMProducts	0.65		
ChatProEnvironment	0.56		
ProEnvBehaviour	0.44		
SatLikeMode	0.79	0.766	F5: Mode pleasure

UseWhyLike	0.79		
SatSafe	0.80	0.694	F6: Safe travel
UseLesAcident	0.67		
GiveOutOld	0.76	0.720	F7: Aware consumerism
LendItems	0.74		

* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 38: Factor interpretation for cluster 2

Variables*	Loads	Cronbach Alpha	Factor (F)
LikRechUnknDest	0.90	0.837	F1: Travel pleasure
LikDiscNewPlace	0.75		
LikDareTravl	0.75		
LikTravlAltrntiv	0.61		
UseLesAcident	0.77	0.753	F2: Eco-friendly & safe
UseLeastPolutnt	0.72		
UseCheap	0.60		
SatSafe	0.54		
PT_MoreClean	0.86	0.797	F3: Improvement of onboard service quality
PT_MoreSecurity	0.76		
PT_MoreComfort	0.64		
AV_Chatting	0.95	0.762	F4: Activities on AV
AV_Call	0.63		
AV_SocialNetwrk	0.54		
SatComfort	0.81	0.728	F5: Mode performance
SatReliable	0.71		
SatFlexibile	0.57		
Landscape	0.69	0.712	F6: Self-absorbed activity
Think	0.67		
Relax	0.61		
ChatProEnvironment	0.70	0.641	F7: Pro-environment activism
SupportEnvOrganisation	0.53		
ProEnvBehaviour	0.52		
NoOGMProducts	0.49		
UseWhyLike	0.79	0.816	F8: Mode pleasure
SatLikeMode	0.77		
AV_TalkFriend	0.81	0.710	F9: Chatting onboard
TalkFriend	0.67		
AV_ListenMusic	0.73	0.698	F10: Music onboard
ListenMusic	0.69		

* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 39: Factor interpretation for cluster 3

Variables*	Loads	Cronbach Alpha	Factor (F)
UseWhyFelFre	0.77	0.780	F1: Mode pleasure
UseLesDelay	0.67		

UseFast	0.63		
UseWhyLike	0.63		
SatLikeMode	0.53		
SatComfort	0.39		
LikRechUnknDest	0.88	0.838	F2: Travel pleasure
LikDiscNewPlace	0.79		
LikDareTravl	0.74		
LikTravlAltrntiv	0.61		
PT_MoreClean	0.88	0.826	F3: Improvement of onboard service quality
PT_MoreSecurity	0.75		
PT_MoreComfort	0.75		
UseLesAcident	0.78	0.709	F4: Eco-friendly & safe
UseLeastPolutnt	0.59		
SatSafe	0.56		
UseCheap	0.55		
SupportEnvOrganisation	0.69	0.709	F5: Pro-environment activism
ChatProEnvironment	0.68		
NoOGMProducts	0.56		
ProEnvBehaviour	0.54		
SocialNetwrk	0.87	0.787	F6: Self-absorbed activities
Chatting	0.74		
GiveOutOld	0.95	0.664	F7: Aware consumerism
LendItems	0.52		
CarPooling_Driver	0.82	0.645	F8: Willingness to carpool
CarPooling_Pax	0.59		

* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 40: Factor interpretation for cluster 4

Variables*	Loads	Cronbach Alpha	Factor (F)
LikRechUnknDest	0.87	0.806	F1: Travel pleasure
LikDiscNewPlace	0.79		
LikDareTravl	0.71		
LikTravlAltrntiv	0.55		
PT_MoreClean	0.90	0.785	F2: Improvement of onboard service quality
PT_MoreSecurity	0.72		
PT_MoreComfort	0.69		
PT_OnTime	0.46		
Landscape	0.95	0.722	F3: Self-absorbed activities
Think	0.52		
AV_Landscape	0.45		
Relax	0.43		
UseContctLndscp	0.42		
UseWhyLike	0.91	0.850	F4: Mode pleasure
SatLikeMode	0.81		
ChatProEnvironment	0.71	0.658	

SupportEnvOrganisation	0.55		F5: Pro-environment activism
ProEnvBehaviour	0.55		
NoOGMProducts	0.52		
CarPooling_Driver	0.80	0.767	F6: Willingness to carpool
CarPooling_Pax	0.78		
AV_Call	0.75	0.713	F7: Activities on AV
AV_Chatting	0.75		
AV_TalkFriend	0.91	0.662	F8: Chatting onboard
TalkFriend	0.58		
LendItems	0.75	0.691	F9: Aware consumerism
GiveOutOld	0.71		

* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 41: Factor interpretation for cluster 5

Variables*	**Loads**	**Cronbach Alpha**	**Factor (F)**
LikRechUnknDest	0.89	0.843	F1: Travel pleasure
LikDareTravl	0.80		
LikDiscNewPlace	0.76		
LikTravlAltrntiv	0.61		
ChatProEnvironment	0.73	0.721	F2: Pro-environment activism
NoOGMProducts	0.66		
SupportEnvOrganisation	0.56		
EatLessMeat	0.55		
ProEnvBehaviour	0.46		
UseFast	0.73	0.737	F3: Mode pleasure
UseLesDelay	0.68		
SatSpeed	0.66		
UseWhyFelFre	0.55		
PT_MoreClean	0.91	0.800	F4: Improvement of onboard service quality
PT_MoreSecurity	0.73		
PT_MoreComfort	0.65		
AV_Chatting	0.97	0.758	F5: Activities on AV
AV_Call	0.63		
AV_SocialNetwrk	0.59		
UseLesAcident	0.81	0.707	F7: Safe travel
SatSafe	0.66		
UseLesAgreson	0.53		
SatSecure	0.49		
Landscape	0.73	0.688	F7: Self-absorbed activities
Think	0.63		
Relax	0.63		
CarPooling_Pax	0.81	0.758	F8: Willingness to carpool
CarPooling_Driver	0.75		
LendItems	0.92	0.743	F9: Aware consumerism
GiveOutOld	0.62		

* *The detailed description of variables is reported in Table A2 in appendix A.*

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

Table 42: Factor interpretation for cluster 6

Variables*	Loads	Cronbach Alpha	Factors (F)
LikRechUnknDest	0.86	0.789	F1: Travel pleasure
LikDareTravl	0.75		
LikDiscNewPlace	0.69		
LikTravlAltrntiv	0.52		
PT_MoreClean	0.82	0.773	F2: Improvement of onboard service quality
PT_MoreSecurity	0.77		
PT_MoreComfort	0.60		
ChatProEnvironment	0.65	0.659	F3: Pro-environment activism
SupportEnvOrganisation	0.63		
NoOGMProducts	0.52		
ProEnvBehaviour	0.50		
CarPooling_Driver	0.75	0.692	F4: Willingness to carpool
CarPooling_Pax	0.72		
JoinGAS	0.49		
UseWhyLike	0.86	0.794	F5: Mode pleasure
SatLikeMode	0.76		
AV_Chatting	0.78	0.723	F6: Activities on AV
AV_SocialNetwrk	0.73		
LendItems	0.85	0.715	F7: Aware consumerism
GiveOutOld	0.65		

** The detailed description of variables is reported in Table A2 in appendix A.*

The *first factor* is present in all clusters, showing its strength. It is composed by 4 variables which correlation is very high. This factor is labelled *Travel pleasure* because all variables are related to attitudes towards travelling; it measures respondent's preferences to adventurous journeys, trips to unknown destinations, their likeness to move around looking for new places and to experiment with different travel alternatives to reach the same destination. This factor confirms the results from a previous research by Pronello and Camusso (2011), carried out in the city of Alessandria (in the Piedmont region), and it proves the research robustness. To highlight the coherence between the two results the same label is maintained.

The factor *Improvement of onboard service quality* is emerged in all clusters. Variables loading it are focused on the onboard service quality of PT: cleaning, safety, and comfort.

The factor labelled *Activities on AV* represents the attitude towards doing several activities when travelling in Autonomous Vehicles (AV). This factor includes 4 variables related to surfing social network, chatting with messages, relaxing, and watching videos or TV series. This factor is present in all clusters except cluster 3.

The factor *Pro-environment activism* describes the respondents' sensitivity towards the environment. It is composed by 4 variables, related to the behaviours towards pro-environment

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

activities that imply different levels of difficulty to be performed. The first variable refers to giving economic support to environmental organisations. The second variable is related to boycott companies that use pesticides. The third variable represents the involvement in environmental issues by often talking about them with friends. The fourth variable is related to pointing out someone who behaves non-ecologically. This factor is also emerging from all clusters.

The *Mode pleasure* factor contains the two variables regarding the specific attitude towards the pleasure of the trip and of the mode of transport used in the most frequent trip. The result of this factor is also coherent with the previous research by Pronello and Camusso (2011). This factor is mainly composed by two variables (pleasantness of the most important trip-SatLikeMode and pleasure of the used mode-UseWhyLike) in clusters 1, 2, 4 and 6. In cluster 3, beside these two variables, this factor includes four further variables; three are related to the reason of the mode choice that is feeling free, less delay, and it is the fastest mode. The fourth variable is related to the satisfaction about the comfort of the mode used in the most important trip. In cluster 5, the factor contains three variables such as cluster 3 (I am feeling free, less delays and it is the fastest mode), and the fourth variable is related to the satisfaction about the mode used in the most important trip which is fast.

The factor *Safe travel* refers to variables meaning the sense of safety and security of users towards the trip and the mode used in the most frequent trip. This factor is slightly different for cluster 1 and 5. In cluster 1, the variables refer only to the sense of safety felt during the trip and to the reason of selecting the mode because it guarantees less accidents. In cluster 5, beside the same variables related to safety, the factor includes two variables related to security towards the trip and the mode used guaranteeing less aggressions.

The factor *Aware consumerism* is composed by two variables concerning the reuse of things: giving out and lending secondhand items. This factor is present in all cluster except cluster 2.

The factor *Eco-friendly & safe* characterises clusters 2 and 3. Three variables are common to both clusters, referring to the attitude towards the mode used for the most important trip: it guarantees less accidents, it is less polluting, and it is the cheapest mode. In cluster 3, an additional variable refers to the sense of safety felt during the trip.

The factor *Mode performance* is present only in cluster 2 and it is composed by three variables regarding the satisfaction for the most frequent trip, considered comfortable, punctual, and flexible.

The factor *Self-absorbed activities* is present in all the clusters except 1 and 6. In clusters from 2 to 5, the factor does not present the same variables, but the footprint of this factor is related to the activities when travelling during most important trip. Cluster 2 and 5 includes the same three variables related to the activities of thinking, relaxing, and looking at the landscape while travelling. Cluster 4 includes, beside the above variables, two variables related to the landscape: the pleasure of staying in contact with the landscape in the chosen mode and when travelling in AV. Cluster 3, instead, is composed by only two variables related to surfing on social network and chatting when travelling.

The factor *Chatting onboard* is defined by the variables related to talking while travelling. Cluster 2 and 4 come up with this factor.

The factor *Music onboard* is only emerging in cluster 2 with the variables regarding listening music while travelling during most important trip and in AV.

The factor *Willingness to carpool* characterises all clusters except 1 and 2; it is composed by the variables expressing the willingness to carpooling both as driver and passenger.

In total, 13 factors were found characterising the 6 clusters that include a different number of factors. Table 43 shows the synthesis of factor and cluster composition.

Table 43: Factors and clusters relation summarization

		Cluster					
No.	**Factors**	**1**	**2**	**3**	**4**	**5**	**6**
1	Travel pleasure	x	x	x	x	x	x
2	Improvement of onboard service quality	x	x	x	x	x	x
3	Activities on AV	x	x	-	x	x	x
4	Pro-environment activism	x	x	x	x	x	x
5	Mode pleasure	x	x	x	x	x	x
6	Safe travel	x	-	-	-	x	-
7	Aware consumerism	x	-	x	x	x	x
8	Eco-friendly & safe	-	x	x	-	-	-
9	Mode performance	-	x	-	-	-	-
10	Self-absorbed activities	-	x	x	x	x	-
11	Chatting onboard	-	x	-	x	-	-
12	Music onboard	-	x	-	-	-	-
13	Willingness to carpool	-	-	x	x	x	x

Note: x represents the presence of the factor in the cluster; - represents its absence.

4.3.5 Profiling clusters

The last step of the segmentation analysis describes each cluster using the other variables collected through the survey, either included or not in the clustering and Exploratory Factor

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

Analysis (EFA) process. In this phase, all the information that can support the cluster characterisation will be used to interpret the clusters.

Before assigning a label to the six clusters, some analyses have been conducted to better characterize the different groups and support the interpretation of the different profiles. To this end, analyses of the clusters using preferences and attitudes excluded from both clustering and EFA process are carried out, together with a socio-economic and mobility pattern analysis of the individuals in the different groups. Finally, based on these findings, the analyses of the factors characterizing the groups will allow to label the six clusters.

4.3.5.1 Analysis of preferences and attitudes excluded from clustering and EFA process

To evaluate clusters using the 14 variables excluded from clustering, Kruskal-Wallis (KW) nonparametric test is used. To determine whether any of the differences between the medians are statistically significant, the *p*-value is compared to the significance level (0.05) to assess the null hypothesis (no difference among cluster medians or cluster medians are equal) and reported in Table 44. Three variables among those excluded from final clustering are showing significant difference among clusters. The median for each cluster is calculated to understand if the difference among the cluster for these three variables exist or is by chance, as a significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference.[57] By analyzing the median, it is concluded that the difference is insignificant while it seems significant by chance (reported in Table B5 in appendix B). Finally concluding all excluded variables for clustering are not helping to differentiate clusters.

Table 44: KW test results of 14 variables excluded from clustering

No.	Variables*	Chi-Square	df	*p* value	Remark
1	Parking_Origin_Cost	18.341	5	0.003	Sig.
2	WatchMovie	12.138	5	0.033	InSig.
3	TalkStranger	2.347	5	0.799	InSig
4	PT_MoreSpeed	2.717	5	0.743	InSig
5	BioProducts	17.451	5	0.004	Sig.
6	CharityToOrganisation	18.820	5	0.002	Sig.
7	GiveSeatElderly	6.953	5	0.224	InSig.
8	TravelWithoutTickets	6.960	5	0.224	InSig
9	NotCareWaste	3.306	5	0.653	InSig
10	Recycling	2.035	5	0.844	InSig.
11	ReuseShopBag	4.202	5	0.521	InSig
12	EnvOrganActivities	2.561	5	0.767	InSig
13	LikMovOutNeed	2.764	5	0.736	InSig.

[57] https://support.minitab.com/en-us/minitab-express/1/help-and-how-to/modeling-statistics/anova/how-to/kruskal-wallis-test/interpret-the-results/key-results/, accessed on July 30, 2020.

14	LikNoFarHom	5.436	5	0.365	InSig

Note: Sig. is significant (p value <0.05) and InSig. is insignificant (p value >0.05).
** The detailed description of variables is reported in Table A2 in appendix A.*

All the variables (see Table 45) excluded during EFA showing significant (*p* value <0.05) differences among clusters when applying KW test. Hence EFA is performed to summarize the variables to describe clusters using these variables. As the variables are numerous (57 variables – see Table 45), the correlated variables were assigned a factor score using Bartlett score method. Here the purpose is only to understand the correlated variables for easy interpretation with a smaller number of features, hence all the assumptions of EFA were not checked. The loading of variables for corresponding factors are reported in Table 45. The factor name is given by the high loading variables domination; few variables have low loading but not completely related to the factor. Then, the mean is calculated for each identified factor (see Table 46) to interpret the cluster using high and low mean domination on factors.

Table 45: Summarized factors with correlated variables excluded from EFA

No.	Variables*	Load	Factor (F)
1	Read	**-0.754**	F1: Onboard activities
2	Chatting	**-0.752**	
3	SocialNetwrk	**-0.744**	
4	Work	**-0.627**	
5	TalkStranger	**-0.491**	
6	WatchMovie	**-0.358**	
7	Call	-0.207	
8	BuySecondHand	**0.664**	F2: Ecologically aware consumerism
9	SellOldItems	**0.512**	
10	JoinGAS	0.298	
11	LikThinkAlon	0.222	
12	TravelWithoutTickets	0.201	
13	SatPollution	**0.772**	F3: Polluting & Expensive
14	SatExpensive	**0.706**	
15	UseContctLndscp	0.443	
16	UseNoAlternativ	-0.318	
17	ReuseShopBag	**-0.592**	F4: Ecological behaviour
18	Recycling	**-0.577**	
19	LaundryFull	**-0.505**	
20	GiveSeatElderly	**-0.395**	
21	Heating	-0.312	
22	NotCareWaste	0.200	
23	SmartCardTicket	-0.183	
24	PT_MoreFreq	**-0.752**	F5: PT services improvement
25	PT_OnTime	**-0.637**	

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

26	PT_MoreSpeed	**-0.624**	
27	PT_MoreIntegration	**-0.370**	
28	PT_LowerPrice	**-0.345**	
29	SmartphoneTicket	**-0.671**	F6: Pro-Environment-Ticket
30	PaperTicket	**0.568**	
31	PT_More_eTicket	**-0.495**	
32	MobilityPackages	**-0.362**	
33	LikNoFarHom	0.297	
34	LikMovOutNeed	0.246	
35	SatCaryObject	**0.676**	F7: Mode satisfaction
36	SatAccompany	**0.670**	
37	SatSpeed	**0.458**	
38	SatFreeTim	**0.335**	
39	CannedDrinks	0.136	
40	AV_Read	**-0.580**	F8: Activity in AV
41	AV_Relax	**-0.565**	
42	AV_Work	**-0.527**	
43	AV_WatchMovie	**-0.500**	
44	AV_Landscape	**-0.387**	
45	CharityToOrganisation	**-0.670**	F9: Pro-social behaviour
46	CharityToHomeless	**-0.655**	
47	EatLessMeat	**-0.361**	
48	BioProducts	**-0.321**	
49	EnvOrganActivities	-0.294	
50	CriminalRecords	0.139	
51	LaundrySoftner	0.139	
52	Parking_Origin_Cost	**0.532**	F10: Parking availability & cost dissatisfaction
53	Parking_Destin_Cost	**0.497**	
54	Unavailability_at_departure	**0.472**	
55	Unavailability_at_arrival	**0.424**	
56	UseArriveDest	0.117	
57	OpenWindowWinter	0.115	

* *The detailed description of variables is reported in Table A2 in appendix A.*

Table 46: Factor means across clusters to summarize

		Factor means across clusters 1 to 6					
No.	**Factors**	**1**	**2**	**3**	**4**	**5**	**6**
1	Onboard activities	0.05	-0.08	0.02	0.00	0.02	0.00
2	Ecologically aware consumerism	-0.01	0.04	0.05	0.03	-0.07	-0.05
3	Polluting & Expensive	0.02	0.00	-0.06	-0.04	0.06	0.04
4	Ecological behaviour	0.04	-0.04	-0.01	-0.02	0.04	0.00
5	PT services improvement	-0.04	0.02	0.00	-0.01	0.07	-0.04
6	Pro-Environment-Ticket	0.10	0.02	-0.03	-0.02	-0.06	-0.01
7	Mode satisfaction	-0.03	-0.02	-0.05	0.01	0.04	0.06
8	Activities in AV	-0.12	0.13	0.08	0.04	0.02	-0.15

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

9	Pro-social behaviour	-0.01	-0.01	-0.01	0.03	-0.04	0.03
10	Parking availability & cost dissatisfaction	0.10	-0.09	-0.05	-0.12	0.14	0.03

Cluster 1 is high on Parking availability & cost dissatisfaction (agreement with poor parking availability and high parking cost at departure and arrival) during the most important trip and Pro-Environment-Ticket factors, while it is the lowest on Activities in AV. Cluster 2 is high on Activities in AV and low on Parking availability & cost dissatisfaction followed by Onboard activities. Cluster 3 is high on Activities in AV and lowest on Polluting & Expensive factor. Cluster 4 is highest on Activities in AV and lowest on Parking availability & cost dissatisfaction. Cluster 5 is highest on Parking availability & cost dissatisfaction and lowest on Ecologically aware consumerism. Cluster 6 is highest on Mode satisfaction (carry objects, accompany someone, fast, free time for other activities during travelling) factor.

4.3.5.2 Analysis of Socio demographic characteristics and mobility patterns of clusters

Socio demographic information includes gender, age, handicap, occupation, household size, kids in household, owned cars in household, household income, and education level to analyse. The ordinal categorical features were evaluated using Kruskal-Wallis (KW) nonparametric and nominal categorical variables (gender, handicap and occupation) were evaluated using chi square nonparametric test. The test results are reported in Table B6 in appendix B. Gender, handicap, and income are insignificant (with *p* value >0.05), therefore do not show difference among clusters. In Table 47 the socio-demographic characteristics (which show the significant differences) of the six clusters are summarised.

Cluster 1 is the youngest group, (70.7%, with less than 41 years old, with majority of 18-25 years and only 4.53% over 60); consequently, the percentage of students is higher in cluster 1 (52.2%), explaining the highest percentage of secondary and high school diploma (56.99%). As a consequence, the percentage of employees (32.76%) and managers (1.33%) is the lowest one. In cluster 1 the larger HH size prevails; it shows the highest percentage of HH with both 5 persons (8.12%) and kids (11.86%). Cluster 1 show a high car ownership, with the second highest value of >1 cars (64.32%).

Cluster 2 shows the highest percentage (75.44%) of adults and elderly people (26 to >60 years old); consequently, the percentages of users looking for a job (2.3%), employees (49.43%), teachers (4.45%), and self-employed (5.6%) are higher in cluster 2, explaining the highest percentage of university level of education (Bachelor, Master, 5-year degree and doctorate) (49.28%). Consequently, the percentage (34.47%) of unemployed, retired, and students is the lowest. In cluster 2 the lowest presence of kids in HH is observed (10.17%), with the fourth highest value of people owning from 1 and 4 cars (32.18% and 14.37% respectively).

Cluster 3 shows the lowest percentage of youngsters (30.28% with <25 years) and the highest of adults (64.07%, 26 to 60 years) with prevalence of employees and managers and lower percentages of self-employed (3.64%) and workers (0.75%) and a minimum of housewives. In addition, cluster 3 shows the highest number of HHs from 1 to 3 people (63.82%) and with 1 kid (5.08%).

Cluster 4 shows higher number of medium age (41-60 years - 41.18%) people with a high level of education (around 48% holding a university degree); consequently, the percentage of those looking for a job is the lowest (1.23%) and around 49% are employees. In cluster 4 the prevailing HH size is 2 (23.3%) with maximum of two children. Because of small HH size, this cluster owns maximum 1 car (34.16%) with the lowest percentage of HH with more than 2 cars (59.06%).

Compared to other clusters, cluster 5 shows the highest percentage of people with more than 60 years old (5.94%) with the highest percentage of managers (2.49%) and the lowest percentage of teachers (3.31%). Cluster 5 shows the lowest percentage of HH with 3 members (24.59%) and of those owning 2 cars (40.75%) and no cars (4.97%); instead, there is the highest percentage of HH with ≥4 cars.

Cluster 6 is the second youngest group with, in addition, the highest percentage of people in the range of 26-40 years old (25.90%) and the lowest one with >60 years old (4.32%). The educational level is medium-low, being the second highest (52.09%) in terms of people having got till to a high school diploma, and the second lowest at university level, even though having the highest value of people holding a bachelor degree (18.27%) and a doctorate (6.19%). Cluster 6 shows the highest percentage of workers (1.73%) and the second highest percentage of students (48.49%). The cluster shows the most numerous HHs (44.61% of HHs have >3 persons) with the lowest percentage (14.05%) of HH with less than 3 children. The people in this cluster are car oriented, 66.04% own more than one car.

Table 47: Socio demographic characteristics of clusters with significant differences

		Cluster (%)					
Characteristics		**1**	**2**	**3**	**4**	**5**	**6**
Age (years)	<18	1.73	2.16	1.13	3.33	2.21	1.87
	18-25	44.87	28.16	29.15	27.99	36.46	41.44
	26-40	24.10	24.43	25.00	21.70	24.17	25.90
	41-60	24.77	39.51	39.07	41.18	31.22	26.47
	>60	4.53	5.75	5.65	5.80	5.94	4.32
Education	Not Answered	1.07	1.15	0.38	1.97	1.24	0.86
	No degree	0.13	-	0.13	-	-	-
	Secondary school	4.26	4.74	3.89	4.32	2.21	3.60

	High school diploma	52.60	44.25	46.61	44.39	47.93	48.49
	Bachelor	16.91	15.52	17.46	15.29	15.75	18.27
	Master	0.93	1.01	1.26	0.49	0.55	0.43
	5-year degree	18.38	26.72	24.87	27.25	26.24	21.01
	Doctorate	4.93	6.03	5.03	4.93	4.97	6.19
	Other	0.80	0.57	0.38	1.36	1.10	1.15
Occupation	Not Answered	1.07	1.15	0.38	1.85	1.10	0.86
	Looking for a job	1.86	2.30	1.63	1.23	2.07	1.87
	Unemployed	0.53	0.14	0.50	0.74	0.69	0.58
	Retired	1.07	0.57	1.63	1.23	0.69	1.29
	Student	52.20	33.76	36.81	33.91	44.06	48.49
	Housewife	-	0.14	0.13	0.25	-	0.14
	Worker	0.80	0.86	0.75	1.48	0.83	1.73
	Employee	32.76	49.43	48.99	48.95	40.06	34.82
	Manager	1.33	1.58	1.88	1.73	2.49	1.58
	Teacher	4.39	4.45	3.64	3.82	3.31	4.17
	Self-employed	3.99	5.60	3.64	4.69	4.42	4.32
	Other	-	-	-	0.12	0.28	0.14
Household size	Not Answered	1.20	1.15	0.38	1.97	1.38	1.01
	1	10.12	14.22	14.70	13.93	10.91	9.06
	2	19.17	22.13	22.24	23.30	21.13	18.71
	3	26.50	25.00	26.88	25.15	24.59	26.62
	4	32.76	29.89	26.63	28.48	32.60	35.40
	5	8.12	5.46	6.91	6.04	7.46	8.06
	>5	2.13	2.16	2.26	1.11	1.93	1.15
Kids in household	Not Answered	0.20	0.18	0.07	0.36	0.22	0.13
	0	4.72	5.21	6.08	6.37	5.09	3.87
	1	4.25	3.98	5.08	4.71	4.00	4.14
	2	5.90	4.92	4.96	5.50	5.43	6.04
	3	1.49	0.96	1.21	1.12	1.16	1.19
	≥4	0.22	0.31	0.40	0.07	0.27	0.18
Owned cars	Not Answered	1.07	0.57	0.63	0.99	0.97	0.58
	0	5.86	7.47	6.53	5.80	4.97	6.33
	1	28.76	32.18	32.79	34.16	33.84	27.05
	2	44.61	42.82	43.72	43.03	40.75	45.47
	3	16.38	14.37	12.69	12.08	15.06	16.83
	≥4	3.33	2.59	3.64	3.95	4.42	3.74

To understand if modal diversion is an attainable goal, it also important to identify mobility patterns related to the most important trip, namely travel purpose, distance, travel time, mode used and the frequency (Table 48). All these features were evaluated using KW and chi-square nonparametric test to see the significant differences among cluster's mobility patterns. Test results are reported in Table B7, in appendix B. Travel time and frequency of the most important trip are insignificant (p values >0.05) while mode, distance, and purpose show significant differences among clusters (p values <0.05).

Observing Table 48, cluster 1 shows a greater reliance on regional trains (4.53%) and walking (10.52%) while low reliance on car (as a driver or passenger with 25.30%) and bicycle (6.26%), even if trip chain and car are the most used mode in all the clusters. In cluster 1 the lowest percentage of respondents (45.81%) travel for work reason (45.81%) and the highest percentage of travels from Home to School/University (47.80%).

In cluster 2, car is used by the highest percentage of respondents (36.06% either as a driver or passenger) and the lowest percentage (16.95%) use PT (train/bus/tram/metro/suburban bus); the most of respondents travel for work reasons (62.07%) and the lowest from Home to School/University (30.32%). The average travel distance is the longest (23.68 km) as compared to other clusters.

Cluster 3 shows the second highest percentage of respondents (19.85%) using PT (train, bus/tram/metro, suburban bus), with the highest value (2.39%) referred to suburban bus and the lowest value (13.70%) to green modes (bicycle, bike sharing, walk). In cluster 3, there is the highest percentage of respondents travelling for Expenses/Bureaucratic (2.39%) and pick-up/accompany (2.39%) compared to other clusters.

Cluster 4 shows the highest percentage of respondents using trip chain (34.40%) and the lowest one using regional trains (1.85%), with the longest average travel duration of 70.02 minutes. This cluster shows the second highest value of users travelling for work reason (60.05%) and other reasons (Expenses/Bureaucratic, free time, pick-up/accompany-6.66%).

Cluster 5 shows the highest percentage (20.72%) of people using PT (train, bus/tram/metro, suburban bus) and green modes (bicycle, bike sharing, walk – 18.64%) as compared the other clusters, with the lowest number of respondents (5.94%) travelling for other purposes (Expenses/Bureaucratic, free time, pick-up/accompany).

Cluster 6 shows the third highest percentage (16.40%) of respondents using green modes (bicycle, bike sharing, walk), of which 8.20% travel by bicycle, and the lowest percentage using car as a passenger (1.58%) and suburban buses (1.01%). In this cluster travelling for work (2.45%) and during free time (3.31%) prevail as compared to other clusters. This cluster shows the shortest average trip travel distance (21.35 km) and travel time (46.61 minute).

Table 48: Mobility patterns of clusters with significant differences

		Cluster (%)					
Characteristics	**Category**	**1**	**2**	**3**	**4**	**5**	**6**
Travel mode	Trip chain	32.62	29.45	33.04	34.40	31.49	32.52
	Car as driver	23.57	34.48	27.89	30.09	24.17	27.34
	Car as passenger	1.73	1.58	2.14	1.85	1.80	1.58
	Regional tarins	4.53	2.59	3.02	1.85	2.90	3.74
	Bus/tram/metro	17.58	15.23	17.46	15.41	19.20	17.27
	Suburban buses	2.00	1.72	2.39	1.73	1.52	1.01
	AV/IC trains	0.13	0.14	0.25	0.12	-	-
	Car sharing	-	0.14	0.13	0.12	-	-
	Bicycle	6.26	7.90	7.16	7.03	7.04	8.20
	Bike sharing	1.07	0.43	1.01	0.99	1.24	0.72
	Walk	10.52	6.18	5.53	6.41	10.36	7.48
	Other	-	0.14	-	-	0.28	0.14
Travel distance	Average (km)	21.53	23.68	22.39	22.53	23.29	21.35
Travel time	Average (min)	49.75	49.18	46.90	70.02	54.96	46.61
Travel purpose	Home-Work	44.74	59.63	57.91	58.57	52.21	45.32
	Work	1.07	2.44	1.76	1.48	1.66	2.45
	Home-School/ University	47.80	30.32	32.79	32.18	39.78	44.89
	Expenses/Bureaucratic	1.86	1.72	2.39	2.10	2.35	1.87
	Free time	2.80	2.44	2.14	2.71	2.49	3.31
	Pick up/accompany	1.33	2.16	2.39	1.85	1.10	1.29
	Other	0.40	1.29	0.63	1.11	0.41	0.86

4.3.5.3 The users' psychographic profiles

The results from EFA for each cluster are shown in figures from 30 to 32, where extreme values are used to foster cluster interpretation. Each of the six clusters represents a specific combination of attitudes, lifestyle, preferences, showing a unique psychographic profile. Furthermore, all the analysed information from subsections 4.3.5.1 and 4.3.5.2 is also used to support the meaningful labelling of clusters.

As depicted in figure 30a, cluster 1 is very high on safe travel, showing the maximum value (2.94) among all clusters, meaning that respondents belonging to cluster 1 are satisfied about the safety guaranteed by the mode they choose and prefer to use the mode which have less accidents. They show positive value (0.70) on mode pleasure (liking the used mode), followed by a positive but low value on pro-environment activism (0.44) and aware consumerism (0.15) factors, showing a modest sensitivity towards the environment and ecological behaviour. They are dissatisfied with the improvement of onboard service quality of PT by showing a negative value of 2.66. These individuals do not perceive a travel pleasure and not find the usefulness of doing activities when travelling in AV. As also observed in subsection 4.3.5.1, cluster 1 is high on Parking availability & cost dissatisfaction and Pro-Environment-Ticket factors while it is the lowest on Activities in AV, confirms what found here. Looking at subsection 4.3.5.2, cluster 1 is formed by younger people with medium-high level of education, being mostly students and it is composed by large HH with 3 kids. Concerning mobility patterns, they show a greater reliance on sustainable modes (regional trains and walk) while low one on car, mostly travelling for school/university. These characteristics suggest labelling this cluster as "*Eco friendly safe travellers*".

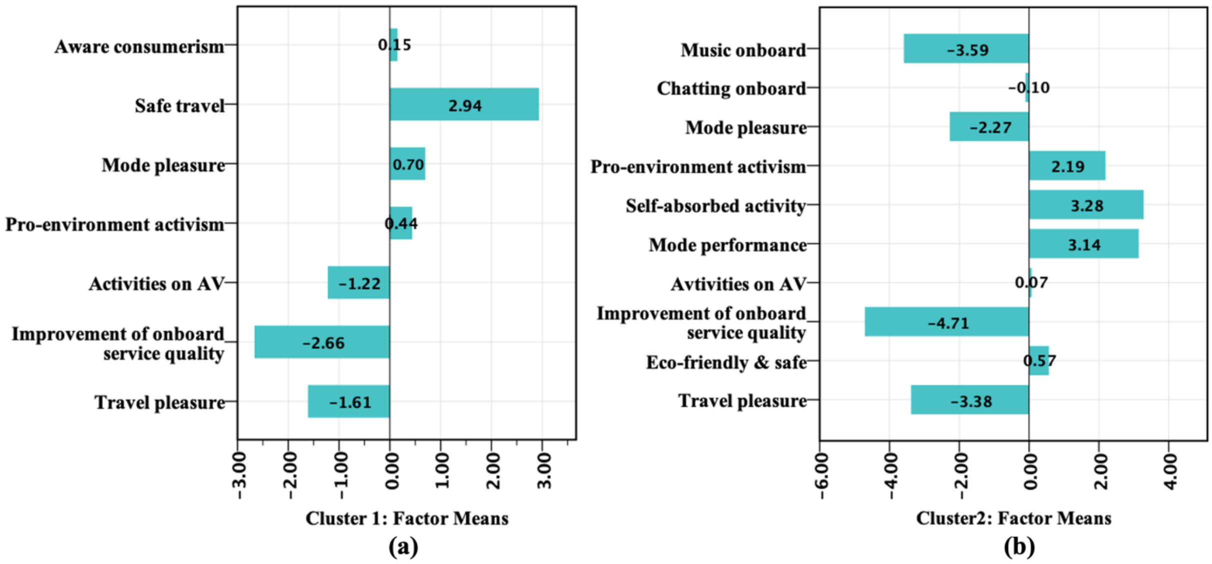


Figure 30: Factor scores for (a) cluster 1 and (b) cluster 2

Figure 30b shows that second cluster is positive on self-absorbed activity (highest-3.28, contact with landscape, thinking and relaxing), mode performance (second highest-3.14, satisfied with the comfort, flexibility and reliability of the mode they use in most important trip), pro-environment activism (third highest-2.19 – in favour to talk for and support pro-environment behaviour), eco-friendly & safe travel (0.57-a few agree that it is economic, safe by having less accidents and less pollution), and on activities on AV (0.07-very little agree to chat, call and social networking in AV). Negative on improvement of onboard service quality of PT (-4.71 the lowest), travel pleasure (-3.38), music onboard (-3.59), mode pleasure (-2.27), and chatting onboard (-0.10). As also observed in subsection 4.3.5.1, cluster 2 shows a low positive value on activities in AV and low negative on parking availability & cost dissatisfaction followed by onboard activities, confirming what found here. Looking at subsection 4.3.5.2, people forming cluster 2 are mostly adults and elderly people having university level of education, with the highest percentage of users looking for a job, employees, teachers, and self-employed, while the lowest percentage of unemployed, retired and students. Car is used by the highest percentage of respondents while the lowest percentage uses PT (train/bus/tram/metro/suburban bus); most of respondents travel for work reasons and the lowest number travels from Home to School/University. In cluster 2, the average travel distance is the longest (23.68 km) as compared to the other clusters. These characteristics suggest labelling this cluster as "*Pro-environment active car addicts*".

Observing figure 31a, cluster 3 is the highest on eco-friendly & safe factor (1.74), followed by travel pleasure (1.69), self-absorbed activities (0.29), and willingness to carpool (0.11). It is the first lowest (-2.60) on improvement of onboard service quality of PT, the second lowest (-1.99) on mode pleasure (do not like the mode they use) followed by, the third lowest (-1.25) on aware consumerism (disagreeing to sell and lend secondhand items), and the fourth lowest (-0.56) on pro-environment activism (not sensitive for sustainability) that expresses the insensitivity to support pro-environment behaviour. As also observed in subsection 4.3.5.1, cluster 3 is low positive on Activities in AV and low negative on Polluting & Expensive factor, which confirms what found here. Observing subsection 4.3.5.2, cluster 3 users are mostly adults with the lowest percentage of workers and self-employed. It shows the second highest percentage of respondents using PT (train, bus/tram/metro, suburban bus) and the lowest percentage of respondents using green modes (bicycle, bike sharing, walk), who travel mostly for other purposes (Expenses/Bureaucratic, free time, pick-up/accompany). These characteristics suggest labelling this cluster as "*Eco friendly and safe travel pleasure addicts*".

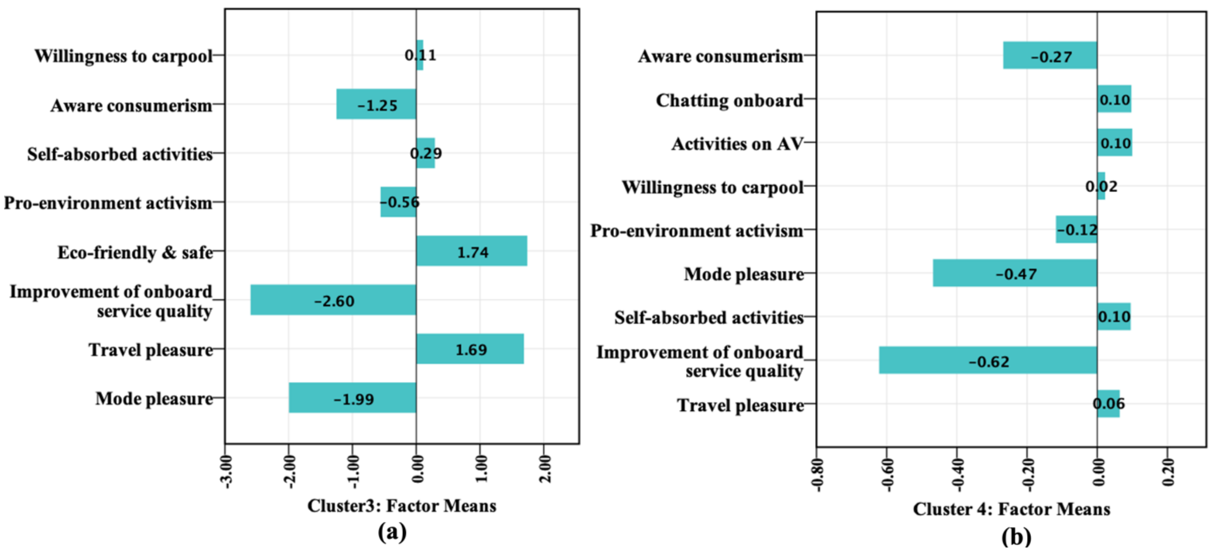


Figure 31: Factor scores for (a) cluster 3 and (b) cluster 4

Cluster 4 (figure 31b) shows small positive values on factors as chatting onboard (0.10), activities on AV (0.10), self-absorbed activities (0.10), travel pleasure (0.06) and willingness to carpool (0.02). These positive attitudes show that people like to use free time in self-absorbed activities while travelling. In addition, they are a little fond of pleasure in travelling and in carpooling. People in this cluster shows negative values – the lowest ones (-0.62) on improvement of onboard service quality of PT, followed by mode pleasure (-0.47), aware consumerism (-0.27), and pro-environment activism (-0.12). These respondents are dissatisfied about their mode of transport and the onboard service quality of PT. In addition, they do not pay much attention to pro-environment behaviour, selling and lending secondhand items. As also observed in subsection 4.3.5.1, cluster 4 is the highest on Activities in AV and the lowest on Parking availability & cost dissatisfaction, which confirms what found here. Observing subsection 4.3.5.2, this cluster shows higher percentage of people in the range of 41-60 years old, with the lowest percentage of secondary and high school diploma. Cluster 4 has the lowest number of people looking for a job. Car ownership is low, the majority own one car, and a low percentage owns ≥2 cars. Trip chain is used by the highest percentage of respondents while regional trains is used by the lowest number of respondents; the purpose is manly for going to work and the longest average travel duration of 70.02 minutes is recorded. The high desirability of using free time in self-absorbed activities, together with other aforementioned characteristics allows to label the cluster as "*Malcontent time addicts*".

Cluster 5 (figure 32a) shows the highest value (+3.38) on pro-environment activism and then, on willingness to carpool (1.21), and a low value (0.10) on mode pleasure. They are showing negative values on self-absorbed activities (-5.37), followed by activities on AV (-2.51), safe travel (-2.42), aware consumerism (-2.25), travel pleasure (-1.19), and then on improvement of onboard service quality of Public Transport (PT) (-0.72). They do not like to spend time in self-absorbed activities during travel and are dissatisfied about the safety of the used mode. Low value on factor aware consumerism shows that they do not prefer to sell and lend secondhand things. People in this cluster are not enjoying travelling without a specific need and are not satisfied with the onboard service quality of PT. As also observed in subsection 4.3.5.1, cluster 5 is the highest on parking availability & cost dissatisfaction and the lowest one on ecologically aware consumerism, which confirms what found here. Observing subsection 4.3.5.2, cluster 5 is characterized by the highest percentage of elderly people (>60 years old), with the highest percentage of managers and the lowest percentage of teachers as occupation. PT (train, bus/tram/metro, suburban bus) and green modes (bicycle, bike sharing, walk) are used by the highest percentage of users with the lowest number of respondents travelling for other purposes (Expenses/Bureaucratic, free time, pick-up/accompany). The highest value on the factor pro-environment activism together with the above information allows to name this cluster as "*Pro-environment active travellers*".

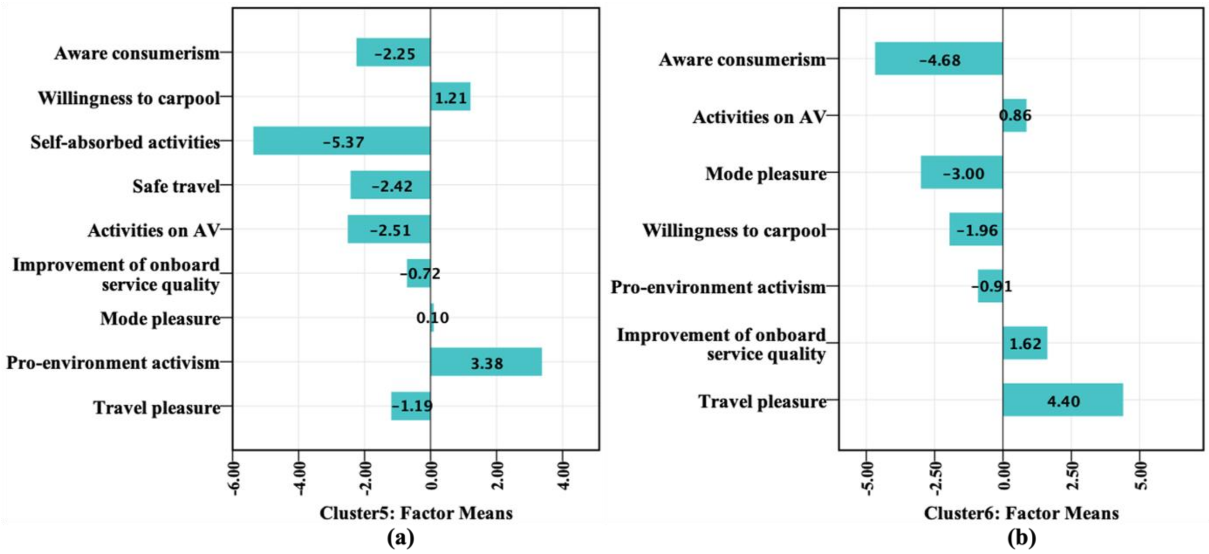


Figure 32: Factor scores for (a) cluster 5 and (b) cluster 6

Cluster 6 (figure 32b) is extremely positive (4.40) on travel pleasure (explore new places and unknown destinations) compared to other clusters, is satisfied with the improvement of onboard service quality of PT with a positive value of 1.62 and agrees to do activities on AV (0.86). They are highly negative (-4.68) on aware consumerism compared to other clusters. Furthermore, they do not like the mode they use (-3.00 on mode pleasure) and are not willing to carpool (-1.96 on willingness to carpool). These users are not in favour of pro-environment behaviour, i.e., they do not like boycotting companies that use pesticides, they are not involved in environmental issues by often talking about them with friends and pointing out someone who behaves non-ecologically (-0.91 on pro-environment activism). As also observed in subsection 4.3.5.1, cluster 6 is low positive on mode satisfaction (carry objects, accompany someone, fast, free time for other activities during travelling) factor. Observing subsection 4.3.5.2, cluster 6 shows the highest percentage of 26-40 years old group and the lowest of >60 years old. The educational level is medium-low, being the second highest in terms of people having got till to a high school diploma, and the second lowest having got a university level, even though having the highest value of people holding a bachelor degree and a doctorate. The highest percentage of workers is recorded and the second highest percentage of students. Car ownership is high with the highest percentage of people owning more than one car. The majority of people travel by green modes (bicycle, bike sharing, walk), recording the highest number of users travelling by bicycle and the lowest number travelling by car as a passenger and by suburban buses; most of them travel for work and free time reason. This cluster shows the shortest average trip travel distance (21.35 km) and travel time (46.61 minute). Considering such information and the extreme value for the factor “travel pleasure”, this cluster is named “*Travel pleasure addicts*”.

Based on the results above, the development of sustainable transport policies can be tailored to each cluster. To this end, we rank-ordered the clusters according to the sustainability of their travel behaviour, assuming that car is the least sustainable transport mode, followed by PT and soft modes (walking and cycling).

Cluster 1 (Eco friendly safe travellers) is the most sustainable group, having less car users (as a driver) compared to other clusters, and including the individuals mostly walking and using regional trains, followed by the second highest use of PT (bus/tram/metro). This cluster shows the highest number of respondents commuting to School/University. Indeed, most of the users are students in the age range between 18-25 years old, mainly using PT and walking, and showing a positive attitude towards PT and soft modes. As this group is not afraid to use PT and soft modes (mainly walking), they are already inclined to promote sustainable mobility and the challenge is to maintain them sustainable also when they will start working, when the probability of buying and/or using a car could increase. However, the young generation mind can be maintained or diverted towards a sustainable travel behaviour by a well-planned mobility education policy. Therefore, it is of utmost importance to involve the young generation (mainly students) in campaigns and events to promote sustainable mobility. Gaming (such as marathon, bike race) can also be included in sustainable policy making by giving incentives to engage them to maintain this habit with specific target to students. A collaboration between universities and public transport companies in organising the aforementioned events can be beneficial.

Cluster 2 (*Pro-environment active car addicts*) is the least sustainable group, using mainly car (as driver) for the most important trip. Number of PT, trip chain, car as a passenger, and bike sharing users are less compared to other clusters, and the average travel distance is the largest one (23.68 km). This finding shows that this group use less the PT. Looking at the residential location distribution in cluster 2, after urban areas (as most of the users live in the city of Torino), the second largest number of respondents live in rural areas, with more limited access to PT systems. Users in this group like to use free time during travelling in self-absorbed activities (watching the landscape, thinking, relaxing). A counterintuitive result is that this cluster, even mostly using the car, shows, compared to all other clusters, the second highest positive value on the factor Pro-environment activism. This behaviour shows the clash between the attitude towards the environment and the travel behaviour because the engagement in pro-environment activities and concern towards the environment does not necessarily mean that people chose sustainable modes. This is referred as attitude-behaviour gap (Moraes *et al.*, 2012) or behaviour intention gap (Sheeran, 2002). Thus, this group does not seem very inclined to policies promoting sustainable transport; as the car orientation is so strong, probably only a diversion to less-polluting cars (electric vehicles) could be obtained, increasing the sustainable travel behaviour of this group.

Cluster 3 (Eco friendly and safe travel pleasure addicts) is the third least sustainable group. The third highest number of car users (27.89%), showing their positive attitude towards car use, belongs to this group. This cluster is also the third highest among PT and bike users while a small percentage of users walk. 48.99% are employees, followed by 36.81% of students. Looking at the age, 39.07% are 41-60 years old, followed by 29.15% of 18-25 years old and 25% of 26-40 years old. This shows that the majority are elderly people who own a car; a similar result was found by De Angelis *et al.*, (2021) who observed that the young people use more PT and bike as they cannot afford a car. De Angelis *et al.*, (2021) also identified a segment of "private car-oriented commuters" composed by elderly people showing positive attitude towards the use of private vehicle due to its comfort. As people become older, they tend to rely on driving and on comfortable travels by car. In this cluster, the respondents show a positive attitude towards eco-friendly (polluting less and cheap) and safe (safe, secure, less aggression and less accidents) travelling. The eco-friendly positive attitude is mainly referred to young people who are more inclined to promote sustainable travel policies and are concerned about the environmental consequences of their behaviour. Therefore, the young people can be continuously targeted to sustainable promotion policies to maintain the virtuous habit in the future. Talking about the people from 41 to 60 years old, they can be attracted towards sustainable modes by providing more secure and safe travels. The seat reservation policy/priority can work well for them, inducing to use more PT. Moreover, as they are willing to carpool, the travel pleasure and using travel time in self-absorbed activities are positive attitudes towards sharing the vehicle with others; then, making them aware about the environmental impacts they could generate travelling can help in attracting them towards the sustainable modes.

Cluster 4 (Malcontent time addicts) is the second least sustainable group with the second highest number of car users after trip chain. The average trip duration is the longest compared to other clusters. One of the reasons of using car is due to living in rural areas (compared to other clusters, cluster 4 shows the highest number of respondents with residential location in rural areas), where the PT supply is scarce and less accessible, as shown by the longest duration of trips. Similarly, De Angelis *et al.*, (2021) also found that being too far from the destination could force people to adopt transport modes that they do not prefer such as people who lived far from the destination tended to adopt PT even if it was negatively perceived. Users in cluster 4 show positive attitude towards chatting onboard, activities on AVs, willing to carpool, self-absorbed activities and travel pleasure. Therefore, strategies related to the possibility of providing internet services to use available time for other activities such as work, study, or leisure activities or to obtain more real-time information about PT services by reducing scheduling costs could be effective. As suggested by De Angelis *et al.*, (2021), in Italian context using sustainable modes (notably PT) can work well for this cluster.

The Pro-environment active travellers (cluster 5) include the highest percentage of PT users, followed by the second highest percentage of users walking (10.36%), after trip chain and car. This group is the second most sustainable, dominated by students in the range of 18-25 years old, followed by employees (41-60 years old). This group likes the used mode and shows a high positive attitude in engaging pro-environmental behaviour and activities. Sustainable policies are not necessary for those already having a high awareness but, to maintain the perceived utility of sustainable modes, it is important to improve quality of PT and of infrastructures, to make them feel secure/safe while walking.

Finally, the Travel pleasure addicts (cluster 6) presents the largest number of cyclists (8.20%), showing a strong bike orientation, and the second highest percentage of people using regional train, after trip chain, car, and PT. This group is identified as the third most sustainable, showing a high positive attitude towards travel pleasure (visit new places, adventurous travel). This group is showing a real pleasure and the great enjoyment when travelling which implies a certain flexibility to use any mode allowing them to enjoy the pleasures of freedom, discovery and adventure, as also reported by Pronello and Camusso (2011). Therefore, actions and interventions to improve and expand cycling infrastructures to maintain the habit of cyclists, can work well for this cluster. However, in urban areas, improvements in existing road infrastructures might be difficult due to the proximity of settlements to the network, as suggested by De Angelis *et al.*, (2021), for the Italian context. An alternative way to increase the network level of service is to improve the comfort experience on the road, making better use of the existing roads (Bravo *et al.*, 2016). Moreover, as they like travelling, the car users could be shifted to PT/alternative modes if such modes were substantially improved in their efficiency by guaranteeing time saving. In fact, this is the second group using more train and enjoying the service and showing the positive attitude of undertaking other activities while travelling.

4.4 Dichotomous Rasch measures and estimates

This section presents the results of Dichotomous Rasch Model (DRM) by following the various steps described in the methodology section. Unidimensionality is assessed in four steps and assumptions to follow for validating the attitude towards the General Ecological Behaviour (GEB) questionnaire. Table 49 presents the estimates of item parameters ("Measure") from Winsteps together with their corresponding observed and expected point biserial correlation, Infit and Outfit statistics. Additional information includes the raw score on items ("Total

Score") as well as the percentage of observed and expected positive answers for each item (Exact Match). In Table 49 items are ordered by decreasing misfit order.

Point biserial correlation: point biserial correlations (Point-bis. Corr.) report the extent to which this is true for each item (Table 49). We want to see noticeably positive correlations. So that higher-valued responses to the items (correct answers) correlate positively with the person measures. When the data fit the Rasch model, CORR. (observed correlation) should approximate EXP. (expected correlation). When CORR. is greater than EXP., the item is over-discriminating between high and low performers. When CORR. is less than EXP., the item is under-discriminating between high and low performers. When EXP. is near to zero, then the item is very easy or very hard, and it is off target to the person distribution. Negative and close-to-zero correlations sound alarm bells. Small positive correlations may need further investigation.

All items' correlations are positive and pointing in the same direction. However, three small positive correlations are observed and analysed hereafter:

- *Item AE6_REVC* (In winter, I leave the windows wide open for a long period of time to let in fresh air) has a low correlation (0.05) near to zero. When assessing closely this item, 74.17% users agree (1), and 25.83% disagree (2), showing that this is one of the easiest behaviours to engage into (Measure=-0.76);
- *Item CS6_REVC* (Sometimes I ride public transport without paying a fare) has a low correlation (0.09) near to 0.1, which is not very low as zero. When closely assessing this item, 90.38% users agree (1), and 9.62% disagree (2); like the previous item, this is also one of the easiest behaviours to engage into (Measure=-2.08). Almost most of the users disagreed to using public transport without tickets, which may cause the low correlation;
- *Item CS4* (If I were an employer, I would not hesitate to hire a person previously convicted of crime) has a low correlation (.08) near to 0.1 which is not very low as zero. Analysing this, no big difference among the answered categories of the respondents (46.77% disagree and 53.23% agree) were found. This item seems to have medium difficulty across all respondents (Measure = 0.31).

These three items will be assessed by looking at fit statistics in the next section.

Table 49: Estimates of item parameters, infit, outfit, and point biserial correlations

Entry No.	Total Score	Measure	Model S.E.	Infit		Outfit		Point-bis. Corr.		Exact Match (%)		Item
				MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	
10	7336	-0.76	0.04	1.24	9.90	1.55	9.90	A 0.05	0.33	70.9	75.7	AE6_REVC
5	8019	-2.08	0.05	1.10	2.54	1.48	6.48	B 0.09	0.24	90.4	90.4	CS6_REVC
4	6454	0.31	0.03	1.27	9.90	1.43	9.90	C 0.08	0.38	53.0	65.8	CS4
6	7938	-1.86	0.05	1.08	2.17	1.31	4.87	D 0.15	0.26	88.0	88.5	R1_REVC
19	6418	0.35	0.03	1.20	9.90	1.29	9.90	E 0.16	0.38	56.6	65.8	RR2_REVC
25	5712	0.46	0.04	1.15	9.90	1.24	9.90	F 0.20	0.37	58.6	65.5	T1
11	6248	0.53	0.03	1.14	9.90	1.22	9.90	G 0.23	0.38	59.8	65.8	CE1_REVC
26	5285	0.78	0.04	1.09	7.13	1.12	6.22	H 0.28	0.38	61.4	66.6	T2
8	7203	-0.58	0.04	0.99	-0.72	0.99	-0.26	I 0 .35	0.34	73.9	73.3	AE4
13	5535	1.37	0.04	0.97	-1.91	0.95	-2.17	J 0.40	0.37	72.7	72.5	CE7
1	5491	1.43	0.04	0.96	-2.25	0.94	-2.33	K 0 .41	0.37	74.1	73.1	CS1
14	5812	1.03	0.03	0.96	-3.36	0.93	-3.66	L 0.42	0.38	70.1	68.8	CE8
18	8185	-2.69	0.07	0.94	-1.15	0.87	-1.55	M 0.26	0.19	94.4	94.3	RR1
2	5949	0.87	0.03	0.93	-5.96	0.91	-5.22	m 0 .45	0.38	70.8	67.5	CS2
7	8176	-2.64	0.07	0.93	-1.22	0.76	-2.93	l 0.27	0.20	94.1	94.1	R5
3	8136	-2.48	0.06	0.92	-1.62	0.76	-3.29	k 0.30	0.21	93.2	93.2	CS3
9	7985	-1.98	0.05	0.92	-2.03	0.85	-2.45	j 0.32	0.25	90.2	89.6	AE5
16	6673	0.06	0.03	0.91	-7.93	0.88	-7.00	i 0.47	0.37	70.6	66.8	CE14
17	6441	0.32	0.03	0.91	-8.75	0.86	-8.55	h 0.48	0.38	70.7	65.8	CE15
12	5911	0.92	0.03	0.90	-8.18	0.87	-7.59	g 0.48	0.38	72.5	67.8	CE6
21	4586	3.13	0.06	0.90	-2.48	0.72	-4.61	f 0.38	0.27	91.5	91.3	V2
22	6715	0.01	0.03	0.90	-8.58	0.87	-7.08	e 0.47	0.37	72.2	67.2	V3
15	7134	-0.49	0.04	0.89	-7.71	0.83	-6.86	d 0.47	0.35	76.3	72.2	CE9
20	6625	0.11	0.03	0.88	-9.90	0.83	-9.90	c 0.50	0.37	72.4	66.6	V1
24	5391	1.56	0.04	0.88	-6.88	0.83	-6.85	b 0.48	0.36	78.2	74.8	V5
23	4912	2.33	0.04	0.83	-6.48	0.66	-8.91	a 0.50	0.32	84.9	84.0	V4
Mean	6548.8	0.00	0.04	0.99	-1.0	1.00	-0.9	-	-	75.4	75.7	-
P.SD	1059.6	1.50	0.01	0.12	6.0	0.24	6.7	-	-	12.0	10.6	-

Fit statistics: item AE6_REVC (In winter, I leave the windows wide open for a long period of time to let in fresh air) with the highest mean-square outfit (1.55) is the first listed. This item may be the one with the worst fit to the Rasch model. From guidelines accepted Outfit values are (0.5-1.5), here 1.55 is slightly greater with a small difference of 0.05, which may not degrade the measurement. Items CS6_REVC (Sometimes I ride public transport without paying a fare) and CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime) have Infit 1.10, 1.27 and Outfit 1.48, 1.43 respectively within the acceptable range. Our item reliability is 1 which is perfect, hence we are not excluding any item from the model computation. As reported in methodology, we find that the items are within acceptable ranges of MNSQ (MeaN-SQuare), hence we are not investigating ZSTD (Z-STanDardized).

Principle Component Analysis of Residuals (PCAR): Table 50 presents the results of the Rasch-residuals based on PCAR and figure 33 its associated scree plot. Unidimensionality is assessed according to the criteria suggested by Reckase (1979). Firstly, the amount of variance explained by measures is 34.2% with 11.5% of raw variance explained by persons and 22.7% raw variance explained by items which is larger than the requirement of 20% demonstrating a unidimensional trait of the data (Reckase, 1979). Secondly, the unexplained variance by first contrast is 5.4%, which is slightly greater than 5%, but the eigen values of first contrast is 2.14. The first, second, third, fourth, and fifth unexplained variance accounted for eigenvalues are 2.14, 1.8, 1.55, 1.40, and 1.26 which are good by referring the criteria. The results of the data analysis suggested that the unidimensionality is hold across the whole test (see Table 50) which satisfies the criteria of Rasch unidimensionality.

Table 50: Standardized residual variance in eigenvalue units

	Eigenvalue	Observed		Expected
Total raw variance in observations	39.5	100.0%		100.0%
Raw variance explained by measures	13.5	34.2%		34.2%
Raw variance explained by persons	4.55	11.5%		11.5%
Raw variance explained by items	8.95	22.7%		22.7%
Raw unexplained variance (total)	26.0	65.8%	100%	65.8%
Unexplained variance in 1st contrast	2.14	5.4%	8.2%	
Unexplained variance in 2nd contrast	1.80	4.6%	6.9%	
Unexplained variance in 3rd contrast	1.55	3.9%	6.0%	
Unexplained variance in 4th contrast	1.40	3.5%	5.4%	
Unexplained variance in 5th contrast	1.27	3.2%	4.9%	

```
      VARIANCE COMPONENT SCREE PLOT
     +--+--+--+--+--+--+--+--+--+--+--+
 100%+  T                             +   T    : Total
     |                                |
V 63%+              U                 +   U    : Unexplained
A    |                                |
R 40%+                                +
I    |     M                          |   M    : Measures
A 25%+                                +   I    : Items
N    |           I                    |
C 16%+                                +
E    |                                |
  10%+        P                       +   P    : Persons
L    |                                |
O  6%+                                +
G    |                 1              |   1..5 : Contrast
|  4%+                    2           +
S    |                       3  4  5  |
C  3%+                                +
A    |                                |
L  2%+                                +
E    |                                |
D  1%+                                +
     |                                |
 0.5%+                                +
     +--+--+--+--+--+--+--+--+--+--+--+
        TV MV PV IV UV U1 U2 U3 U4 U5
       VARIANCE COMPONENTS
```

Figure 33: Scree plot of the PCA standardized residual variance components

Furthermore, the right way to interpret Table 50 is to compare the columns observed and expected which in our case matches perfectly and exactly. The loading of items on the 1st contrast of the residual based PCA are plotted in figure 34 where we clearly see that this possible subdimension is implied by 2 items A and B with the largest loadings. In fact, item A (AE6_REVC-In winter I leave the window open for a long time to let in fresh, clean air), and B (CS6_REVC-Every now and then I take public transport without paying the ticket) are quite far away from the general cluster created by the other items. Hence, the possible subdimension can be by these two items as indicated the eigen values of first contrast is 2.14 (~2 items) in Table 50. To see the items corresponding to the alphabets represented in figure 34 refer to Table 49.

```
       STANDARDIZED RESIDUAL CONTRAST 1 PLOT

      -5            -3            -1             1             3             5
      -+-------------+-------------+-------------+-------------+-------------+- COUNT CLUSTER
      |                                   |                                   |
C  .5 +                                   | A                                 + 1      1
O     |                              B    |                                   | 1      1
N  .4 +                                   | ECD                               + 3      1
T     |                                   |                                   |
R  .3 +                    F              |                                   + 1      1
A     |                      G            |    H                              | 2      1
S  .2 +                                   |                                   +
T     |                                   |                                   |
   .1 +                               I   |                                   + 1      2
1     |                                   |                                   |
   .0 +----------------KJ-----------------|-----------------------------------+ 2      2
L     |                     L             |                                   | 1      2
O -.1 +                                   | M                                 + 1      2
A     |                  m                |          l                        | 2      3
D -.2 +                                   h     gi  k           j             + 5      3
I     |                                   |     f                             | 1      3
N -.3 +                                   |d        e                         + 2      3
G     |                                   |               c                   | 1      3
  -.4 +                                b  a                                   + 2      3
      |                                   |                                   |
      -+-------------+-------------+-------------+-------------+-------------+-
      -5            -3            -1             1             3             5
                                    ITEM MEASURE
 COUNT:                2 1 111       111  21311121  21    1     1
```

Figure 34: Item loadings on the first contrast

Follow up analyses evaluated the "clusters" of items which were identified in the PCAR. The text of items (see Table 4 for items descriptions) is reviewed in each cluster (Cluster 1: 8 items - AE6_REVC(A), CS6_REVC(B), CS4(C), R1_REVC(D), RR2_REVC(E), T1(F), CE1_REVC(G), T2(H); Cluster 2: 5 items – AE4(I), CE7(J), CS1(K), CE8(L), RR1(M); Cluster 3: 13 items – CS2(m), R5(l), CS3(k), AE5(j), CE14(i), CE15(h), CE6(g), V2(f), V3(e), CE9(d), V1(c), V5(b), V4(a)) and concluded that although the items marked different parts of the trait, the items all involved in one trait.

We also examined the level of disattenuated correlation between the person measures using each cluster of items. The correlations of the person measures computed with each cluster of items were as follows: Cluster 1 and 2: r = 1.0, Cluster 1 and 3: r = 0.0587, Cluster 2 and 3: r = 1.0. Cluster 1 and 3 having low correlation, the subdimension might be because of the items in cluster 1 as discussed above by items A and B. The detailed obtained correlation statistics are reported in Table B8 in appendix B.

***Local independence**:* according to the Linacre guidelines[13] all items correlation is <0.4, hence no item residuals are correlated, respecting the local independence assumptions of Rasch analysis. The correlation among all variables is reported in Table B9 in appendix B.

***Reliability and Separation of Measures**:* person measure reliability is 0.67 and item measure reliability is 1 (perfect) which is acceptable according to Stelmack *et al.*, (2004) with the less variability of the measurement attributed to measurement error. These results indicate that the estimated measures are highly reliable (i.e., 33% and 0%, respectively, of person and item measure variability can be attributed to measurement error). Here we see that our GEB questionnaire items attributed to zero (0%) percentage of measurement error, which is validating the test items perfectly because we have large sample size to validate it. The person separation is 1.44, indicates that this test can distinguish between high and low performers (1.44, ~2 levels of performers) in the sample. The results satisfy the criteria defined by Miller and Dishon (2006) and represent good level of separation. The item separation is 34.22 (huge). With this large person sample, the item difficulties are estimated exceedingly precisely and validating the GEB construct validity, which is >3.00, represent excellent level of separation (Duncan *et al.*, 2003). According Boone *et al.*, (2014) the real person reliability gives the lower limit of the instrument's consistency, reliability of the person measures, hence we reported real reliability and separation indexes.

Differential Item Functioning (DIF)*:* DIF analysis is conducted by comparing a reference group (typically the majority group) with a focal group (typically the minority group) (Martinková *et al.*, 2017). For gender, female, and for residential location, urban, are the reference group, the remaining ones are focal groups. Only the variables which have DIF are shown in Table 51. The Mantel-Haenszel (MH) statistics for all variables are reported in Table B10 and B11 in appendix B.

Table 51: DIF based on MH statistics

Groups	Chi square	*p* value	Size CUMLOR	Item	DIF remark
Female, Male	62.59	0.00	0.63	CE9	slight to moderate
Female, Male	38.15	0.00	–0.47	V1	slight to moderate
Urban, Rural	23.51	0.00	0.90	R5	moderate to large
Urban, Suburban	21.47	0.00	1.12	R5	moderate to large
Urban, Rural	34.44	0.00	0.44	T1	slight to moderate

According to the criteria defined by Zwick *et al.*, (1999) we see from the Table 51, 2 items have DIF of slight to moderate size by gender, CE9 (Sometimes, I offer goods I don't use anymore) with *p* value 0.00 and DIF size 0.63, and V1 (I often talk with friends about problems related to the environment) with *p* value 0.00 and DIF Size -0.47. By residential location, 2 items R5 (I sort glass wastes for recycling) and T1 (Usually, I do not drive my automobile in the city) having moderate to large and slight to moderate DIF respectively. R5 with *p* value 0.00, DIF size 0.90 for urban and rural; *p* value 0.00, DIF size 1.12 for urban and suburban. T1 with *p* value 0.00 and DIF Size 0.44. We see that the variables causing DIF have largest MH chi square statistics.

Table 51 only shows the items cause DIF, but do not identify the difficulty across subgroups. For that, item difficulty across 2 subgroups with item parameter estimates are plotted against each other in figure 35 and 36, with 95% of confidence interval for both dimensions. The graph compares the reference and focal group item difficulty. The diagonal line represents along which all items would lie within 95% confidence interval if there were no differences between subgroups. If the items fall within range of 95% confidence interval, we can conclude that items are homogenous across subgroups i.e., they have same difficulty.

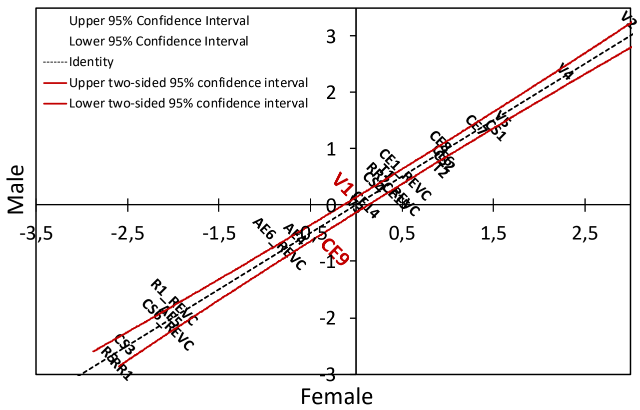


Figure 35: Pair plot for DIF identification by gender

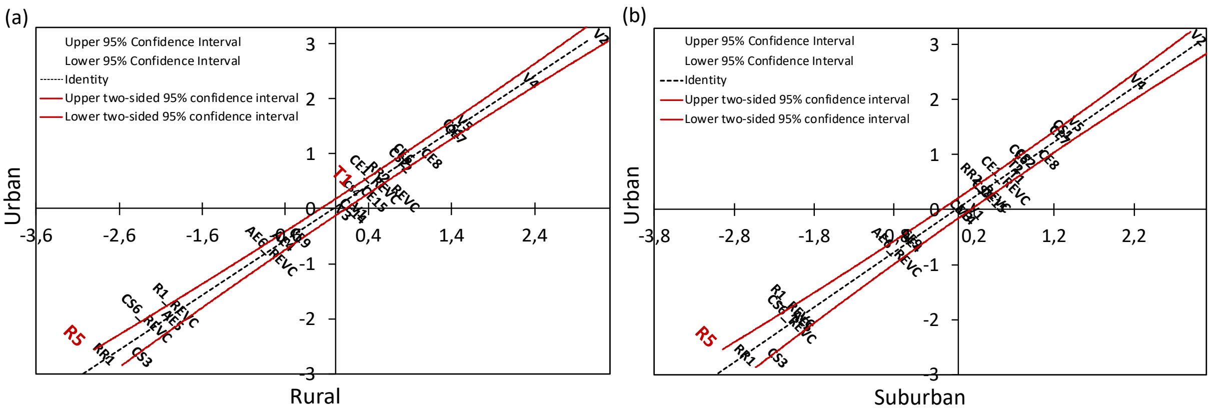


Figure 36: Pair plot for DIF identification by residential location

From the figure 35, we see that item CE9 (Sometimes, I offer goods I don't use anymore) is more difficult for females, seems that females are not agreeing to give away items they use less as compared to men. Item V1 (I often talk with friends about problems related to the environment) is more difficult for males, seems that males talk less often about environmental problems as compared to females. Item R5 (I sort glass wastes for recycling) in figure 36 is more difficult for urban, the reason might be the differential garbage collection has not been enacted in all the subzones in urban areas as compared to suburban and rural areas. The reason of more difficulty for item T1 (Usually, I do not drive my automobile in the city) for urban might be for them it is not possible to avoid driving in big cities, as they are living in those areas and may use cars frequently (see figure 36a). While for rural areas, it may be so long to drive in big cities, and they took train/long bus for commuting, hence easy to avoid drive in big cities. The difficult items are highlighted in red across different subgroups in figures 35 and 36.

Write map: in figure 37 the left side of the map contains person measures, and the right side contains item measures. Persons at the top had the least difficulty endorsing items, while persons at the very bottom had the most difficulty endorsing items. Items can be interpreted in a similar manner. Items at the very top of the map were the most difficult to endorse, whereas items at the bottom of the map were the easiest to endorse. When an item is aligned with a person, then the person is predicted to have a 50% probability of succeeding on the item. So, the more difficult items at +3 logits align with the most able persons, and the easier items at -3 logits with the least able persons. When an item is at the level as a person, then the item is "targeted" on the person. A gap of more than a logit may mean that some major concepts may have been missed by the manner in which items define the trait (Boone *et al.*, 2014). Equivalently, when an item is 1.1 logits more difficult (or easier) than the measure of attitude towards the environment for an individual, this individual has a 25% (or 75%) probability of engaging the behaviour (Gaborieau and Pronello, 2021). With these considerations, we can state few observations from figure 37:

- the most difficult item is V2 (I am a member of an environmental organization) followed by item V4 (I sometimes contribute financially to environmental organizations), both belongs to the category environment activism;
- the easiest items are R5 (I sort glass wastes for recycling), RR1 (I re-use plastic bag from the groceries), followed by CS3 (If an elderly or disabled person enters a crowded PT vehicle, I offer him/her my seat). These three items are not targeting to any person, but there are some persons above and below these items which are less aggregable to GEB, so these items do not contribute anything more useful to the GEB measurement but still fall within the user's ability range;
- items CS1 (Sometimes I give money to panhandlers), V5 (I boycott companies using OGM or pesticides), appears to measure similar portions of the trait and therefore, from a measurement perspective, are redundant. This appears to also be the case of items CE6, CS2, T2; items CE1_REVC, T1; CE15, CS4, RR2_REVC; CE14, V3; AE4, CE9; AE5, CS6_REVC and R5, RR1 (refer Table 4 for items descriptions). Within groups of items, individual items can be removed with little measurement precision lost;

- we do not see the gap between items more than a logit, but the write map shows the need for items to fill the measurement gaps, for example between V4 (I sometimes contribute financially to environmental organizations) and CS1 (Sometimes I give money to panhandlers) and between items AE6_REVC (In winter, I leave the windows wide open for long periods of time to let in fresh air) and R1_REVC (I put dead batteries in the garbage). This explains the relatively poor value of the individual separation reliability.

Finally, figure 38 shows person ability and item difficulty distribution, which often have a normal distribution. According to Seong (1990) and Stone (1992) if the distribution were not gaussian then estimates would be biased. In our case both items' difficulties and person's abilities fit a normal distribution, hence it can be concluded that all the items are well distributed and targeted within user's ability.

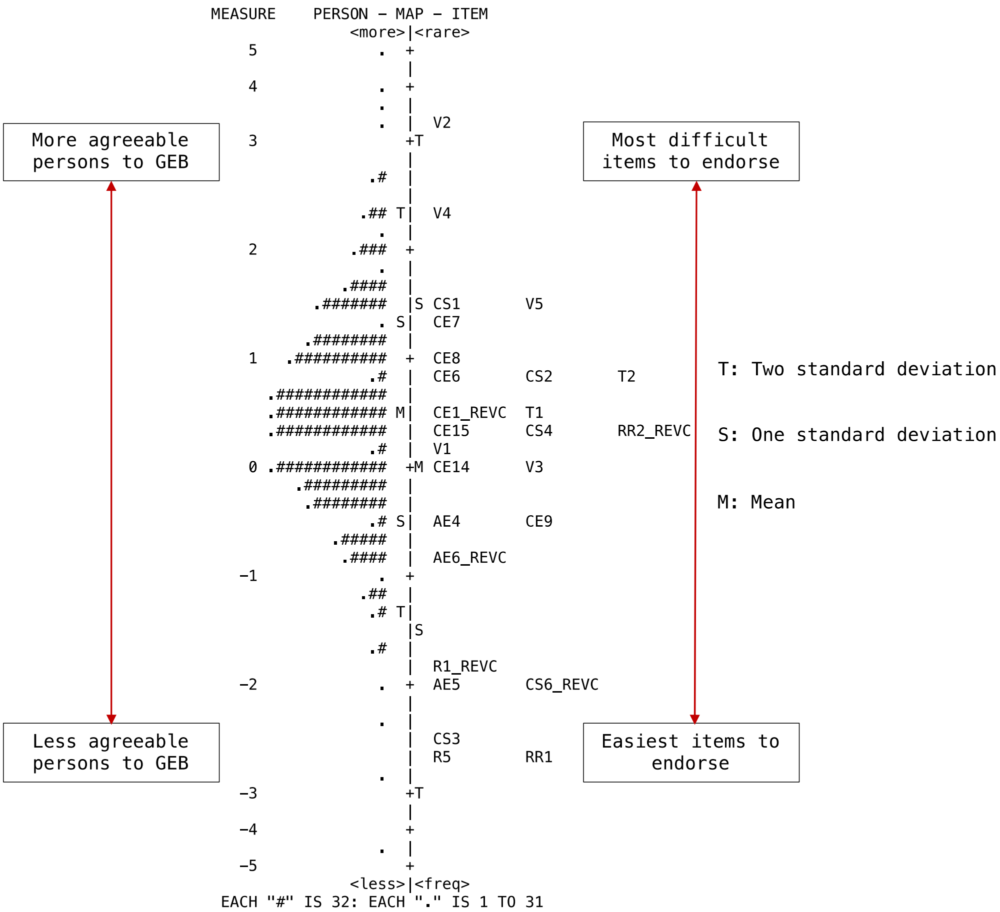


Figure 37: Write map

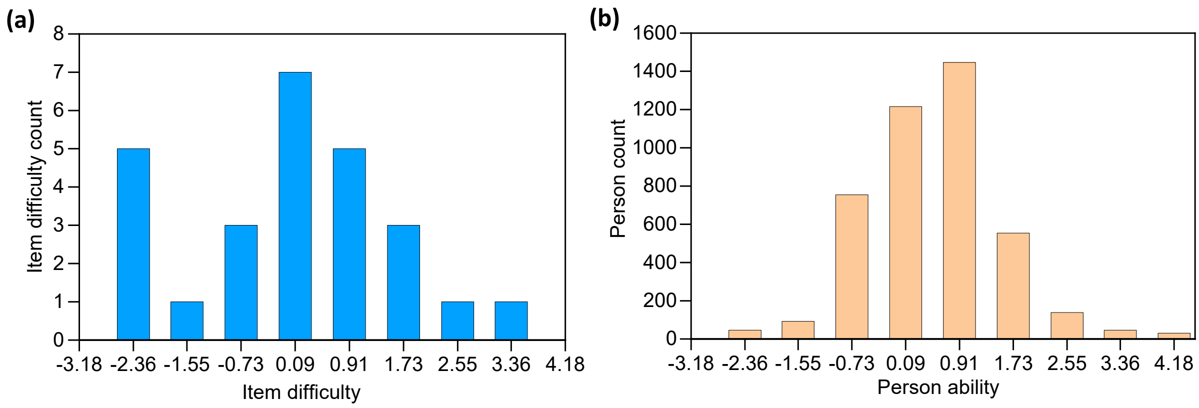


Figure 38: (a) Item difficulty and (b) person ability distribution

Item Characteristics curves (ICCs): figures 39 and 40 represent, for each item category, the joint plot of ICCs. They represent the probability of engaging in a certain behaviour as a function of the position of an individual on the latent trait. In our case this corresponds to the probability of engaging in specific behaviours as a function of a measure of general attitudes towards the environment.

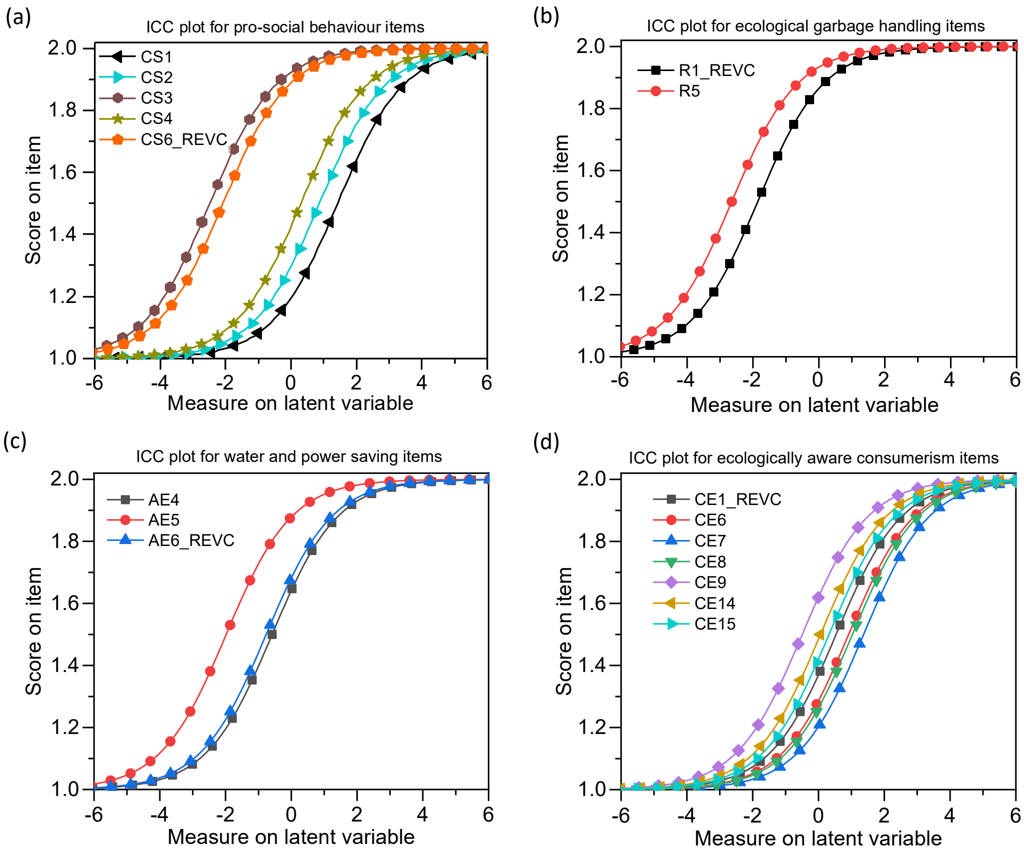


Figure 39: ICC plots for (a) pro social behaviour, (b) ecological garbage handling, (c) water and power saving and (d) ecologically consumerism items

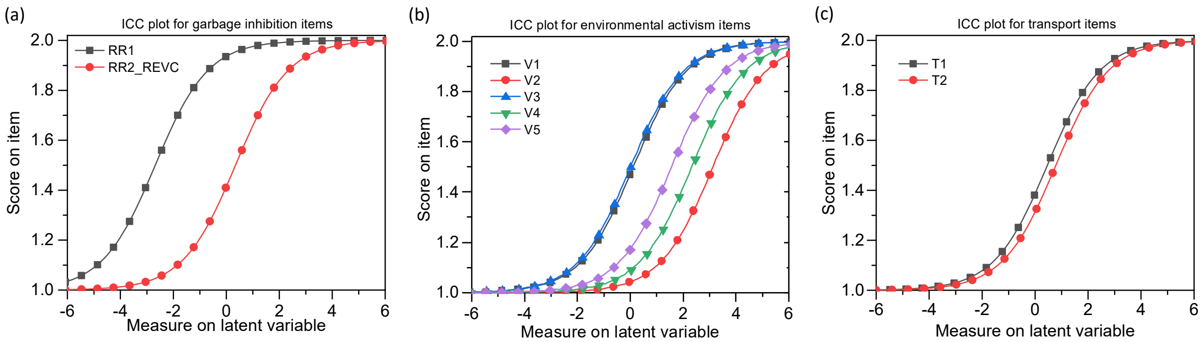


Figure 40: ICC plots for (a) garbage inhibition, (b) environmental activism, and (c) transport items

ICCs are useful indicators of the most appropriate position for a given item (or behaviour) on the latent trait continuum. In the case of the Rasch model, all the curves have the same shape but vary in terms of position on the latent trait (Gaborieau and Pronello, 2021). We do not see any complete ICC overlaps; hence each item reveals unique information measuring the attitude

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

measure towards GEB and well distributed on the latent dimension concerning each item category.

The results suggest that using the DRM, the proposed questionnaire is able to effectively measure the pro-environment behaviour of travellers. Unidimensionality, the perfect level of item reliability of 1, the high item separation of 34.22, the absence of larger differential item functions, and the local independence are all good indicators of a valid model. We may conclude that GEB-26 shows acceptable approximation to the Rasch requirements and presents good psychometric properties when using DRM to validate the scale. Some further analyses may be useful to verify the three items (AE6_REVC- In winter, I leave the windows wide open for long periods of time to let in fresh air, CS6_REVC- Sometimes I ride public transport without paying a fare and CS4- If I were an employer, I would not hesitate to hire a person previously convicted of crime) that are borderline, with low point–biserial correlations. In fact, the effect of a larger sample size and the good selection of items in GEB-26 (by excluding problematic items identified in GEB-40 and GEB-51) generated a perfect level of reliability of 1, while during GEB-40 (Gaborieau and Pronello, 2021) and GEB-51 (Duboz, 2018) analysis, the obtained item reliability values were, respectively, 0.96 and 0.94. Moreover, the total raw variance explained by the GEB-26 Rasch measures was 34.2%, which is higher than that of GEB-40 (Gaborieau and Pronello, 2021) at 31.6% (for GEB-51 raw variance by measures was not reported). The DRM results has been published in *Sustainability* journal and presented in Transportation Research Board (TRB) 101st Annual Meeting, 9-13 January 2022.

Further research is needed to deepen our understanding of the GEB and to devise appropriate measurement instruments. Therefore, we do not suggest excluding any item by looking only at the dichotomous scale measurement. Item exclusion will be further assessed after measuring the original six-scale polytomous questionnaire in the next section 4.5, using the Rasch rating scale model to validate and select the most appropriate measurement scale to measure the GEB of users. As suggested by Linacre[58], scales with more categories are expected to give better and higher person reliability and separation.

4.5 Polytomous Rasch measures and estimates

This section presents the results of Rating Scale Model (RSM), by following the various steps described in the methodology section. During RSM, after initial analysis, the unexpected responses were removed by looking very high/low z residual values (out of range ±2) in item response Table to reach the MNSQ (MeaN-SQuare) values within threshold by iterative process

[58] https://www.winsteps.com/winman/reliability.htm, accessed on January 26, 2021.

of checking MNSQ values. Items CS4, AE6_revc, CS6_revc, T1, R1_revc, and R5 were having values out of range for MNSQ, negative or near to zero point biserial correlation, which were analysed for high/low z residual to achieve MNSQ in range. The initial Rasch fit measures and statistics are shown in Table B12 in appendix B. After removing the unexpected responses, the final obtained fit statistics are reported in Table 52 and satisfies the Rasch fit statistics and assumptions.

Unidimensionality is assessed in four steps and assumptions to follow for validating the attitude towards the GEB questionnaire as mentioned in the methodology. Table 52 presents the estimates of item parameter ("Measure") from Winsteps together with their corresponding observed and expected point biserial correlation, Infit and Outfit statistics. Additional information includes the raw score on items ("Total Score") as well as the percentage of observed and expected positive answers for each item (Exact Match). In Table 52 items are ordered by decreasing misfit order.

Point biserial correlation: all items have point measure correlation values above 0.3 cutoff except 6 items CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime), AE6_revc (In winter, I leave the windows wide open for long periods of time to let in fresh air), RR2_revc (I sometimes buy beverage in cans), CS6_revc (Sometimes I ride public transport without paying a fare), T1 (Usually, I do not drive my automobile in the city), CE1_revc (I use fabric softener with my laundry). We do not have any negative correlations. But we have zero and two small positive correlations. We see 0.00 for item CS4 and 0.09 for item AE6_revc which is reverse coded. The EXP. (expected correlation) shows what the correlation would be, 0.42 and 0.39 respectively if the data matched the Rasch model. 0.00 is far away from 0.42 and 0.09 is a little far away from 0.39, which indicates some investigation for these 2 items.

Fit statistics: we examined item statistics with Outfit and Infit MNSQ values. MNSQ fit ranges between 0.5 to 1.5 provide evidence of unidimensionality (O'Connor *et al.*, 2016). Infit and Outfit MNSQ item statistics range from 0.63 to 1.49.

Table 52: Estimates of item parameters, infit, outfit, and point biserial correlations (items ordered by increasing point measure correlation)

Entry No.	Total Score	Measure	Model S.E.	Infit		Outfit		Point-bis. Corr.		Exact Match		Item
				MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	
4	15655	0.14	0.01	1.13	7.38	1.34	9.90	a 0.00	0.42	23.7	20.8	CS4
10	18094	-0.12	0.01	1.07	3.97	1.25	9.90	b 0.09	0.40	25.3	21.7	AE6_revc
19	15065	0.20	0.01	1.22	9.90	1.30	9.90	c 0.20	0.42	19.1	20.8	RR2_revc
5	22593	-0.94	0.02	1.48	9.90	1.43	9.66	g 0.22	0.27	50.7	50.1	CS6_revc
25	13167	0.22	0.01	1.47	9.90	1.48	9.90	d 0.25	0.41	13.5	20.7	T1
11	14426	0.26	0.01	1.37	9.90	1.42	9.90	f 0.27	0.42	15.2	21.0	CE1_revc
26	12414	0.29	0.01	1.19	9.80	1.23	9.90	e 0.30	0.42	18.0	21.1	T2
6	22050	-1.14	0.02	1.49	9.90	1.31	6.37	l 0.32	0.25	69.3	64.5	R1_revc
18	23546	-1.13	0.02	1.42	9.14	1.27	5.66	m 0.33	0.24	69.7	63.7	RR1
3	22705	-0.85	0.02	0.98	-0.69	0.90	-2.68	L 0.37	0.29	47.0	43.1	CS3
8	19060	-0.23	0.01	1.23	9.90	1.26	9.90	h 0.37	0.38	17.3	22.7	AE4
13	11785	0.54	0.01	1.01	0.57	1.01	0.32	j 0.39	0.42	24.6	23.3	CE7
9	21567	-0.60	0.01	0.86	-5.31	0.88	-4.18	I 0.39	0.33	36.3	30.3	AE5
7	23551	-1.39	0.03	1.43	7.85	0.97	-0.55	J 0.41	0.21	82.9	77.1	R5
14	12772	0.43	0.01	0.94	-3.29	0.94	-3.00	k 0.42	0.42	23.3	22.3	CE8
1	11782	0.54	0.01	0.94	-3.32	0.93	-3.46	F 0.43	0.42	25.5	23.3	CS1
21	7165	1.28	0.02	1.24	6.91	1.09	2.45	B 0.46	0.32	38.6	38.3	V2
16	15992	0.10	0.01	0.78	-9.90	0.78	-9.90	M 0.48	0.42	27.7	20.8	CE14
2	13542	0.35	0.01	0.88	-7.43	0.88	-6.65	E 0.49	0.42	23.2	21.6	CS2
15	18035	-0.11	0.01	0.81	-9.90	0.80	-9.90	K 0.51	0.40	24.4	21.6	CE9
12	13835	0.32	0.01	0.64	-9.90	0.64	-9.90	H 0.51	0.42	31.1	21.4	CE6
22	16427	0.06	0.01	0.75	-9.90	0.76	-9.90	G 0.52	0.41	27.0	20.8	V3
17	15533	0.15	0.01	1.01	0.44	0.99	-0.43	I 0.52	0.42	18.4	20.8	CE15
24	11102	0.62	0.01	1.06	2.92	1.03	1.31	D 0.55	0.41	20.6	24.1	V5
23	8957	0.92	0.01	0.95	-2.21	0.86	-5.35	A 0.56	0.38	28.5	27.6	V4
20	16141	0.09	0.01	0.63	-9.90	0.63	-9.90	C 0.58	0.42	28.8	20.8	V1
Mean	16037.0	0.00	0.01	1.07	1.4	1.05	0.7	-	-	31.9	30.2	-
P.SD	4476.3	0.64	0.00	0.26	7.6	0.25	7.5	-	-	17.6	15.8	-

Principal Component Analysis of Residuals (PCAR): Table 53 presents the results of the Rasch-residuals based on PCAR and figure 41 its associated scree plot. Unidimensionality is assessed according to the criteria suggested by Reckase (1979). Firstly, the amount of variance explained by measures is 44.8% with 13% of raw variance explained by persons and 31.8% raw variance explained by items, which is larger than the requirement of 20% demonstrating a unidimensional trait of the data. Secondly, the unexplained variance by first contrast is 5.1%, which is slightly greater than 5%, but the eigen values of first contrast is 2.41. The first, second, third, fourth, and fifth unexplained variance accounted for eigenvalues are 2.41, 2.06, 1.89, 1.74, and 1.28 which were good by referring the criteria. The results of the data analysis suggested that the unidimensionality is hold across the whole test (See Table 53) which satisfies the criteria of Rasch unidimentionality. Furthermore, the right way to interpret Table 53 is to compare the columns observed and expected which in our case matches nicely, just having slight differences.

Table 53: Standardized residual variance in eigenvalue units

	Eigenvalue	Observed		Expected
Total raw variance in observations	47.1332	100.0%		100.0%
Raw variance explained by measures	21.1332	44.8%		46.0%
Raw variance explained by persons	6.1221	13.0%		13.3%
Raw Variance explained by items	15.0111	31.8%		32.7%
Raw unexplained variance (total)	26.0000	55.2%	100.0%	54.0%
Unexplned variance in 1st contrast	2.4060	5.1%	9.3%	
Unexplned variance in 2nd contrast	2.0603	4.4%	7.9%	
Unexplned variance in 3rd contrast	1.8907	4.0%	7.3%	
Unexplned variance in 4th contrast	1.7474	3.7%	6.7%	
Unexplned variance in 5th contrast	1.2892	2.7%	5.0%	

By plotting the loading of items on the 1st contrast of the residual based PCA (figure 42), we clearly see that this possible subdimension is implied by 2 items, A(V4) and B(V2), with the largest loadings. In fact, item A (V4 - I sometimes contribute financially to environmental organizations), and B (V2 - I am a member of an environmental organization) are quite far away from the general cluster created by the other items. Hence, the possible subdimension can result by these two items as indicated the eigen values of first contrast is 2.4 (~2 items) in Table 53. To see the items corresponding to the alphabets represented in figure 42 refer to Table 52.

Follow up analyses evaluated the clusters of items which were identified in the PCAR. The text of items (refer Table 4 for items descriptions) is reviewed in each cluster (cluster 1: 4 items - V4(A), V2(B), V1(C), V5(D); Cluster 2: 16 items - CS2(E), CS1(F), V3(G), CE6(H), CE15(I), R5(J), CE9(K), CS3(L), CE14(M), RR1(m), CS6_revc(g), AE4(h), AE5(i), CE7(j), CE8(k), R1_revc(l); Cluster 3: 6 items - CS4(a), AE6_revc(b), RR2_revc(c), T1(d), T2(e), CE1_revc(g)) and concluded that although the items marked different parts of the trait, the items all involved one trait.

```
      VARIANCE COMPONENT SCREE PLOT
     +--+--+--+--+--+--+--+--+--+--+--+
 100%+  T                              +   T     : Total
     |                                 |
V 63%+                                 +   U     : Unexplained
A    |              U                  |
R 40%+     M                           +
I    |           I                     |   M     : Measures
A 25%+                                 +   I     : Items
N    |                                 |
C 16%+                                 +
E    |        P                        |
  10%+                                 +   P     : Persons
L    |                                 |
O  6%+                                 +
G    |                 1               |   1..5  : Contrast
|  4%+                    2  3         +
S    |                          4      |
C  3%+                             5   +
A    |                                 |
L  2%+                                 +
E    |                                 |
D  1%+                                 +
     |                                 |
 0.5%+                                 +
     +--+--+--+--+--+--+--+--+--+--+--+
        TV MV PV IV UV U1 U2 U3 U4 U5
       VARIANCE COMPONENTS
```

Figure 41: Results of PCAR and scree plot of variance components

```
       STANDARDIZED RESIDUAL CONTRAST 1 PLOT

      -2            -1            0             1             2             3
      -+-------------+-------------+-------------+-------------+-------------+- COUNT  CLUSTER
      |                            |            A                             | 1      1
   .6 +                            |                                          +
      |                            |                                          |
C  .5 +                            |                 B                        + 1      1
O     |                            |C       D                                 | 2      1
N  .4 +                            |                                          +
T     |                            |                                          |
R  .3 +                            |    E  F                                  + 2      2
A     |                            |G                                         | 1      2
S  .2 +                            | I  H                                     + 2      2
T     |                            |                                          |
   .1 +         J      L         K |                                          + 3      2
1     |                            |                                          |
   .0 +------------lm--------------|M-----------------------------------------+ 3      2
L     |                            |                                          |
O -.1 +                    i    h  |     k j                                  + 4      2
A     |               g            |                                          | 1      2
D -.2 +                            |                                          +
I     |                            |   f                                      | 1      3
N -.3 +                            |   e                                      + 1      3
G     |                            |  d                                       | 1      3
  -.4 +                            |  c                                       + 1      3
      |                          b |                                          | 1      3
  -.5 +                            | a                                        + 1      3
      -+-------------+-------------+-------------+-------------+-------------+-
      -2            -1            0             1             2             3
                                    ITEM MEASURE
```

Figure 42: Item loadings on the first contrast

Local independence: according to the Linacre guidelines[13] all correlation is <0.4, hence no item residuals are correlated, respecting the local independence assumptions of Rasch analysis. Two items among all 26 items having correlation of 0.41, which is not considerably larger than 0.4. The detailed obtained correlation statistics are reported in Table B13 in appendix B.

Reliability and Separation of measures: person measure reliability is 0.75 and item measure reliability is 1 (perfect), which is acceptable according to Stelmack *et al.,* (2004) with the less variability of the measurement attributed to measurement error. These results indicate that the estimated measures are highly reliable (i.e., 25% and 0%, respectively, of person and item measure variability can be attributed to measurement error). We can observe that our GEB questionnaire items attributed to zero (0%) percentage of measurement error, which is perfectly validating the test items, because we have available a large sample size to validate it. The person "separation" is 1.75, indicates that this test can distinguish between high and low performers (1.75, ~2 levels of performers) in the sample. The results satisfy the criteria defined by Miller and Dishon (2006) and represent good level of separation. The item separation is 43.39 (huge). With this large person sample, the item difficulties are estimated exceedingly precisely and validating the GEB construct validity, which is >3, represent excellent level of separation (Duncan *et al.*, 2003). According to Boone *et al.*, (2014) the real person reliability gives the lower limit of the instrument's consistency, thus we reported real reliability and separation indexes.

Differential Item Functioning (DIF): DIF analysis is conducted by comparing a reference group (typically the majority group) with a focal group (typically the minority group) (Martinková *et al.*, 2017). The reference groups are: for gender, female; for residential location, urban; and for age, old. The remaining ones are focal groups. Only the variables which have DIF are shown in Table 54. The Mantel statistics for all variables are reported in Table B14, B15 and B16 in appendix B.

Table 54: DIF based on Mantel test statistics

Groups	Chi square	*p* value	Size CUMLOR	Item	DIF remark
Female, Male	96.26	0.00	0.59	CE9	slight to moderate
Urban, Rural	17.87	0.00	0.52	R5	slight to moderate
Urban, Suburban	8.79	0.00	0.45	R5	slight to moderate
Old, Medium	31.28	0.00	–0.43	CS1	slight to moderate
Old, Young	51.44	0.00	–0.52	CS1	slight to moderate
Old, Medium	64.17	0.00	–0.61	CS2	slight to moderate
Old, Young	99.99	0.00	–1.08	CS2	moderate to large
Old, Medium	75.31	0.00	–1.02	CS6_revc	moderate to large
Old, Young	99.99	0.00	–1.24	CS6_revc	moderate to large
Old, Young	37.89	0.00	0.51	AE5	slight to moderate

Old, Medium	38.71	0.00	0.48	CE7	slight to moderate
Old, Young	89.35	0.00	0.69	CE7	moderate to large
Old, Medium	92.97	0.00	0.75	CE8	moderate to large
Old, Young	99.99	0.00	1.05	CE8	moderate to large
Old, Medium	44.02	0.00	0.52	CE14	slight to moderate
Old, Young	99.99	0.00	0.92	CE14	moderate to large
Old, Young	88.57	0.00	–0.67	CE15	moderate to large
Old, Medium	87.94	0.00	0.75	V3	moderate to large
Old, Young	99.99	0.00	1.16	V3	moderate to large
Old, Young	48.88	0.00	–0.56	V4	slight to moderate
Old, Medium	39.76	0.00	–0.50	V5	slight to moderate
Old, Young	99.99	0.00	–0.96	V5	moderate to large
Old, Young	80.18	0.00	0.68	T1	moderate to large

According to the criteria defined by Zwick *et al.*, (1999), Table 54 shows that item CE9 (Every now and then, I give away things I no longer use) has DIF of slight to moderate size by gender with p value 0.00 and DIF size 0.59. By residential location item R5 (I separate the glass from other waste to recycle it) has slight to moderate DIF with p value 0.00, DIF size 0.52 for urban and rural; for urban and suburban, p value 0.00 and DIF size 0.45. By age, items CS1, AE5, V4 have slight to moderate DIF size. Items CS6_revc, CE8, CE15, V3, T1 have moderate to large DIF size. Items CS2, CE7, CE14, V5 have DIF size slight to moderate for old and medium group while moderate to large for old and young groups (refer Table 4 for items descriptions). In total 12 out of 26 items show DIF. We see that the variables causing DIF have largest chi square statistics.

Table 54 only shows the items cause DIF but does not identify the difficulty across subgroups. To this end, item difficulty across two subgroups with item parameter estimates are plotted against each other in figures 43, 44, and 45, with 95% of confidence interval for both dimensions. The graph compares the reference and focal group item difficulty. The diagonal line represents along which all items would lie within 95% confidence interval if there were no differences between subgroups. If the items fall within range of 95% confidence interval, we can conclude that items are homogenous across subgroups, that is they have same difficulty. Slight to moderate DIF is not degrading the measurement, therefore we highlighted the items with moderate to large DIF size to consider and reflect in red colour in corresponding figures. By gender and residential location, items showing slight to moderate DIF, hence not highlighted in figures 43 and 44.

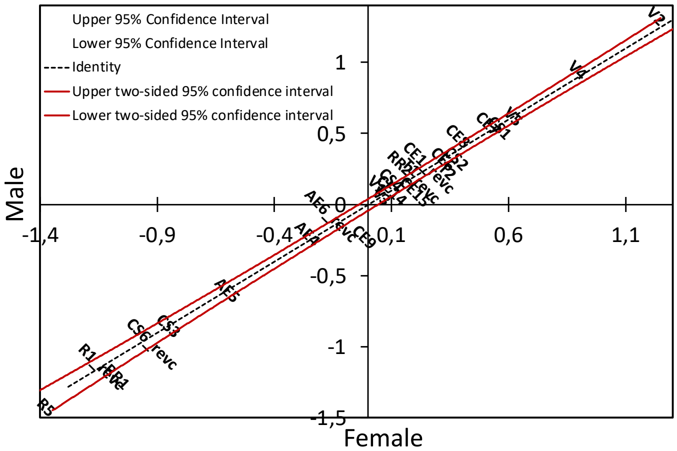


Figure 43: Gender DIF Pair plot for DIF identification

Figure 45a shows that items CE7, CE8, V3 are more difficult for old age group compared to medium groups and item CS_revc is more difficult for medium age group compared to old one. Likewise, figure 45b shows that items CS6_revc, CE15, CS2, and V5 are more difficult for young group compared to old one and items CE7, CE8, CE14, T1, and V3 are more difficult for young age group compared to old one (refer Table 4 for items descriptions). We see noticeably more difficulty difference among items between young and old age groups.

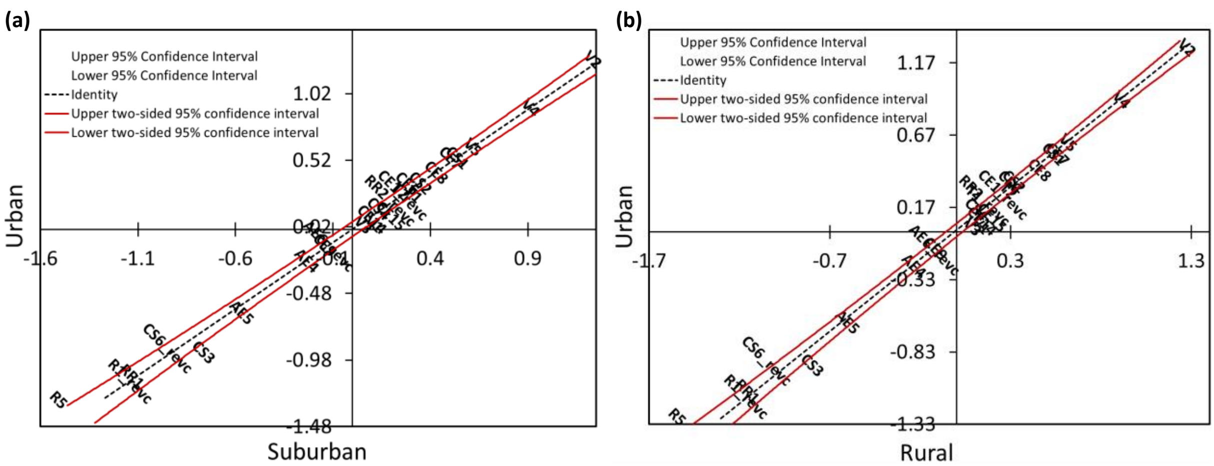


Figure 44: Residential location DIF identification pair plot for (a) urban and suburban, (b) urban and rural

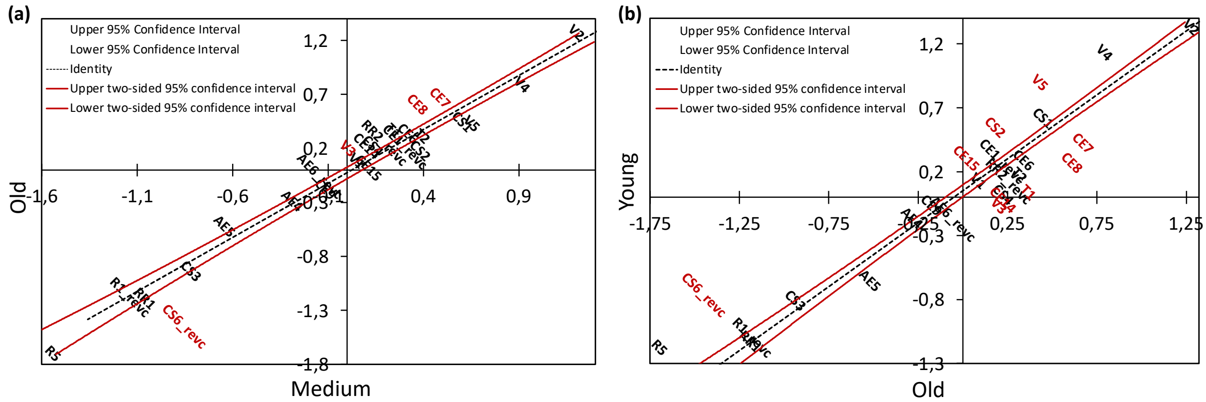


Figure 45: Age DIF Pair plot for DIF identification for (a) Medium and Old, (b) Young and Old

Write map: in figure 46 the left side of the map contains person measures, and the right side contains item measures. Persons at the top had the least difficulty endorsing items, while persons at the very bottom had the most difficulty endorsing items. Items can be interpreted in a similar manner. Items at the very top of the map were the most difficult to endorse, whereas items at the bottom of the map were the easiest to endorse. When an item is aligned with a person, then the person is predicted to have a 50% probability of succeeding on the item. So, the more difficult items about at +2 logits align with the most able persons, and the easier items at -3 logits with the least able persons. When an item is at the level as a person, then the item is “targeted” on the person. A gap of more than a logit may mean that some major concepts may have been missed by the manner in which items define the trait (Boone *et al.*, 2014). Equivalently, when an item is 1.1 logits more difficult (or easier) than the measure of attitude towards the environment for an individual, this individual has a 25% (or 75%) probability of engaging the behaviour (Gaborieau and Pronello, 2021). With these considerations, we can state few observations from figure 46:

- the most difficult item is V2 (I am active in an environmental organization) followed by item V4 (I sometimes contribute financially to environmental organization), both belong to the category environment activism;
- the easiest items are R5 (I separate the glass from other waste to recycle it), followed by RR1(I reuse the shopping bag for the next few times), and R1_revc (Throw out of stock batteries in undifferentiated). These three items are not targeting to any person, but there are some persons above and below these items which are less aggregable to GEB, so these items do not contribute anything more to the GEB measurement but still fall within the user’s ability range;

- items CE7 (Sometimes, I sell goods I don't use anymore), CS1 (Sometimes I give money to panhandlers) seem to measure similar portions of the trait and therefore, from a measurement perspective, are redundant. This appears to be also the case of items CE6, CS2; items CE1_revc, T2; CE15, CS4, RR2_revc, T1; CE14, V1, V3; AE6_revc, CE9; and R1_revc, RR1 (refer Table 4 for items descriptions). Within groups of items, individual items can be removed with little measurement precision lost;
- it is not observed a gap between items more than a logit, but the write map shows the need for items to fill the measurement gaps, for example between V4 (I sometimes contribute financially to environmental organization) and V5 (I boycott companies using OGM or pesticides) and between items AE4 (I turn off the heat at night) and AE5 (I wait until I have a full load before doing my laundry). This explains the relatively poor value of the individual separation reliability.

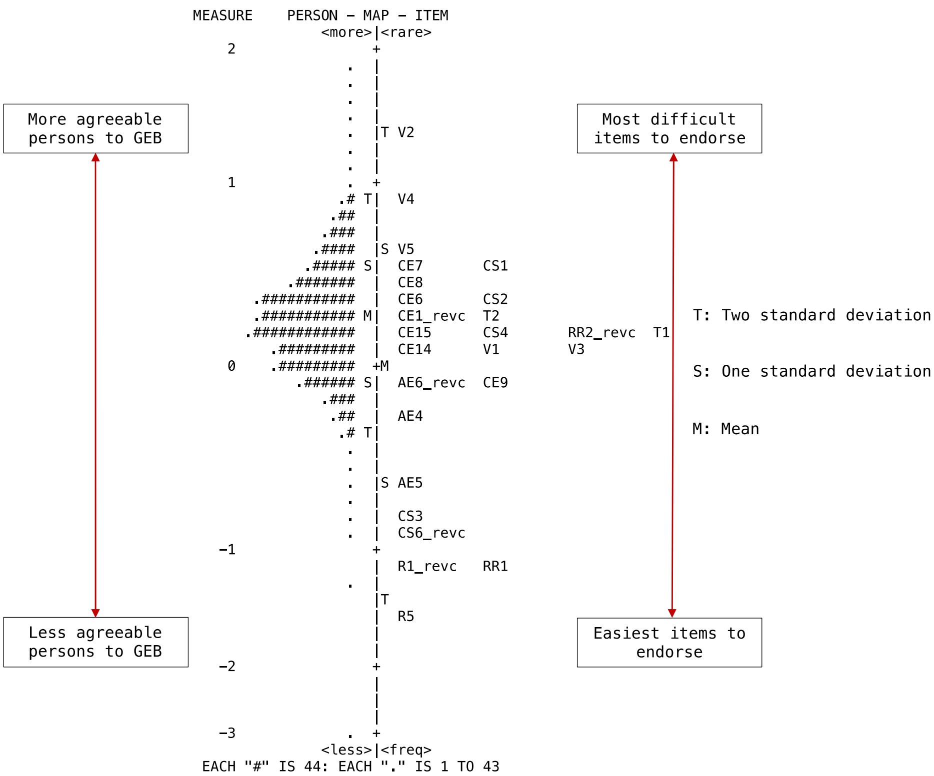


Figure 46: Write map

Finally, figure 47 shows person ability and item difficulty distribution, which often have a normal distribution. According to Seong (1990) and Stone (1992) if the distribution were not gaussian, then estimates would be biased. In our case both items' difficulties and person abilities fit a normal distribution, hence it can be concluded that all the items are well distributed and targeted within user's ability.

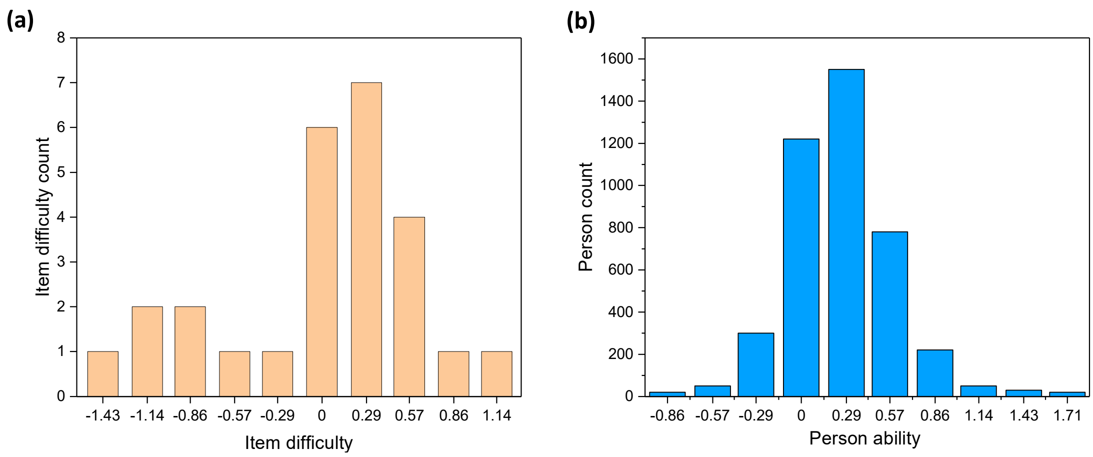


Figure 47: Person ability and Item difficulty distribution

Item Characteristics curves (ICCs): figures 48 and 49 represent the joint plot of ICCs for each item category. They represent the probability of engaging in a certain behaviour as a function of the position of an individual on the latent trait. In our case this corresponds to the probability of engaging in specific behaviours as a function of a measure of general attitudes towards the environment. ICCs are useful indicators of the most appropriate position for a given item (or behaviour) on the latent trait continuum. In the case of the Rasch model, all the curves have the same shape but vary in terms of position on the latent trait (Gaborieau and Pronello, 2021). ICC plots also helps to check the problematic items, where and if they are not useful for the measurement. Focusing on activism and volunteering items, we observe that ICC overlaps V1(I often talk to my friends about environmental problems) and V3 (It happens that you point out to someone to behave non-ecologically). These items produce the same information. Concerning other item categories, any ICC overlaps are not observed; hence each item reveals unique information measuring the attitude measure towards GEB and is well distributed on the latent dimension concerning each item category.

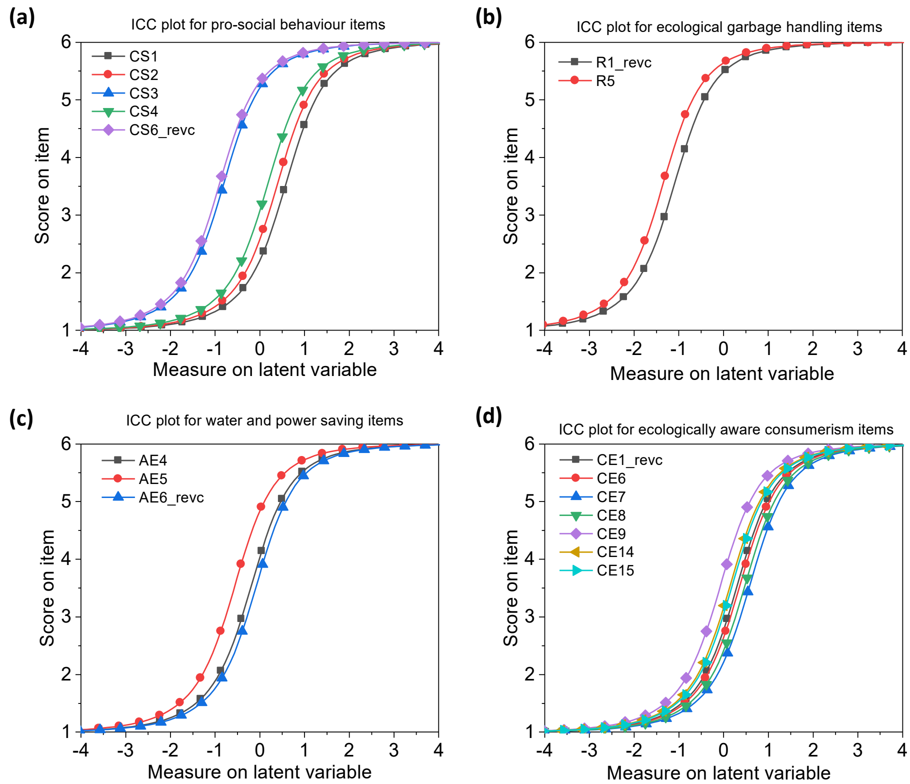


Figure 48: ICC plot for (a) Pro social behaviour items (b) Ecological garbage handling (c) water and power saving items (d) consumerism items

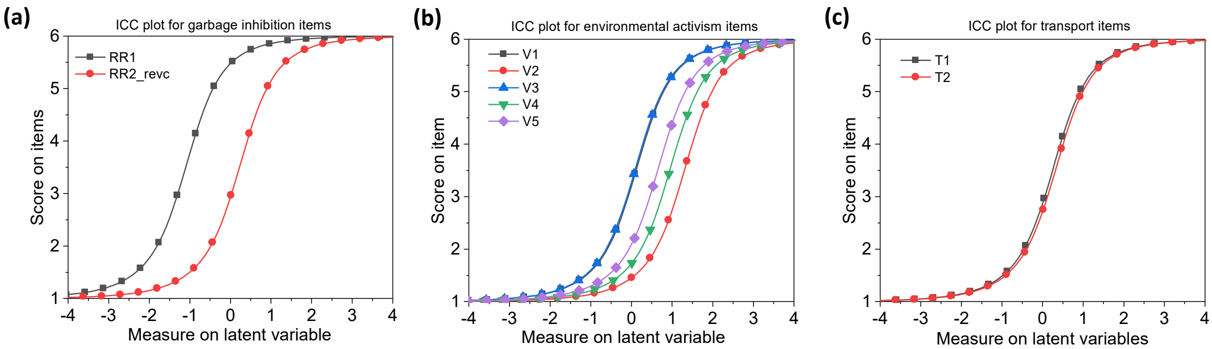


Figure 49: ICC plot for (e) garbage inhibition items (f) environmental activism items (g) transport items

ICC plots are separately analysed for the problematic items to see where the problem is and if they are not useful for the measurement (figure 50).

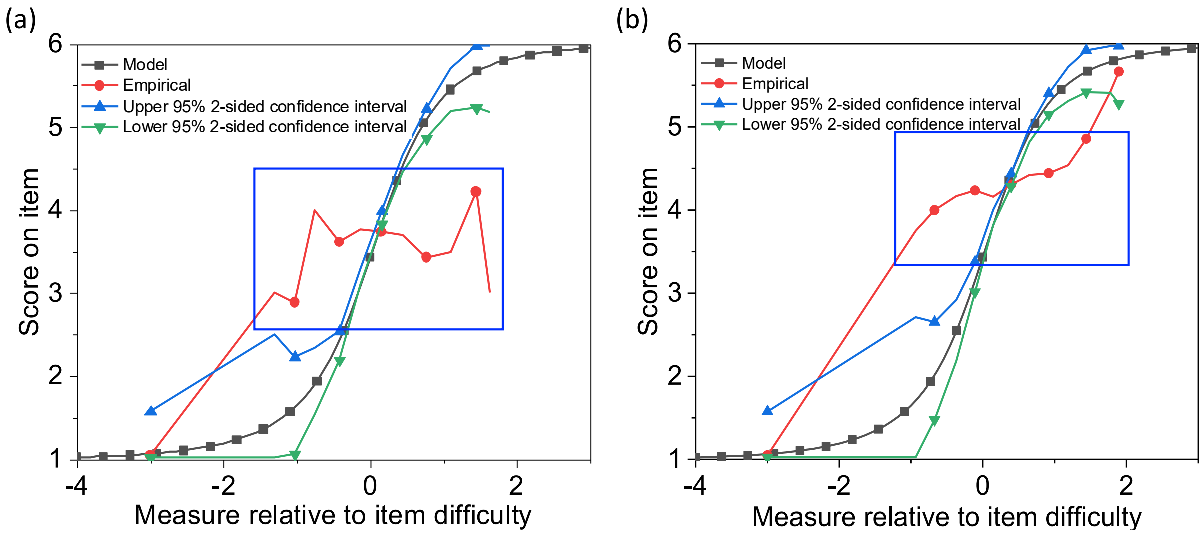


Figure 50: ICC plot for (a) Item CS4 (b) item AE6_revc

Responses outside the 95% confidence interval are unexpected. Blue box shows the most unexpected cluster of responses to the item CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime) and AE6_revc (In winter, I leave the windows wide open for long periods of time to let in fresh air). For item CS4 the problem is in the area where we expect responses (y-axis) between category 2 to 5. The empirical ICC (red line) is almost flat (horizontal). The correlation between responses to the item and the abilities/attitudes of the sample (x-axis) is low in this region. They were also much more homogeneous in their overall responses. This item does not seem useful for measurement. Item AE6_revc has unexpected cluster of responses between categories 3 to 5. They are also much more homogeneous in their overall responses. The empirical (red) curve is flat. This is another item which is not helping to construct measurement.

Empirical item category measures: to investigate if all the items agree in defining the latent variable, the empirical item category measures are analysed in figure 51. Red box shows the average measures for each data-code for each item. These are squashed together on each line. Orange box shows the empirical average measures for all 6 categories which are close together except disordered for 2 items 213456 (CS4), 213456 (AE6_revc). This item does not agree with the other items in defining the latent variable, thus it must be investigated.

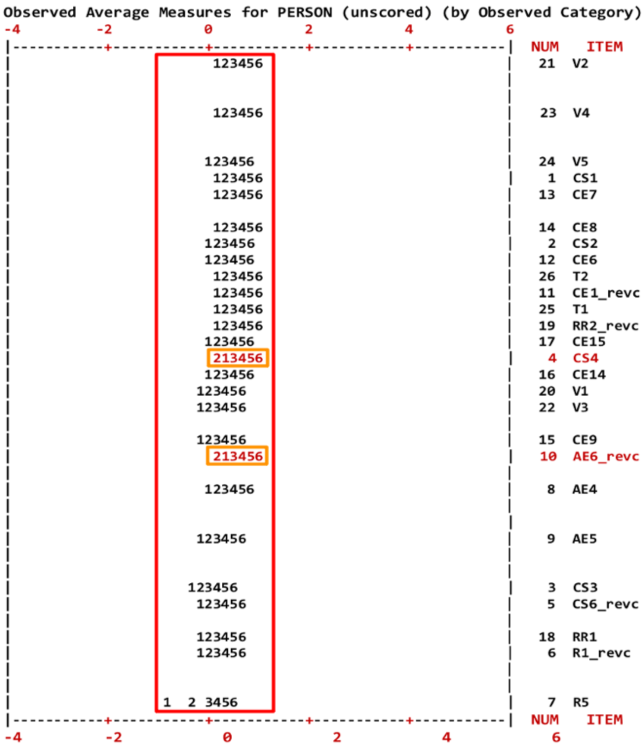


Figure 51: Empirical item category measures for GEB questionnaire

Evaluation of Linacre's six rating scale guidelines

The GEB items were evaluated using 8 rating scale guidelines suggested by Linacre (1999, 2002), as reported in the methodology section.

Table 55: Summary of Rasch item measures and category structure for the GEB questionnaire

Category Label	Observed Count	%	Observed Average	Sample Expect	Infit MNSQ	Outfit MNSQ	Andrich Threshold	Category Measure
1	16563	15	–0.42	–0.42	1.08	1.23	None	(–1.77)
2	14890	14	–0.19	–0.21	1.05	1.16	–0.21	–0.68
3	14949	14	0.00	–0.02	1.03	1.06	–0.12	–0.17
4	14166	13	0.16	0.19	0.90	0.77	0.13	0.22
5	15905	15	0.38	0.49	1.09	0.96	0.22	0.70
6	31597	29	0.91	0.87	0.96	0.99	–0.01	(1.66)

Note: Observed Average is mean of measures in category. It is not a parameter estimate.

Guideline 1: as presented in Table 55, each rating scale category had a frequency count greater than 10 and larger, indicating that locally stable estimates of the rating scale structure can be produced.

Guideline 2: the observation counts first decreases from 1 to 4 with slight difference among category 2 and 3, where category 3 increases a little, and then starts to increase from 4 to 6. So, we are observing that the ratings confirm a regular bimodal distribution.

Guideline 3: it was observed that the average measure increases from the rating scale step of Completely Disagree to that of Completely Agree. Thus, the GEB suits the criteria that average measures advance monotonically with rating scale category from -0.42 (minimum for Completely Disagree) to 0.91 (maximum for Completely Agree) logits. This advance is the empirical confirmation that higher categories are intended to reflect higher measures. The advances across categories, however, are uneven. This may be symptomatic of problems with the use of the rating scale or may merely reflect the item and sample distributions. The expected measure (column "Sample Expect") is close to observed measures, which indicates that our sample well fits the model.

Guideline 4: regarding guideline 4, the average Outfit MNSQ (MeaN-SQuare) is below 2.0 for all categories.

Guideline 5: we observe an ordered series of step calibrations (Andrich Threshold) that advance in monotonic way until category 5; for category 6, this value decreases showing disordered step calibration. The step calibrations correspond to the intersections in the probability curve plot (figure 52). Probability curves provide an excellent tool to visually view how well the rating scale is working. With a rating scale working well, a series of distinguishable hills should be present. Each hill should somewhat stand alone, as hills that tend to blend in with other hills indicate categories which respondents may have found difficult to endorse. Figure 52 shows that, in categories 1, 3, and 6, there are instances when a category is most likely to appear on the top trace for at least some portions of the graph, from left to right. However, the lack of hills (as a top trace) for categories 2, 4 and 5 suggests that the items might not be measuring as well as possible with these categories.

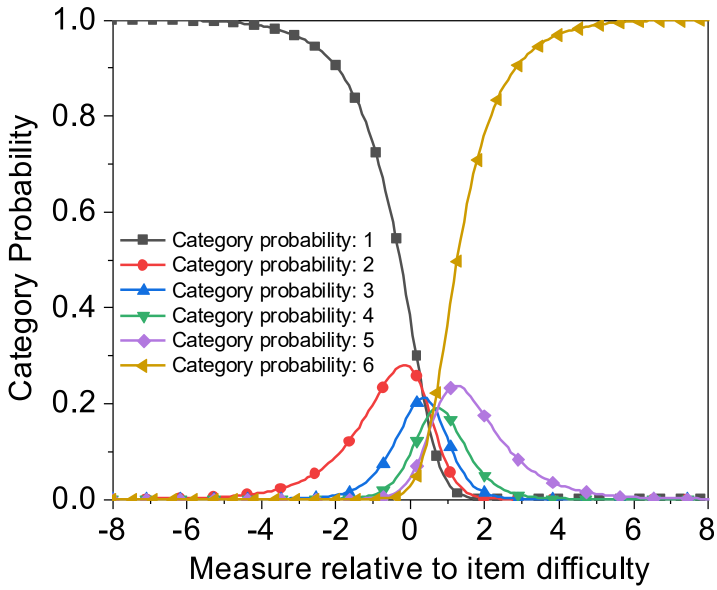


Figure 52 : Category probability curve

Guideline 6: this is useful for inference and for confirming the construct validity of the rating scale. This is true when the observed values of the average measures for each category approximate their expected values.[59] This is true for our data by looking Observed Average and Sample Expect columns in Table 55.

The computation of coherence is outlined in Table 56 where the "Coherence" columns report the empirical relationship between ratings and measures for the GEB data. M→C (Measure implies Category %) reports what percentage of the ratings, expected to be observed in a category (according to the measures), is observed in that category.

Table 56: Analysis of GEB rating scale data

Category	Andrich	Category	Coherence		
Label	**Threshold**	**Measure**	**M→C**	**C→M**	**RMSR**
1	NONE	(-1.77)	82%	7%	1.9004
2	-.21	-.68	27%	29%	1.3681
3	-.12	-.17	22%	40%	1.0119
4	.13	.22	20%	38%	.9382
5	.22	.70	23%	30%	1.2460
6	-.01	(1.66)	84%	40%	1.3831

Note: M→C is measures imply category, C→M is category imply measures

[59] https://www.rasch.org/rn2.htm, accessed on February 20, 2021.

Consider the M→C of category 1, 82% of the ratings that the measures would place in category 1 were observed to be there. The inference of measures-to-ratings is generally successful. The C→M (Category implies Measure %) for category 1 is more troublesome. Only 7% of the occurrences of category 1 were placed by the measures in category 1. The inference of ratings-to-measures is generally less successful. The inference from measures to ratings for category 1 is strong, but from ratings to measures is less. This suggests that local inference for these data would be more secure when categories 1 and 2 are combined.

***Guideline** 7*: the gaps between categories was computed to evaluate the distance between categories, using the Andrich thresholds. The gaps are 0.09 (-0.12 to -0.21), 0.25 (0.13 to -0.12), 0.09 (0.22 to 0.13), -0.13 (-0.01 to 0.22). Linacre did not recommend logit values of minimum step threshold increment for scales other than those with three and five categories; he merely suggested that the minimum increment in step thresholds between adjacent categories would decrease with an increasing number of categories. Because this study used a six-category scale, we adopted the criteria of 1.0 logit as the minimum increment in step thresholds to be conservative. None of the gaps between categories are 1.0, hence not meeting this criterion.

Guideline 8: in all cases, the gaps between response options or step difficulties are less than 5.0 logits.

Results suggests that using the RSM, the proposed 26 items questionnaire is able to effectively measure pro-environmental behaviour of travellers with better estimates than DRM and previous studies (GEB-40 and GEB-51). Unidimensionality, perfect level of item reliability (1) and huge item separation (43.39), absence of larger differential item functioning, local independence, and no overlap among item characteristics curves and satisfying the Linacre's essential rating scale guidelines are all good indicators of a valid scale measurement. Moreover, we obtained person measure reliability of 0.75 and person separation of 1.75 (~2) which shows good level of person ability range (high and low performers) and higher compared to DRM which resulted person measure reliability of 0.67 and person separation of 1.44. It is clear here that more categories are expected to give better and higher person reliability and separation. Two items CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime) and AE6_revc (In winter, I leave the windows wide open for long periods of time to let in fresh air) were identified not agreeing with the other items in defining the latent trait. These two items indicate some attention in future research analysis.

4.6 Mode choice modelling using Structural Equation Model (SEM)

This section presents the results of each stage of Structural Equation Model (SEM), as provided in the methodology.

4.6.1 Variable selection and construction

For trip chain analysis a dominant mode is selected manually by looking in detail each record with the largest distance among all modes in trip chain and/or the most important selected mode out of the sequence of modes. Among all used modes during the most important trip, trip chain is used by 1368 (32.49%) users. The trip chain is then further analysed based on residential location and travel distance (km). The distribution of 1368 records by residential location shows that the rural population is the largest one (653-47.73%) among all trip chain users followed by, respectively, urban (437-31.94%) and suburban (278-20.32%).

The trip chain distribution is then analysed by distance (figure 53a) and the distance corresponding to the residential location (figure 53b, 54a, 54b). Looking at the trip chain distance, maximum trips are with 5-10 km, followed by 11-20 km, <5 km, 21-30 km, 31-40 km. The maximum trips are under 20 km distance. This helps to understand that the distance and residential location really matters in choosing the travel mode.

People living in urban areas have highest trip chain length of 5-10 km followed by <5 km. Suburban areas have highest trip chain distance of 11-20 km followed by 5-10 km, then 21-30 km. Rural areas have long trip chain distance as compared to urban and suburban areas. The highest trip chain length in rural areas is 31-40 km followed by 21-30 km, 41-50 km, 61-80 km, 51-60 km, and then 11-20 km. Hence, the trip length mainly depends on the residential location of the respondents and, likewise, the mode choice. For this reason, this variable is used in SEM mode choice model as mediation variable.

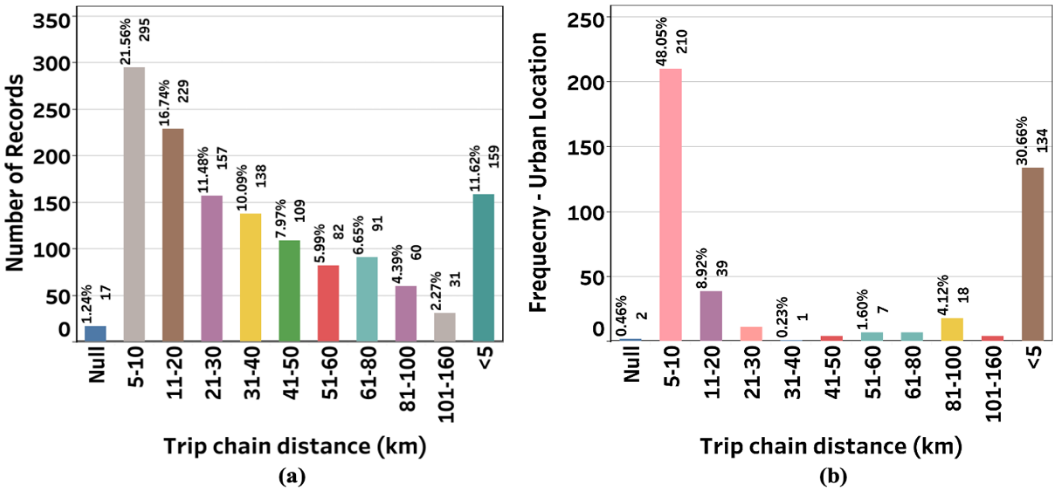


Figure 53: Trip chain distribution (a) by distance and, (b) distance by urban location

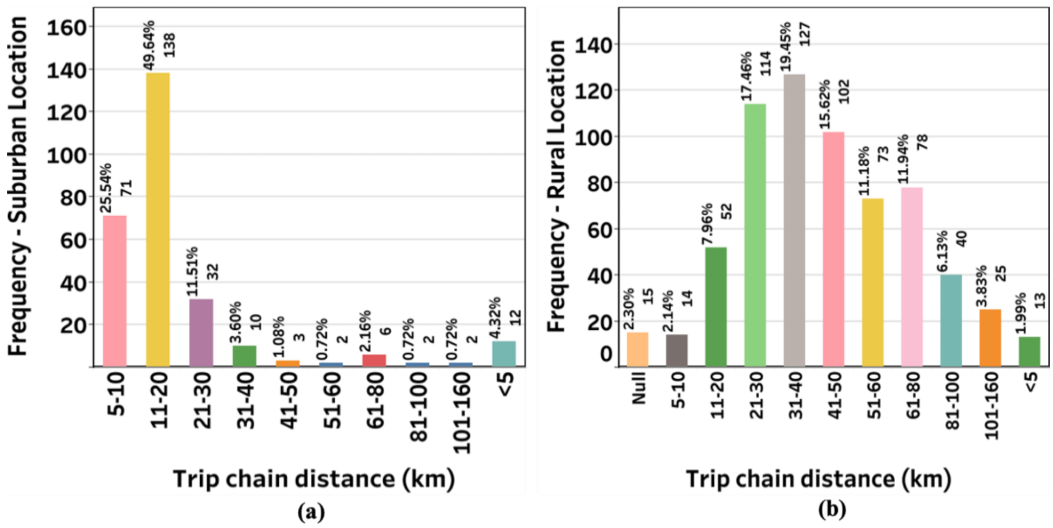


Figure 54: Trip chain distance distribution by (a) suburban and (b) rural location

The distribution of modes of selected 3955 records is shown in figure 55 while the distribution of modes by residential location is shown in figure 56. The distribution of dependent variables shows, concerning ModBin, that 1421 people (35.93%) use private mode and 2534 (64.07%) use PT and Soft modes. Instead, regarding ModTrin, 1421 (35.93%) use private mode, 1799 (45.49%) use PT and 735 (18.58%) soft modes. The distribution of dependent variables is then analyzed by location as shown figure 57.

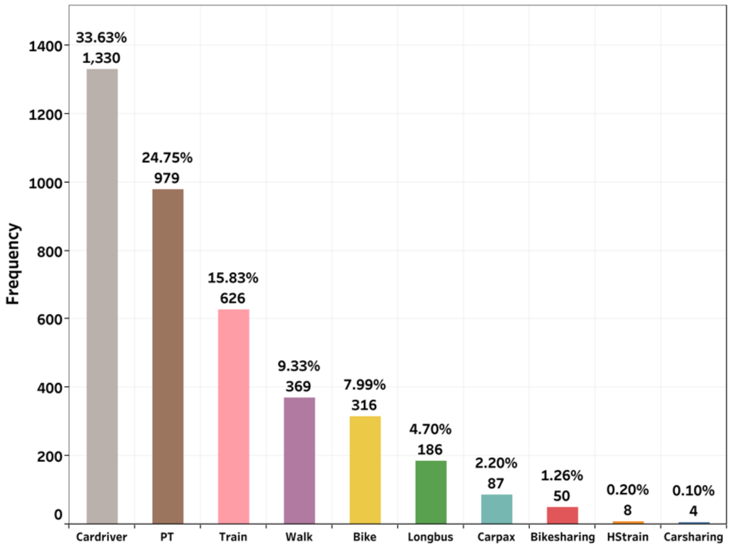


Figure 55: Distribution of modes used by 3955 users

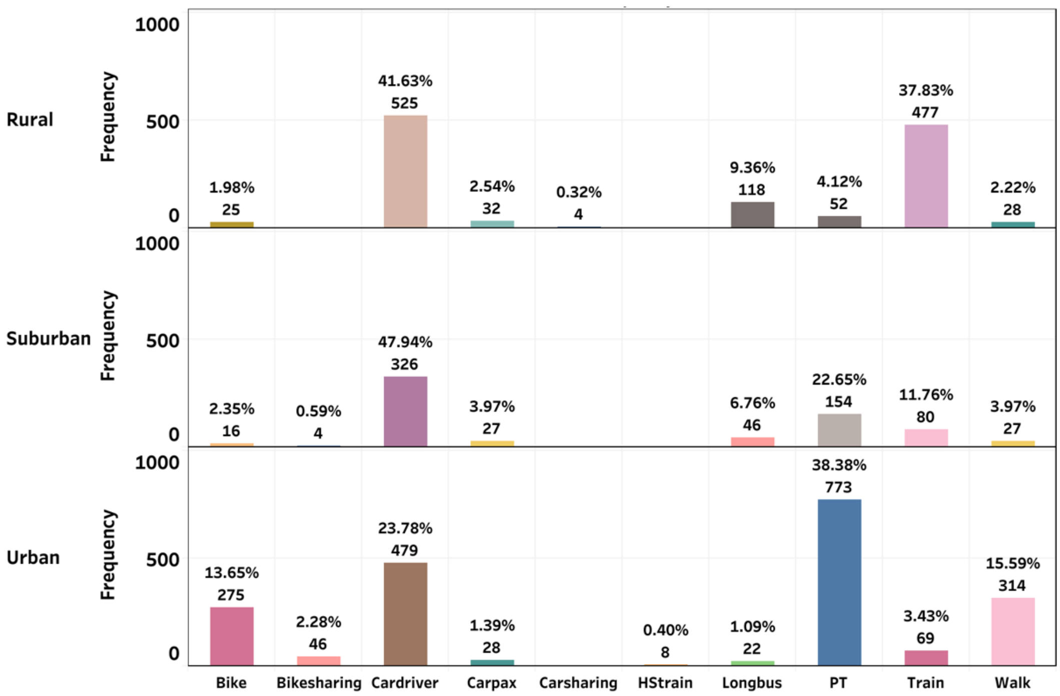


Figure 56: Distribution of modes by location

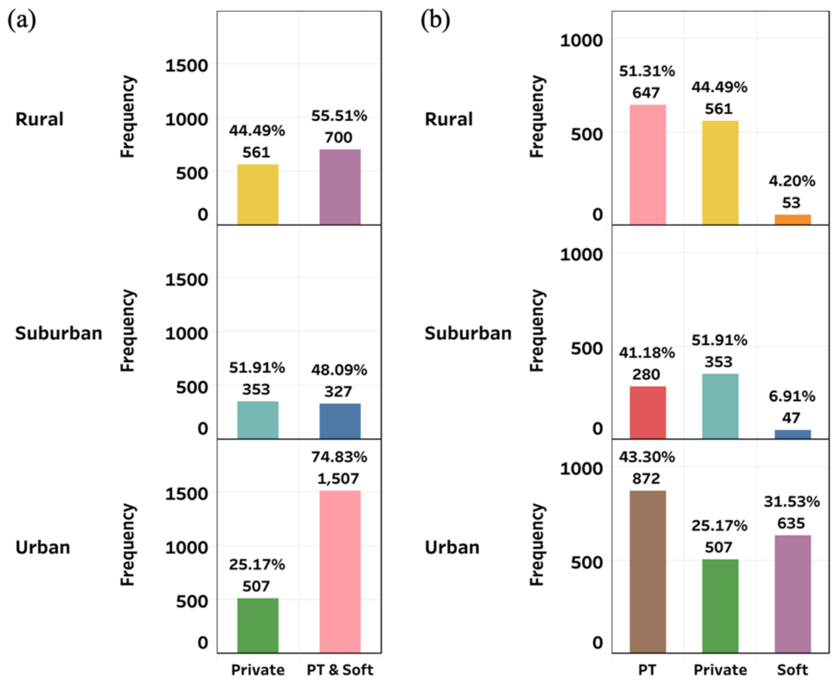


Figure 57: Distribution by residential location of (a) ModBin and (b) ModTrin

4.6.2 Analysis and modelling

This section describes the results of each step adopted in this study for mode choice modelling using SEM to identify important psychological factors behind the mode choice decision making of users. As a result, two important factors emerged with other three variables in the model which affect the mode choice.

Stage 1: defining individual constructs

After applying an iterative process of variables selection to obtain reliable constructs, two factors, *Mode Pleasure (MP)* and *Travel Pleasure (TP)*, were obtained using Exploratory Factor Analysis (EFA), including 8 variables. All the assumptions as described in EFA section to perform EFA are checked and reported here. Descriptive statistics of the 8 observed variables used in EFA are reported in Table B17, in appendix B.

The variables are non-normally distributed, according to Kolmogorov Smirnov and Shapiro Wilk test. Sample size is >100 and *variable:observation* ratio is 8:3955 (<0.1). Multicollinearity is assessed by observing absolute values >0.3 in correlation matrix and determinant of correlation matrix is 0.019 >0.00001, which satisfies the condition to apply EFA. Selected variable's MSA values in the diagonal of Anti Image Correlation Matrix is high >0.7. Kaiser-Meyer-Olkin (KMO) measure is 0.825 which is meritorious, and Bartlett's test of sphericity is significant with chi square value of 15690.31, df of 28 and *p* value of 0.000, which is the sufficient condition that correlation exists among the variables to proceed. Total variance explained is 63.16% which is greater than the requirement of 50%. For factor extraction PAF with varimax rotation is used because no correlation was observed among the factor correlation matrix with values >0.32 by applying oblimin rotation. According to Kaiser criteria (eigen value >1), scree plot and parallel analysis, two factors were retained, as shown in figure 58a and Table 57. The selected eight variables rotated factors loadings and reliability using Cronbach Alpha are reported in Table 58. Cronbach Alpha reliability is very high >0.8 for both factors.

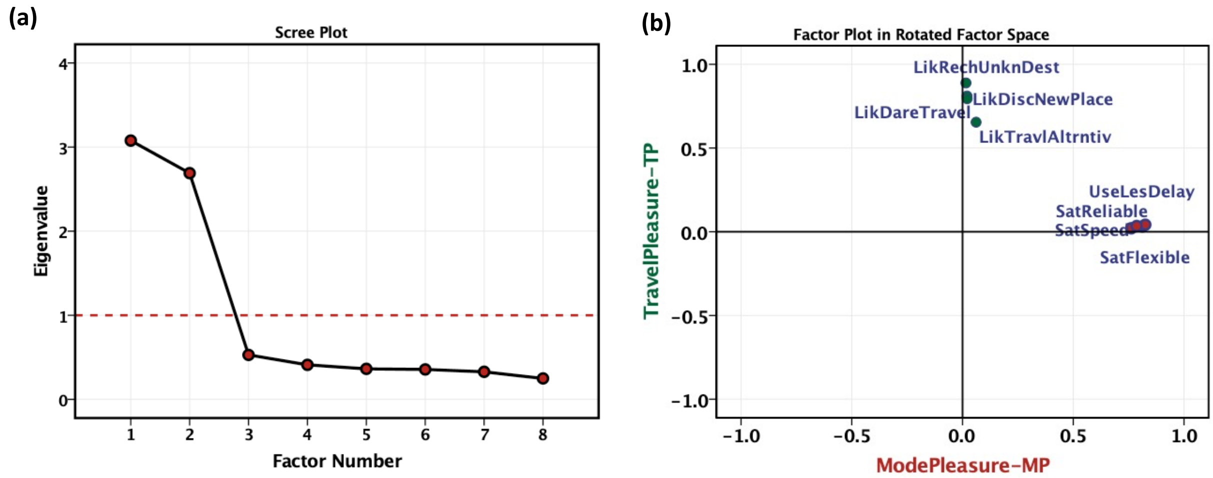


Figure 58: (a) Scree plot to retain factors, and (b) Factor plot in rotated factor space

Table 57: Kaiser criteria of eigen values >1 and parallel analysis for factor retention

No.	Eigen values >1	Parallel analysis
1	3.077	1.090449
2	2.690	1.058542
3	0.528	1.035616
4	0.410	1.018131
5	0.362	1.002510
6	0.356	0.985034
7	0.327	0.969676
8	0.249	0.949882

Table 58: Rotated factor loadings and reliability of factors

Variables*	Loading	Factor	Reliability
SatReliable	0.825	F1: Mode Pleasure (MP)	Cronbach Alpha = 0.873
SatFlexible	0.812		
UseLesDelay	0.786		
SatSpeed	0.762		

LikRechUnknDest	0.889	F2: Travel Pleasure (TP)	Cronbach Alpha = 0.863
LikDareTravel	0.810		
LikDiscNewPlace	0.795		
LikTravlAltrntiv	0.654		

* *The detailed description of variables is reported in Table A2 in appendix A.*

The *first factor* is composed by 4 variables and their related correlation is very high. This factor is labelled as "*Mode Pleasure (MP)*" because all variables related to attitudes towards the satisfaction of the mode they use or prefer to use, whether it is fast, reliable with time, flexible and having less delay which confirms the previous work of Gaborieau (2016). The *second factor* is composed by 4 variables and their related correlation is also very high. This factor is labelled as "*Travel Pleasure (TP)*" because all variables related to attitudes towards the pleasure of travelling, such as like to reach unknown destinations, dare to travel, discover new places, and try alternatives for travelling. The factor loadings plot is shown in figure 58b.

Stage 2: developing the overall measurement model

The constructs obtained in first stage were then used to develop measurement model (Confirmatory Factor analysis - CFA) by drawing a path diagram.

Stage 3: designing a study to produce empirical results

This stage is to assess the adequacy of sample size, select the estimation method and missing data approach. We have ordinal data and very large sample size >250 (4210) with 0.37% missing values (255 missing values for 1 variable AFF (I like to drive)), which are not missing but the choice of respondents as "Not Applicable" to the item; thus, it was decided to use pairwise deletion of missing cases (all-available approach). Now the sample size becomes (4210 – 255) 3955 records which is still satisfying the initial assumptions of the model by having sample size >250. Mardia's coefficient is significant with value 50.430, (i.e., the critical ratio is largely greater than 1.96 in magnitude), hence the data is not normally distributed. The multivariate kurtosis is also large 29.398, showing non normal data. Univariate normality is also checked using Kolmogorov-Smirnov and Shapiro-Wilk test which results significant p value <0.05 for all variables, hence the data is not normally distributed as expected with 95% confidence level, justified by having ordinal data and large sample size. As suggested by Hair *et al.,* (2010), our data is not multivariate normally distributed, so we selected Asymptotically Distribution Free (ADF) estimation method for parameter estimation due to its insensitivity to non-normality of the data, as its requirement of large sample size is also satisfied in the study.

Stage 4: assessing measurement model (CFA) validity

Measurement model validity is assessed according to the criteria defined in the methodology section. First looking at overall model fit and second validating the constructs as following.

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

Model fit: overall we obtained good and satisfied model fit as reported in Table 59.

Table 59: Measurement (CFA) model fit

Parameter	Estimation
Chi-square (CMIN - χ^2)	50.418
Degrees of freedom (df)	19
Probability (*p*) value	0.000
Normed chi square (CMIN/df)	2.654
Goodness of Fit Index (GFI)	0.997
Comparative Fit Index (CFI)	0.994
Root Mean Square Error of Approximation (RMSEA)	0.020

Construct validity: factor loadings and Average Variance Extracted (AVE) is assessed for *convergent validity*. All loadings are >0.7 or higher, as shown in figure 59, and AVE for each construct is >0.5, hence they validated and satisfied the adequate convergence, as shown in Table 60.

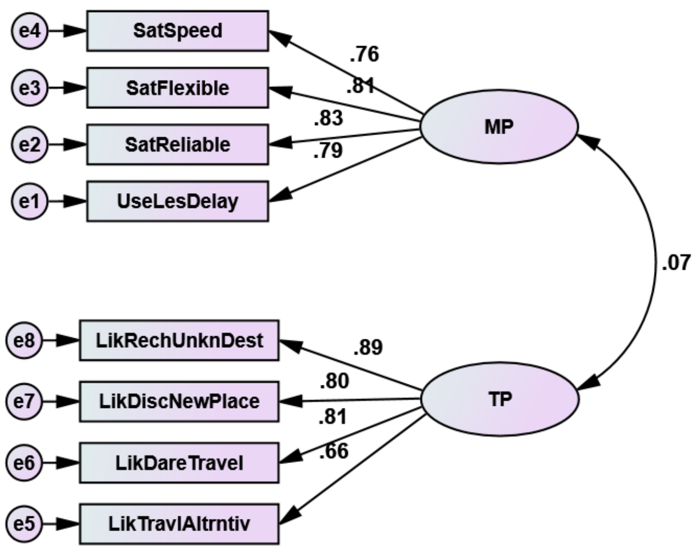


Figure 59: Path diagram of measurement model (CFA)

Table 60: Construct validity of measurement model (CFA)

Variables*	Factor	Loading	AVE	Reliability
UseLesDelay	F1: Mode Pleasure (MP)	0.787	0.63	Cronbach Alpha = 0.873, Construct Reliability = 0.70
SatReliable		0.828		
SatFlexible		0.811		
SatSpeed		0.762		
LikTravlAltrntiv		0.658	0.63	Cronbach Alpha = 0.863,

LikDareTravel	F2: Travel Pleasure (TP)	0.810		Construct Reliability = 0.75
LikDiscNewPlace		0.801		
LikRechUnknDest		0.895		

* *The detailed description of variables is reported in Table A2 in appendix A.*

The Cronbach Alpha reliability and Construct Reliability test values are >0.7, suggesting good reliability. Squared correlation estimate between constructs is 0.005 which is <AVE, hence discriminant validity is also validated. Covariance between the constructs is significant with value 0.120. Correlation between the two constructs is also significant with value of 0.071, as shown in figure 59.

Stage 5: specifying the structural model and assess validity

The model is specified using path diagram shown in figures 60 and 61. Mode Pleasure (MP) and Travel Pleasure (TP) are exogenous constructs in this model. After specifying the relationships, the model is now estimated and assessed using the overall model fit reported in Table 61. The path estimates are shown in figure 60 and 61. Overall, we achieved good and satisfied model fit respecting the threshold values. With larger sample size, increased model complexity and non-normality of data, chi square becomes large and *p* value becomes significant.

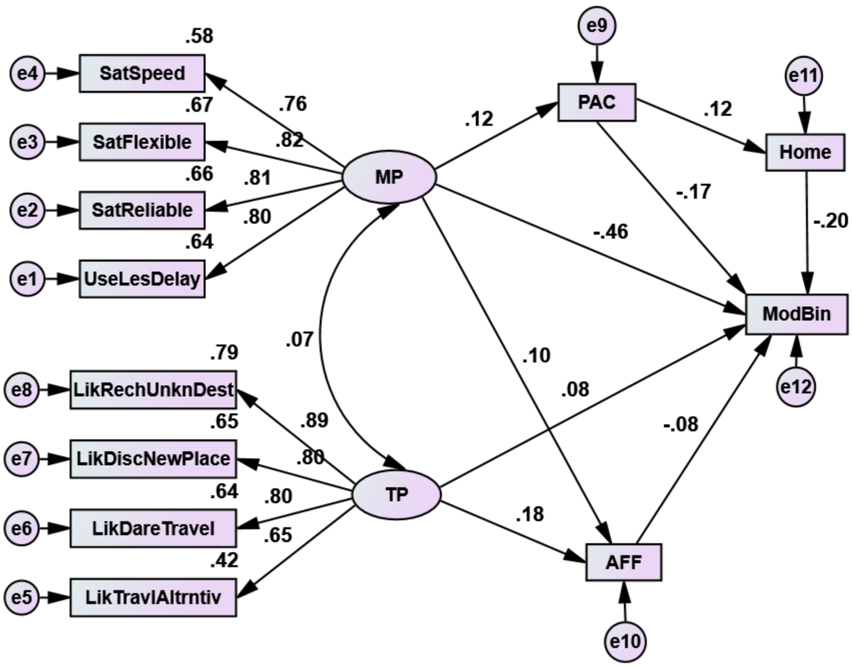


Figure 60: Path diagram with standardized estimates for ModBin

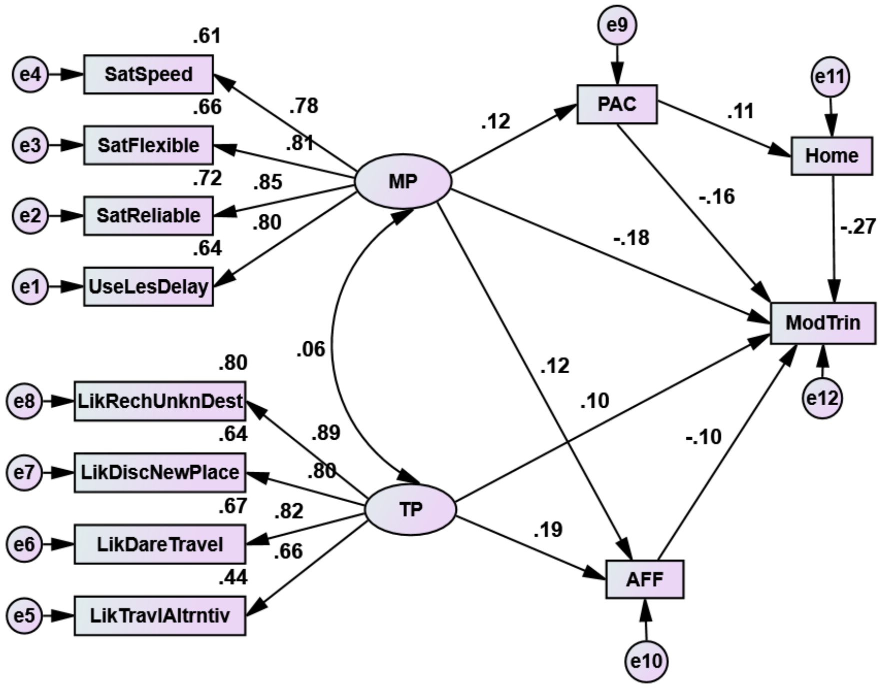


Figure 61: Path diagram with standardized estimates for ModTrin

Table 61: Structural model goodness of fit measures

GOF index	ModBin Estimation	ModTrin Estimation
Chi-square (CMIN - χ^2)	460.743	414.375
Degrees of freedom (df)	48	48
Probability (*p*) value	0.000	0.000
Normed chi square (CMIN/df)	9.599	8.633
Goodness of Fit Index (GFI)	0.981	0.990
Root Mean Square Error of Approximation (RMSEA)	0.047	0.044
90% confidence interval of RMSEA	0.043 to 0.051	0.040 to 0.048
Root Mean squared Residual (RMR)	0.048	0.056
Comparative Fit Index (CFI)	0.977	0.946

Then, the individual parameter estimation of the hypothesized structural relationships is assessed to check if they are significant and meaningful. Table 62 shows the unstandardised structural path estimates for ModBin, and Table 63 shows the same for ModTrin. All proposed hypotheses are significant. The level of significance is based on the Critical Ratio of the regression estimate, which is the ratio of each parameter estimate to its standard error. Thus, when Critical Ratio values exceeds 1.96, it indicates 0.05 level of significance, when it exceeds 2.56, it indicates 0.01 level of significance (Hoyle, 1995).

Table 62: Unstandardized path estimates of direct effects for ModBin

Hypotheses	Estimates	Standard Error	Critical Ratio	*p value*
H_1: MP → PAC	0.018	0.002	7.193	***
H_2: MP → ModBin	-0.174	0.006	-28.73	***
H_3: MP → AFF	0.136	0.022	6.26	***
H_4: TP → ModBin	0.028	0.005	5.36	***
H_5: TP → AFF	0.226	0.021	10.87	***
H_6: PAC → ModBin	-0.445	0.036	-12.43	***
H_7: AFF → ModBin	-0.024	0.004	-5.97	***
H_8: Home → ModBin	-0.108	0.007	-14.78	***

*Note: *** is p < 0.01, ** is p < 0.05, and * is p < 0.1.*

Table 63: Unstandardized path estimates of direct effects for ModTrin

Hypotheses	Estimates	Standard Error	Critical Ratio	*p* value
H_1: MP → PAC	0.017	0.002	8.71	***
H_2: MP → ModTrin	-0.096	0.008	-11.43	***
H_3: MP → AFF	0.157	0.021	7.456	***
H_4: TP → ModTrin	0.054	0.008	6.750	***
H_5: TP → AFF	0.240	0.021	11.32	***
H_6: PAC → ModTrin	-0.617	0.024	-25.19	***
H_7: AFF → ModTrin	-0.043	0.006	-6.74	***
H_8: Home → ModTrin	-0.212	0.011	-19.58	***

*Note: *** is p < 0.01, ** is p < 0.05, and * is p < 0.1.*

The results (Table 62 and 63) revealed that all the proposed hypotheses are supported and shows a significant impact on modal choice. The model depicts that the user behaviour when choosing the transport mode is significantly influenced, positively by TP and negatively by MP, PAC, AFF (I like to drive) and residential location (Home), having 0.01 level of significant effects (Critical Ratio >2.56).

Mediation analysis

Mediation analysis was performed to assess the mediating role of PAC, AFF and Home on modal choice with indirect effects. Table 64 and 65 shows, respectively for ModBin and ModTrin, the bootstrap estimates based on 2000 bootstrap resamples and 95% confidence lower and upper bounds for the population values of the specific indirect effects with corresponding significance level of *p* values.

Table 64: Unstandardized path estimates of indirect effects for ModBin

Hypotheses	Estimate	95% confidence interval		*p* value
		Lower bound	Upper bound	
H_9: MP → PAC → ModBin	-0.008	-0.009	-0.006	0.001
H_{10}: MP → AFF → ModBin	-0.003	-0.005	-0.002	0.001
H_{11}: TP → AFF → ModBin	-0.005	-0.008	-0.003	0.001
H_{12}: PAC → Home → ModBin	-0.061	-0.079	-0.044	0.001

The results (Table 64 and 65) revealed that all the proposed hypotheses of indirect effects are supported and show a significant impact on modal choice (ModBin and ModTrin) with mediator. The estimate value of all indirect effects (from H_9 to H_{12}) fall within lower and upper bound with 95% confidence interval with *p* value of 0.001, which is significantly different from zero at the 0.01 level.

Table 65: Unstandardized path estimates of indirect effects for ModTrin

Hypotheses	Estimate	95% confidence interval		*p* value
		Lower bound	Upper bound	
H_9: MP → PAC → ModTrin	-0.010	-0.013	-0.007	0.001
H_{10}: MP → AFF → ModTrin	-0.007	-0.010	-0.004	0.001
H_{11}: TP → AFF → ModTrin	-0.010	-0.015	-0.006	0.001
H_{12}: PAC → Home → ModTrin	-0.116	-0.152	-0.078	0.001

It can be observed that the direct effect of MP, TP, and PAC on modal choice (ModBin, ModTrin), as well as the indirect effects of these variables using mediation, are significant with *p* value of 0.001, which is statistically significant at the 0.01 level. The significance of both indirect and direct effects shows the partial mediation.

Chapter 5

Discussion

In this chapter a critical analysis of the results is proposed. The analysis starts from a discussion on the case study of mobility apps highlighting the issues and weaknesses which lead us to use Travel Surveys (TS) for the purpose of this study. Then, the importance of the findings, similarities, and dissimilarities of the existing literature with the obtained results of market segmentation, assessment of General Ecological Behaviour (GEB) measure using Rasch model and a check of the hypotheses of the methodological approach of mode choice modelling using Structural Equation Model (SEM) is discussed by arguing in terms of policy implications.

Analysing 81 apps, the majority were funded by European programmes and were discontinued after the end of each project, thus stopping the data collection. Furthermore, the biggest difficulty encountered in this review has been the lack of sufficient information on the technical characteristics. As a matter of fact, apps seldom publish exact descriptions of how data cleaning and mode of transport identification are performed. Anomalies in the data need to be cleansed even if individuals have confirmed the data. Likewise, the behaviour of the user of the app is often unknown, i.e., if the users have to turn each respective app on/off, or what information on trips made is available (e.g., lists of trips made over a week). Furthermore, it is not possible to test most part of the apps without participating in a specific test; finally, some of those apps are not available on Google play/Apple store and cannot be tested by users outside the development context.

In the last ten years, a lot of progresses have been done and many applications were developed, broadening the individual purpose of tracking. Arguably, the idea was that a more intensive use of mobile phones and apps could facilitate their use as an “educational tool” to spur modal diversion, making people aware about their ecological footprint. However, even though the improvement of accuracy is increasing, thanks to the combination of multiple methods, representativeness of the collected data remains an unanswered question. In many cases, it is unclear whether the apps are being used often enough: that could prove that many of them have not been tested in real world or to any large extent. All the apps (24 apps selected for SWOT analysis) reported in this review have been tested, as described in the previous sections, but there are very few before and after analyses of the effect of their use, notably about changing travel behaviour towards more sustainable mobility. Furthermore, all these studies involve limited samples, and no one lasted long enough to understand potential long-term effects. Arguably, if the results of such studies would show positive outcomes, then transport authorities might be inspired to adopt similar applications in their territories. Moreover, one of the main issues is that, at present, there is little knowledge about the performance of new data collection methods compared with the traditional ones. Thus, more studies are needed in which data are collected using, in parallel, new and old data collection tools so that the difference can be accurately assessed. Such comparison could shed light about potential synergies as well as interoperability between different methods, supporting the formulation of standards. The reason is that there is so far not any app able to completely replace the TS, providing a reliable and complete picture of the individual travel patterns; instead, a collaborative approach among methods seems the most effective way for data collection, knowing that the challenge is performing a data fusion of very diverse data, often related to different sample sizes.

The understanding of various available data sources and the benchmarking of apps induced to use data from a TS in form of a web survey to properly reach the objectives of the research but including the section on mobility focused on tracking the precise points of origin and destination of the trips, beside a wide set of questions investigating the psycho-social variables that could influence travel behaviour.

Indeed, implementing measures to improve transport systems requires detailed knowledge of potential travellers' behaviour and underlying psychological factors (von Behren *et al.*, 2018). The method of market segmentation was adopted to understand travel behaviour of respondents, notably the mode choice, and to investigate how the users can be attracted towards sustainable modes by identifying the psychological determinants behind their decisions.

The results shows that the mix of modes (trip chain) is the most chosen option for the most important trip, followed by car as a driver, for all the clusters except cluster 2 (Pro-environment active car addicts). Pro-environment active car addicts use car (as a driver) as preferred mode (34.48%), followed by trip chain as second most selected mode (29.45%). The third mode used in all clusters is PT (bus/tram/metro); the fourth mode is walking in cluster 1 (Eco-friendly safe travellers) and 5 (Pro-environment active travellers), followed by bicycle; the opposite applies to clusters 2 (Pro-environment active car addicts), 3 (Eco friendly and safe travel pleasure addicts), 4 (Malcontent time addicts) and 6 (Travel pleasure addicts). The transport mode differentiates only cluster 2 while it cuts across the clusters because there is not a large differences about the mode chosen for the most important trip, confirming the findings of Pronello and Camusso (2011). Pronello and Camusso (2011) also found car as the most used mode among in the Italian city of Alessandria (in Piedmont region). The main factor influencing the choice of car is "mode performance" that includes comfort, safety and cleaning. This finding confirms what found in Pronello and Camusso (2011), stating that car is preferred for the intrinsic pleasure derived from its use, observing in this case a lower disposition towards the use of more sustainable modes.

However, it is very important to improve the quality of Public Transport (PT) such as cleaning, security, comfort, safety, and reliability to attract more users to PT, mainly the Pro-environment active car addicts. One of the factors present in all clusters is "Improvement of onboard service quality", negative in all clusters except cluster 6 (Travel pleasure addicts). This finding shows that the low quality of the onboard service is a main reason for not using PT while infrastructure shortage is the barrier for using soft modes. Therefore, increasing PT frequency and cleaning or creating dedicated bike paths and bus priority lanes to reduce travel time could increase the shares of those modes, as also suggested by Ilahi *et al.,* (2021).

Travel pleasure and mode pleasure are the factors present in all six clusters, which were also reported as two important factors by Pronello and Camusso (2011) in the city of Alessandria. Cluster 1 (Eco friendly safe travellers), 2 (Pro-environment active car addicts), and 5 (Pro-environment active travellers) show negative values for travel pleasure, showing that these users mainly travel for the sake of need and do not find any pleasure while travelling. On the contrary, cluster 3 (Eco friendly and safe travel pleasure addicts), 4 (Malcontent time addicts), and 6 (travel pleasure addicts) shows positive values for this factor. The highest positive value is reported by cluster 6 (travel pleasure addicts), showing that travelling for pleasure (adventurous journeys, trip to unknown destinations, visit new places with different travel alternatives) can be one of the determinant factors when selecting the mode for the most important trip; this finding will be further discussed when commenting the SEM model.

Mode pleasure is found positive in cluster 1 (Eco friendly safe travellers) and 5 (Pro-environment active travellers) while negative in cluster 2 (*Pro-environment active car addicts*), 3 (Eco friendly and safe travel pleasure addicts), 4 (Malcontent time addicts), and 6 (Travel pleasure addicts). These findings show that, in cluster 1 and 5, the positive value is due to the perception of the used mode as faster, comfortable, having less delay and feel free while travelling. Instead, for cluster 2, 3, 4, and 6 such attributes are not relevant. The results allow to state that even if PT is chosen for the most important trip, this does not imply that the users are satisfied with the quality of the service that needs to be improved, and this should be the focus of policy makers. Mode pleasure factor is also considered in investigating the main determinants of mode choice as it emerged as important factor among all clusters, worthy to be considered in SEM.

Pro-environment activism is also present in all six clusters with positive values in clusters 1 (Eco friendly safe travellers), 2 (Car addicts), and 5 (Pro-environment active travellers) while negative values refer to clusters 3, 4 and 6. The presence of this factor in all clusters shows its importance to be tested in mode choice model using SEM to assess if it really has an impact on mode choice or vice versa. For that first a single GEB measure of a pro-environmental attitude is estimated using Rasch model.

Analysing the socio-demographic variables, gender, presence of handicaps and income are insignificant to differentiate the clusters while age, occupation, household size, number of children, number of cars and education were found to be significant. By interpreting clusters using mobility patterns information, travel time and frequency of the most important trip are insignificant to distinguish the clusters while mode, distance, and purpose show significant differences among clusters. Similarly, Pronello and Camusso (2011) found that gender and income are irrelevant indicators in respect to clusters' difference, while age and education showed differences among clusters. According to Anable, (2005), "attitudes and opinions seem largely cut across demographic characteristics" as variables traditionally considered significant (income and gender) are not determinant of attitudes, and the other variables listed above play a role in differentiating some clusters, but not transversal to all.

Haustein (2021) found out that for car-owning households, access to a private parking space decreased the likelihood of abolishing a car and increased the likelihood of getting another car. Therefore, the potential for reducing car ownership is linked to the place of residence and in particular to the availability of a private parking space, which is probably partly a result of residential self-selection (De Vos and Witlox, 2016; van Wee *et al.*, 2019). Municipalities that aim for a reduction of the number of cars in a city, could either increase the price of private parking spaces or reduce the number of these. To motivate people who already own a parking place to abandon the car, municipalities could offer a reduced price/packages for PT/soft modes for renting out the parking space. To be successful and publicly accepted, parking management strategies should be accompanied by measures to reduce car dependence (Mattioli and Colleoni, 2016). As the city-specific results of Jochem *et al.*, (2020) show, the availability of sharing systems and city characteristics that facilitate car-free living make car ownership reduction more likely to obtain.

The highest number of cars are two in each cluster, followed by 1 and 3. Transport policies may reduce the number of owned cars by creating a quota for each household for owning a private vehicle; another option is making difficult for people to afford a car or controlling the number of cars on the road, as suggested by Ilahi *et al.,* (2021). Having a strong car-commuting habit decreases the probability of mode shift to a sustainable mode. For example, stimulating

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

e-cycling may be most effective if targeted at specific groups who are not currently engaged in active modes (de Kruijf *et al.*, 2018). Indeed, within short and medium distances, cycling habits could be crucial to reducing car use. A lower level of satisfaction, on the other hand, was expressed in terms of perceived safety, which remains a barrier especially in mixed traffic environments for cycle and walk users.

Therefore, safety and security are also required to ensure that people accept the development of sustainable modes of transport. Comfort, cost, accessibility, reliability and duration seemed to be key attributes in choosing a travel mode as also reported by De Angelis *et al.*, (2021). Examining whether the relatively low bicycle attitudes of people are caused by low perceived quality of bicycle parking facilities, bike paths and priorities at crossings may be an interesting avenue for further research. Understanding and accurately predicting travel behaviour can help us developing appropriate and successful policies for the future.

The present results can help in understanding the tendency of the new generation to prefer the use of greener modes. Other authors support the possibility of a new generation more inclined to express inherently different attitudes and pro-environmental values, which manifests in more sustainable-friendly lifestyle choices over time (Kuhnimhof *et al.*, 2012; Krueger *et al.*, 2020), which is also evident in the present research by finding students those in favour of sustainable modes.

Overall, after trip chain, car is largely used by each cluster. The attachment to car has been reported in many travel behaviour segmentation studies in other regions and countries - Jakarta Greater area, Indonesia (Ilahi *et al.*, 2020), Cagliari (Italy) (Sottile *et al.*, 2020), Alessandria (Italy) Pronello and Camusso (2011), Berlin (Germany) and San Francisco (U.S.) (Magdolen *et al.*, 2021).

Beecroft and Pangbourne (2015) suggest that PT operators generally do not know the characteristics of their customers, showing a lack of a targeted approach to information provision. Particularly in areas characterised by infrequent use of PT or where PT services are perceived as unreliable, provision of targeted, multi-platform information will be necessary to meet the needs of consumers. The obtained segmentation approach can help to target different groups with different needs. Moreover, it allows us to identify important psychological factors present in all clusters and then assess if they impact the mode choice using SEM.

The emerging transport solutions are being conceptualised around smartphone-based technological possibilities, therefore mobile app use (and implicitly smartphone use/ownership) for sourcing pre-travel information will likely become a significant tool to provide information together with data collection. For design processes, the implementation, and the assessment of customer-oriented transport solutions (e.g., emerging technologies such as car sharing),

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

travellers' requirements and their likely acceptance of these solutions needs to be known. The results suggest that emotions towards travelling are the most important discriminating factor amongst groups by identifying the variables forming the factors travel pleasure and mode pleasure.

Beside the variables related to emotions, that influence mode choice, other variables can play a role in user decision making. Among these variables, pro-environment activism is observed in all clusters as above-mentioned, showing a concern and positive attitudes towards the environment of the respondents. Moreover, this factor showed positive values on 3 clusters (even cluster 5 is showing highest positive value on this factor and labelled as Por-environment activism) and low negative values (<1) on other 3 clusters. The second cluster (Pro-environment active car addicts), being the highest car users' group, shows a second highest positive value on pro-environment activism factor. The similar behaviour is also reported by Pronello and Camusso (2011), where the paying ecologists (cluster 2) showed a pro-environment attitude through both a high environmental concern and willingness to reduce air and noise, but their behaviour was strongly geared to car use. Another factor, aware consumerism, presenting the importance of general ecological behaviour, is also observed in 5 clusters. These findings show the importance of pro-environment behaviour among the respondents and the intention of respect towards the environment sustainability. Kaiser *et al.*, (1999) reported that GEB predicted by environmental attitude extended by responsibility feeling. To this end, the analysis of psychometric properties of the GEB-26 questionnaire was made using Rasch model to validate and compare the scale with those used in previous research and to understand if GEB affects travel behaviour and, notably, mode choice. To this end Rating Scale Model (RSM) for polytomous data and Dichotomous Rasch Model (DRM) for dichotomous data analysis were used.

From DRM, model fit indicators suggest that the scale contains one particularly misfitting item, AE6_REVC (In winter, I leave the windows wide open for long periods of time to let in fresh air), with only slightly high outfit MNSQ (MeaN-SQuare) value (0.05), that is not threatening the validity of the scale, so that it is not suggested to delete it. The fact that item AE6_REVC was the only item with poor fit warrants further investigations as it offers potential insights into the structure of GEB. It is well known that negatively coded items, especially if there are only a few items and located at the end of the questionnaire, may be confusing for the respondents (Schmitt and Stuits, 1985). However, it is also possible that the item did not confuse the respondents, but not behaving ecologically may actually not be seen as an inverse conceptualization of ecological behaviour, but rather a (partly) different construct in its own right. Moreover, local independence, reliability, and separation indexes assumptions were confirmed with good Rasch measures validity.

We have obtained perfect level of reliability of 1, separation of 34.22 for items, and sufficient level of person separation and reliability. Although, person (test) reliability mainly depends on the variance of sample ability and on the number of categories per item. If we have more categories, then we might achieve higher person reliability. So, in this study we first validated the questionnaire by converting polytomous scale to dichotomous scale to compare the results from the previous studies (GEB-40 and GEB-51) and to verify how the selected test performs with larger sample size as also person separation and reliability are sample dependent. The most important aspect is to validate the questionnaire items that have been selected, to revise them, if necessary, for designing the next survey.

Observing DIF analysis, item CE9 (Sometimes, I offer goods I don't use anymore) is more difficult for females and V1 (I often talk with friends about problems related to the environment) is more difficult for males. This shows the cultural, societal, and attitudinal difference as determinant factors to engage in a certain behaviour. The Differential Item Functioning (DIF) size for these two items was slight to moderate, hence we are not considering excluding these items for the next questionnaire. This aspect is also part of Campbell's paradigm (Campbell, 1963) of attitude, which states that some behaviour may be more difficult in certain contexts than in others. This applies also to the residential location (R5- I sort glass wastes for recycling) and the related land use; the results show how a well shared habit of sorting glass for recycling is easier for people living in rural areas due to the different organisation of collection points of glass located at single homes, differently from the scattered patterns of collection points in the cities. The way of living in rural areas also makes people less used to drive in congested urban traffic (T1- Usually, I do not drive my automobile in the city), reason why urban citizens are more used and, thus, inclined to use car to travel inside the cities; differently, those living outside prefer travelling to the city by train or suburban bus to avoid traffic and parking problems. So, what stated by Arnold *et al.,* (2018) holds true, showing the importance of surroundings and contextual elements in the daily routine. The DIF size for R5 is moderate to large, which requires some attention to consider in further analysis; instead, item T1 has slight to moderate DIF, not necessarily indicated for deletion.

The second aspect that was investigated, concerning the validity of GEB in influencing the modal choice, is key in the current debate on climate change that calls for major changes in people's daily lifestyles (Otto *et al.*, 2014). A frequent question arising is: do what people report to protect the environment converge with their environmental impact? If, theoretically speaking, this could hold true, under an empirical observation our results show the opposite. We observed that out of selected sample of 4212 respondents, for the most important trip (that with longest distance), 1368 (32.48%) use trip chain, followed by 1156 (27.45%) using car, 729 (17.31%) using PT, 330 (7.83%) walking, and 310 (7.36%) cycling. Looking into trip chain, car as driver is used by the highest percentage of respondents, 1333 (31.65%), followed by 1096 people (26.02%) using PT, 667 travelling by train, 401 walking, and 322 cycling. This finding shows how people do not do what they intent/say to do. Hence, behavioural measures of ecological lifestyles may reflect actual environmental impact in some other contexts such as in electricity consumption, as reported by Arnold *et al.*, (2018), but they do not apply in transport sector by looking at results and as shown in previous studies (Pronello and Camusso, 2011). This is referred as attitude-behaviour gap (Moraes *et al.*, 2012) or behaviour intention gap (Sheeran, 2002), demonstrating the volatility of the concepts of attitude or intention (Pronello and Gaborieau, 2018). Ajzen and Cote, (2008) also reported that global attitudes fail to predict specific behaviours because they are too general to be relevant for a specific performance, even if they are strong. The results obtained in this research also contradict what found in Gaborieau and Pronello (2021), where the high GEB score was correspondent to those users who use soft modes (walking or bike) for their most frequent trip, followed by PT (regional train, bus, tram or metro) and, then, private motorised vehicles (car or motorbike). One reason of this contradiction might be that the trip chain was excluded by Gaborieau and Pronello (2021) and the sample was smaller (108 users). This discrepancy will be further investigated in the continuation of the research.

It should also be recalled that the sample sizes in previous studies - in Italian context (GEB-40 and GEB-51), in Swedish and Swiss context (Kaiser and Biel, 2000), and in Californian context (Kaiser and Wilson, 2000) - were comparatively too small, although still within acceptable boundaries, according to Linacre (1994). Nevertheless, replication in a larger sample is highly desirable as suggested in current research. Regarding the generalizability of the results, it must be noted that the composition of samples of previous studies was formed thanks to a stratified sampling plan. Thus, different results may be observed when the sample follows the snowball sampling approach and the participants are, as in this case, younger and/or with a bit lower educational level. Finally, it needs to be emphasized that even excellent internal validity is no assurance that a given scale will also exert good external validity.

Analysing the results from polytomous RSM, after excluding the unexpected responses and assessing the model fit as reported in methodology, we find that the items are within acceptable ranges of MNSQ, then we are not investigated ZSTD (Z-STanDardized). The extreme standardized statistics reflect the huge sample size. When sample sizes become huge, then all misfit becomes statistically significant. Here the sample sizes are in the thousands. Even the substantively trivial mean-square within range 0.5-1.5 is reported as statistically significant. But the mean-squares are not excessive, so these data support measurement. The size of the departure in the data from the Rasch model is not overwhelming. It is a small departure, but we are certain that it did not happen due to the randomness predicted by the Rasch model. We observed the Model Standard Error is small and near to zero which indicates the high precision in measurement as we have low standard error as 0.01, 0.02, and 0.03.

The observed correlations differ somewhat from their prediction, but the Infit and Outfit mean-squares tell us this is not a serious cause of concern, except the items with >1.5 MNSQ values. Also, the point-measure correlations are all nicely positive. So, the scoring of our items is oriented with our new latent trait (Linacre, 2011) except 2 items CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime) and AE6_revc (In winter, I leave the windows wide open for long periods of time to let in fresh air). Both items having average difficulty measures, 0.14, -0.12, the reason of this unmatching correlation is the average ability does not ascend with category score, which is one of the assumptions of guidelines of Linacre Rating scale Rasch analysis. Maximum respondents among the answered users, agreed the behaviour of the items. So, we decided to keep both items. We observed that the response to the categories increases until 5 for variable AE6_revc then decreases while for variable CS4, after category 3 it decreases, which was expected to increase.

Despite of satisfying the criteria of holding unidimensionality in Principal Component Analysis of Residuals (PCAR), 2 items V4 (I sometimes contribute financially to environmental organizations) and V2 (I am a member of an environmental organization) indicated the reason of possible subdimension other than the latent trait GEB. Investigating in depth, items V4(A) and V2(B) belongs the category of "environment activism". There might be something to find this difference intriguing, but for us environment activism is slightly different, but the difference (eigenvalue 2.4 out of 26) is far too small to bother with analyzing the environment activism measure for each person. In fact, the persons who involved more in environment activities tend to behave more ecologically. The numerical values are not as important as the substance of the items. If the content of the items is indistinguishable, then this contrast may only be the randomness predicted by the Rasch model. In conventional factor analysis, loadings need to be greater than ±0.40 to be considered important, but in our analysis the clustering of the items is more important. It is clear that "environment activism" is somewhat different from all the other items, and these items are more difficult than other items for respondents (Linacre, 2012), observing the write map. The reason of finding these two items most difficult might be that people prefer to behave ecologically in daily life habits but to contribute financially to organizations (they may not be willing to contribute financially) and to be a member of environmental organization is difficult for them and it is more a professional responsibility.

Moreover, we obtained person measure reliability of 0.75 and person separation of 1.75 (~2) which shows good level of person ability range (high and low performers) and higher compared to DRM. This is evident here that more categories are expected to give better and higher person reliability and separation. We have obtained perfect level of item reliability of 1 and huge item separation of 43.39, which is showing the good validity of GEB-26 questionnaire. These results indicate that the estimated measures are highly reliable. The item reliability is maximum achieved by both DRM and RSM, but the item separation is higher in RSM. With this large person sample, the item difficulties are estimated exceedingly precisely and validating the GEB construct validity by representing excellent level of separation.

Observing the DIF analysis, we do not find any items causing moderate to large DIF by gender and residential location. In contrast to this, the age subgroups classification is not beneficial to get non uniform DIF. The large number of items (12) showing DIF is not good to consider for good measurement test study. This is to say that different age groups behave differently for GEB having different level of agreeability for different items based on their habits and perceptions.

Construct validity is evaluated by write map. In contrast to two (V4 - I sometimes contribute financially to environmental organizations and V2 - I am a member of an environmental organization) difficult items, three items were identified as the easiest – R5 (I separate the glass from other waste to recycle it), followed by RR1(I reuse the shopping bag for the next few times), and R1_revc (Throw out of stock batteries in undifferentiated) – which were not contributing to the GEB measurement but still fall within the user's ability range. The reason might be that the habits and norms corresponding to these three easy items are normal and part of daily life of inhabitants. Nevertheless, R5 requires some attention to consider in further analysis, as was also found causing moderate to large DIF by residential location, redundant and one of the easiest items from DRM.

Looking at Item Characteristic Curve (ICC) plots, we observe overlapping of items V1(I often talk to my friends about environmental problems) and V3 (It happens that you point out to someone to behave non-ecologically), producing the same information. In fact, the two variables were found redundant in write map by measuring similar portions of the trait. Therefore, one of these items can be excluded with a little measurement precision lost. Comparing the DRM and RSM analysis, we suggest excluding item V1, targeting few personas compared to V3 from write map analysis and causing slight to moderate DIF by gender from DRM.

In addition to the assessment of general requirement analysis of Rasch model, Linacre's six rating scale guidelines were evaluated together with the assessment of empirical item category measures for polytomous data. Two items CS4 (If I were an employer, I would not hesitate to hire a person previously convicted of crime) and AE6_revc (In winter, I leave the windows wide open for long periods of time to let in fresh air) did not agree with the other items in defining the latent trait. These two items suggest some attention in future research analysis and survey design, changing the wording of the questions related to these items, even though item AE6_revc was found only misfitting item in DRM analysis.

The current study's data set suited the guidelines with only two exceptions. In guideline 5, the orderly step calibration observed until category 5 but not category 6. As suggested by Linacre (2002), it can be seen that step-disordering may result when a higher category is relatively rarely observed, or a lower category is chosen by respondents with higher measures. Hence, as we observed in results, lower category chosen with higher number of respondents may cause the last step disordering. Furthermore, evaluating the category probability plot, the absence of independent hills for categories 1, 4 and 5 suggest that if additional data are collected, then an analyst should monitor the use of categories 1, 4 and 5. If the pattern persists, then the category might be removed, or the wording changed. Moreover, a second analysis should then be conducted to evaluate data quality. Measurement is optimized when each rating scale category is most probable at some point in the plot, immediately above, as suggested by Boone *et al.*, (2016).

In guideline 7, none of the gaps between categories was 1.0. Although this criterion is not necessary for evaluating the rating scale measurement, it is only helpful for making inference for next sample as suggested by Linacre (2002). The possible solution to meet this criterion is to combine the categories or edit the data but may not be attainable.[59] However, the necessary guidelines to meet and evaluate the measure stability and accuracy (fit) of the scale is 1 to 4: the remaining are helpful but not essential, as reported by Linacre (2002). In summary, the guidelines proposed by Linacre for a Rasch analysis of rating scale data were generally met with a few exceptions. Linacre (2002) mentioned that the rating scale analysis rules are only guidelines; not all apply and not all are good under all circumstances. We need to keep a good eye on what is happening at the item level. The more we collapse categories, the more statistical and diagnostic information we lose.[59]

All the identified psycho-social factors in market segmentation and GEB Rasch person measures, as the pro-environmental attitude, have been considered to model the mode choice of the respondents using SEM to support the reorganisation of the existing transport, to better suit the users' needs, and to forecast the future needs of users thanks to the insight into preferences and requirements of commuters (Sekhar, 2014).

Before identifying the statistically validated factors behind the decision making for mode choice of users, it is important to understand which kinds of mode they use or prefer in their most important trip. We found that the Trip chain (multimodal) was used by the highest number of respondents (32.49%) among the collected sample which shows a general environmental friendly travel behaviour, as multimodal transport is widely believed to be more sustainable and environmental friendly, and to enable transport equity (Krygsman *et al.*, 2004) for wider sections of society (Minal *et al.*, 2021). Therefore, improving the multimodal transport systems focused more on PT and active modes by improving the access, egress, waiting and transfer time, could be helpful in maintaining for long run a sustainable habit.

Going in deeper analysis of mode by residential location (urban, suburban, and rural), we found that PT is used by maximum respondents (773, 38.38%), followed by car (479, 23.78%), walking (314, 15.59%) and cycling (275, 13.65%) in urban locations. In suburban context, car is used by the majority (327, 47.94%), followed by PT (154, 22.65%), and train (80, 11.76% users). People living in rural areas use mostly car (525, 41.63%), followed by train (477, 37.83% users), and suburban bus (118, 9.36% users). This analysis highlights the importance of residential location in mode choice and reveals significant negative impact on modal choice, validating our hypothesis. Looking into more detail the ModBin (binomial mode choice), PT and soft modes are more used by respondents living in urban and rural areas compared to private mode. In ModTrin (trinomial mode choice), PT is used by large part of respondents, followed by soft and private modes in urban locations. For suburban population, car is used more, followed by PT and soft modes. For rural population, PT is the most used, followed by private and soft modes. We have seen that PT is preferred more in urban and rural areas while in suburban areas car is used more. Soft modes are preferred only in urban location, while few people use them in suburban and rural areas; car is preferred mainly in suburban areas. This finding supports our selection of residential location as an important variable in predicting travel behaviour, as also reported by others researchers (Wee *et al.*, 2003; Frank *et al.*, 2007; Pinjari *et al.*, 2007). The negative effect of residential location on modal choice shows that as the trip distance increases (suburban or rural areas) the dependency on car is increases and tendency to use PT/soft modes decreases. The higher negative significant impact of residential location (Home) on ModTrin is because the soft modes are used by few persons. Therefore, as the distance increases (going into suburban and rural areas) the tendency to use PT/soft modes decreases.

Car as a first preferred mode is frequently reported in literature as dominant mode in many market segmentations (Pronello and Camusso, 2011; Ilahi *et al.*, 2020; Sottile *et al.*, 2020) and mode choice studies (Devika *et al.*, 2020). The car is preferred mainly due to comfort, safety, less aggression, cleaning, and flexibility and, sometimes, as a status symbol as pointed out by Steg *et al.*, (2005) that showed as the car in modern society represents a myth, symbols and strong affective constructs. Therefore, we used AFF (I like to drive) as one of the determinants of modal choice and found that it has a significant negative impact on modal choice in both binomial and trinomial mode choice modelling. The higher negative effect observed for

ModTrin (PT, private, and soft) compared to ModBin (PT/soft and private) shows that, when increasing the availability of sustainable modes, a decrease in the affect towards car use is recorded.

Two important factors Mode Pleasure (MP) and Travel Pleasure (TP) emerged as the most important factors as determinant behind the decision making of users among other variables resulting from Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) (also in market segmentation). MP have a significant negative effect on modal choice while TP having significant positive influence. The negative effect of MP shows that the main reason of preferring unsustainable mode (car) is the dissatisfaction with the service quality of PT with a higher negative impact for ModBin, compared to ModTrin. As the increase of quality of PT or soft mode infrastructures decrease the tendency to use car, the opposite holds true (the decrease in infrastructures' quality increases the tendency to use more the car).

Nevertheless, the positive significant impact of MP on Perceived Accessibility (PAC) reveals that the pleasure of mode depends also on the availability of the alternative modes. The higher availability of comfortable modes makes users feeling more pleasure while travelling. This helps us to understand that the car restriction policies (higher parking cost, higher fuel cost, increase car cost) may imply to make car less available for them and shift them to alternative available greener modes.

In contrast to this, the negative significant impact of PAC on modal choice reveals that even if the alternative modes to car (PT/bike/bike sharing/walking) are available for user most important trip, the tendency to use them would decrease. As we have seen, as the attachment to car is high despite the availability of other modes, users would not prefer to use them and continue to use the car. This holds even more true in case of unavailability of alternative modes, mainly for suburban or rural areas. Therefore, the less other modes are available, the greater is the tendency to use car.

Our hypotheses of significant impact of MP and TP on AFF are also supported for both ModBin and ModTrin with positive impact. This shows that the mode and travel pleasure positively affect the attitude towards car use as said above. Moreover, users show an attitude towards travel for pleasure – like to reach unknown destinations, dare to travel, discover new places, and try alternatives for travelling. MP and TP are determinant for the mode choice, allowing to state that, even if the attraction towards car is stronger, the users can be still diverted towards more sustainable modes if the policy makers and transport planners works on more user-oriented services and infrastructures. The third most chosen mode is PT, followed by walking and bike, showing the positive attitude of the sample towards sustainable modes. Although it is difficult to change the already established infrastructures, the service (flexibility, reliability, less delay, frequency) and onboard quality (cleaning, comfort, safety, security) can be improved. Instead, main concern refers to people's attitudes and perceptions toward active transport, as also reported by Gatersleben and Appleton (2007). Investments in infrastructures may not necessarily meet the expectations if cycling and walking habits do not become stronger. Currently, the use of the bicycle remains restricted to a small minority of people with positive attitudes and perceptions as bicycle and walking are less used. Awareness campaigns can help, but changes in the habits of the population can take longer time as also mentioned by other researchers (Maia *et al.*, 2020).

In addition, the analysis of the mediation effect of PAC, AFF and Home on ModBin and ModTrin revealed a significant negative impact with partial mediation. The partial mediation is comparatively smaller to direct effects, showing that the direct effect is stronger; thus, mediation is not very beneficial but significant. The mediation of PAC by Home is evident from the analysis, where the availability of travel modes depends on the residential location, but the partial mediation reveals that the mode choice is still based on the preference of users and not completely depending on the availability of alternatives. The mediation of MP and TP by AFF is also partial, showing that even though the affect towards car is a strong attitude, the mode and travel pleasure do not completely imply the car choice, but other alternatives can also be used. The mediation effect of MP by PAC is found significant with negative effect. This shows that even the higher availability of alternative modes to car makes users feeling more pleasure while travelling, but the availability of alternative modes does not guarantee to use them.

We have observed in the iterative process of applying EFA, CFA and SEM that the mode choice is not influenced by Personal Norms-PN (how I think I should behave), Subjective Norms-SN (how others think I should behave), general ecological and pro-environmental behaviour. Devika *et al.*, (2020), testing Theory of Planned Behaviour (TPB) in determining mode choice behaviour found that SN and Perceived Behavioral Control (PBC) were not significant in determining the intention to use public transport. Similarly, Pronello and Camusso, (2011) also showed that the moral norms have no strong bearing on the respondents. The outcome of GEB Rasch person measures as a pro-environment attitude was used to assess its impact on mode choice, but it was not found statistically significant. In addition, the variables used to measure the GEB Rasch measures were also individually used to test in SEM the mode choice, but not any influence was detected. Because of insignificant impact of these variables on mode choice we did not use the existing behavioural theories. Moreover, certain amount of criticism has been raised against attitude-based theories, partly because it is difficult to know whether attitudes control mode choice or vice versa. Another shortcoming is that attitude-based theories are not easy to use to predict what happens when the standard of the service, for example travelling time, changes. This is evident from the research work of Gaborieau (2016), where the well-developed theories were tested but they did not perform well to forecast mode choice.

Chapter 6

Conclusions

This chapter concludes the research work, starting with the case study of mobility apps followed by data analysis for understanding travel behaviour by market segmentation, assessing General Ecological Behaviour (GEB) and mode choice modelling.

Concerning the case study of mobility apps, a great deal of effort is required to use apps for Travel Surveys (TS) purposes, not only because of privacy-related issues, but also due to technical methodological concerns that affect the design of the study, and the degree to which the results have external validity. First, smartphone measurement software must be developed and tested. However, ultimately, the careful and balanced approach and the reputation of the organizations involved could be enough to persuade people to participate in these studies. On the positive side, the results are rewarding. Using a mixed method approach, perception-related data can be enriched with measurements of people's actual behaviour. The volume of data available for detailed analysis is impressive and will allow to write extensively on several topics. The data allows to make different cross sections on very detailed levels regarding time as well as location. The quality and quantity of the data is impressive and require a combination of business intelligence tools and traditional statistical analysis but mainly focusing to spatial analysis.

Researchers must be aware that there are no simple solutions and careful rules, and practices must be defined to guarantee people's privacy and at the same time gather reliable information. In the next five years, this type of mixed method research will evolve further and generate new theories and refute existing ones. The main concerns have to do with privacy, representativeness, and data volumes, which require new research questions, hypotheses, and concepts, as well as business intelligence and new algorithms. The use of advanced software to collect data on actual user behaviour will make the domain of mobile media and communication even more interesting and relevant, because of the ubiquitous and pervasive character of mobile and personalized communication (Bouwman *et al.*, 2013).

Based on the findings of this review, recommendations for future research are to:

- explore how accurate the applications are for travel data collection as regards to the different typologies of smartphones, mainly focusing on TS;
- provide guidelines for selecting which are the most appropriate smartphones for the different applications;
- increase the accuracy, at least of mode detection and trip purpose that are the most important features, besides tracking the location, for supporting TS and planning purposes;
- improve the user experience for both facilitating the use of the apps and making them more attractive and useful in the daily mobility;
- better clarify the purpose of the apps to distinguish between research and market apps and the related vision.

The above considerations are the basis of development of the multilanguage application Mobilité Dynamique/Mobilità Dinamica/MyMoby, developed by the research group of the authors. A first android version was released in 2016, followed in 2018 by the iOS version. The app is now "off" because a new release is underway, containing strong improvements as regards the mode detection that has reached an average value of 97% (100% for bike detection). The first version of the app, (downloaded so far by about 1,200 users) was tested within the living labs established in the Oise department, in France, following the vision to allow people to actively participate to transport planning processes. A subtle mix of pedagogy, necessary to create the awareness of current problems, was used to bet on collective intelligence in the days of artificial intelligence. Within this framework, the development of the app was intended as one of the used tools necessary for individuals to transform personal knowledge and experiences into redistributable commons at different geographic and social level. Indeed, the mobile application allows citizens to contribute and inspect community data while a set of back-end services continuously process, store, and distribute provided information. Among these services there are a mobility oriented social network and an interactive visualisation engine aiming at investigating the meaning of collected data and the impact of current mobility behaviours in terms of greenhouse gas emissions, direct and indirect costs (work in progress), perceived quality of service (only in the Myanmar version called MyMoby). Finally, the app aims to become a support tool for decision makers helping to assess and optimize existing services and to better tailor them to the actual users' needs thanks to tailored data sets. All those services when the implementation will be finished, will make the app fulfilling all the three purposes – Travel Data Collection and Analysis (TDCA), Travel Surveys (TS) and Promote Sustainable Mobility (PSM).

The infancy stage of the apps for TS purpose has induced to adopt the mixed method to collect data and use the data of a survey administered through a web questionnaire (by the research group), including some features typical of the apps that is the geo-localisation. The respondents were asked to point on the map the origin and destinations of their trips, allowing to have data like Global Positioning System (GPS) based data of the apps. In addition, such questionnaire was designed to collect several variables related to attitudes, preferences, and habits to better investigate the cognitive mechanisms influencing the travel behaviour. This also allowed to segment the market and define traveller profiles useful to guide an effective reorganisation of the transport systems to better satisfy the user needs.

Six clusters (group of user profiles) - Eco friendly safe travellers (1), Pro-environment active car addicts (2), Eco friendly and safe travel pleasure addicts (3), Malcontent time addicts (4), Pro-environment active travellers (5), and Travel pleasure addicts (6) were defined. Travel pleasure and mode pleasure are the important factors present in all six clusters showing main determinant factors behind the mode choice in the study area that have been also statistically validated in SEM modelling. In contrast, the Pro-environment activism present in all the clusters did not influence the mode choice; despite trip chain was recorded as the most used mode, car is preferred by most of the population. The main reasons of using more the car and less the PT are related to the attributes of transport systems as cleaning, security, comfort, safety, flexibility, and reliability; the factor "Improvement of onboard service quality" was present in all the clusters and negative in five cluster. These findings suggest that the main barriers in using less the PT is the lower onboard service quality and in using soft modes is the infrastructure inadequacy. Therefore, increasing PT frequency, cleaning or creating a bike paths and bus priority lanes to reduce travel time, could increase the shares of those modes, as also suggested by Ilahi *et al.,* (2021).

Discussing the challenges for developing sustainable transport policies tailored to the six groups: cluster 1 is the most sustainable; cluster 2 is the least sustainable; cluster 3 is the third least sustainable; cluster 4 is the second least sustainable; cluster 5 is the second most sustainable; and cluster 6 is the third most sustainable. This identification of psychographic profiles can help decision makers to plan a more sustainable mobility, tested on the population and on its specific living context. Policy makers should focus more on the least sustainable groups to attract them towards more sustainable modes; for example, stimulating e-cycling may be most effective if targeted at specific groups who are not currently engaging in active mobility.

Analysing the socio-demographic variables, gender, presence of handicaps and income cut across the clusters while age, occupation, household size, number of children, number of cars and education were found to be significant to distinguish the clusters. By interpreting clusters using mobility patterns information, travel time, and frequency of most imp trip are insignificant while mode, distance, and purpose show significant differences among clusters.

The market segmentation allows to suggest the following practical policy implications:

- to improve the quality of Public Transport (PT) such as frequency, cleaning, security, comfort, safety, and reliability to attract more users to use PT, mainly pro-environment active car addicts, or creating bike paths and bus priority lanes to reduce travel time could increase the shares of those modes;
- to involve the young generation (mainly students) in campaigns and events to promote sustainable mobility. Gaming (such as marathon, bike race) can also be included in sustainable policy making by giving incentives to engage people to maintain sustainable habits with specific target to students. Cooperation between universities and public transport companies in organizing such kind of events could be beneficial;
- strategies related to the possibility of providing internet services to use available time for other activities such as work, study, or leisure activities or to obtain more real-time information about the state of public transport service by reducing scheduling costs;
- providing the availability of other sharing systems and support city characteristics that facilitate car-free living to reduce car ownership;
- increase the price of private parking spaces or reduce their number. To motivate people who already own a parking place to abandon the car, municipalities could offer a reduced price/packages for PT/soft modes for renting out the parking space. To be successful and publicly accepted, parking management strategies should be accompanied by measures to reduce car dependence;
- policies may reduce the number of cars such as by creating a quota for each household for owning a private vehicle, by making difficult for people to afford a car and controlling the number of cars in the roads.

After having identified the psychosocial profiles of the studied population, the attitude towards a pro-environment behaviour has been studied using Rasch model. To this end, variables characterising the GEB have been defined. Overall GEB-26 shows good psychometric properties when using Dichotomous Rasch Model (DRM) to validate the scale. Results suggest that using the dichotomous Rasch model, the proposed questionnaire is able to effectively measure pro-environment behaviour of travellers. Unidimensionality, perfect level of item reliability of 1, very high item separation of 34.22, absence of larger Differential Item Functioning (DIF), local independence and no overlap among Item Characteristic Curves (ICCs) are all good indicators of a valid model.

One of the limitations of these studies assessing ecological and environmental behaviour is that people may not be aware about their environmental impacts and/or the damage they cause to the environment. As reported by Hamidi and Zhao (2020), the individuals who have greater environmental awareness are more likely to travel by PT or cycling if the physical conditions facilitate using these modes. Similarly, Matthies, *et al.*,, (2002) identified that women are more willing to reduce car use because of their stronger ecological norms and weaker car habits. The importance of habits holds true when considering environment-friendly consumer behaviour; as shown by Dahlstrand and Biel (1997), the environmental concern (environmental values and a sense of responsibility for the environment) is more influential when habits are weak. Therefore, interventions based on the activation of norms related to general ecological behaviour have to be implemented at an early stage when travel habits are not yet well established (e.g., at the age from 14 to 16, or, at the latest, during driving school). Hence, the proper environmental and mobility education is needed to educate people as also suggested by Gaborieau and Pronello (2021) and Pronello and Camusso (2011).

Further research is needed to deepen our understanding of the GEB and to devise appropriate measurement instruments. There was no evidence that individuals with diverging sociodemographic characteristics, such as age, had a different understanding of the items. The item which is difficult could be answered by respondents with high capability, whilst easy items could be answered by respondents with high and low ability. Overlapping items measure different elements with different levels of difficulty (Bond and Fox, 2007), hence we do not suggest to exclude items to design a new survey by looking only at redundancy of items in write map. Some recommendations are worthy to be given for improving the scale. Firstly, more items could be selected with high or low difficulties so that the scale will be able to measure individuals outside an intermediate level of ecological behaviour, particularly to fill in the gaps identified in the study in write map analysis. This is important because limited differentiation capabilities may attenuate existing effects of measuring ecological behaviour. The GEB-26 might not be capable of detecting strong effects potentially attributable to interventions based on ecological behaviour in terms of larger person ability range due to weakness of questionnaire design; in fact, we obtained person measure reliability equal to 0.67 and person separation equal to 1.44, which is acceptable but not excellent. Hence, GEB researchers would profit from more sensitive measurement instruments capable of detecting differences between individuals who are high and low in ecological behaviour. Furthermore, we do not suggest excluding any item by looking only at the dichotomous scale measurement. The item exclusion was decided after measuring the original 6 scale polytomous questionnaire using Rating Scale Model (RSM), continuing to validate and select the appropriate measurement scale to measure GEB of users. As suggested by Linacre[58], the scale with more categories is expected to give better and higher person reliability and separation. This in fact observed in the current study. Comparing dichotomous sand polytomous scale, polytomous scale works well with higher person/item measure separation and reliability. Some items need attention in future analysis. Although, we do not suggest directly excluding items found problematic in this study. The final item exclusion should be done by collecting data on the same questionnaire and rating scale. If the same pattern appears then this allows to exclude the items which are not helpful for the valid GEB measurement.

Future research could test the GEB questionnaire in different cultural and territorial contexts such as different regions, cities, and metropolitan areas of Italy, and different European countries to validate the appropriate GEB questionnaire.

In summary, we can conclude that GEB-26 shows acceptable approximation to Rasch requirements. Improvements, as outlined above can be useful to verify the problematic items that are slightly borderline, are strongly warranted, and may yield a reliable and internally valid measurement device for the measurement of GEB with good psychometric properties.

The final aim of the research is to assist policy makers to define targeted policies inducing sustainable travel choices. To this end, measuring the efficacy of such policies – as, for example, an environment-focused transport education or giving incentives when people uses sustainable modes or the adoption of technology to engage people in pro-environment behaviour with the help of smartphone apps (Pronello and Kumawat, 2021) – would allow to understand if people become aware about their environmental footprints and, thus, more motivated to behave in an ecological and sustainable manner.

The barriers of changing the travel behaviour like the lack of ecological awareness must be considered, resulting in different strategies for different typologies of travellers. Strategies cannot aim at changing the travellers but should address the different groups and focus on favouring the choice of environmentally-friend modes of transport, considering that the behavioural changes can only be achieved by a major societal change.

A wider use of the effective GEB questionnaire (attention paid to inclusion of good items) by practitioners could make identifying good practices easier and to come up with effective public policies and marketing campaigns. Moreover, the specific construction of a Rasch model for measurement purpose allows the development of adaptive surveys that can be used to make questionnaires shorter, selecting the items that matter, matching with the abilities of different individuals.

Mode choice modelling using Structural Equation Model (SEM) allowed to statistically validate the relationship between the identified factors in market segmentation and GEB measure obtained from Rasch model with stated mode choice; we obtained a good and acceptable model fit for both, binomial and trinomial mode choice model. The proposed hypotheses are found significant, proving the empirical support to the proposed model validation. Travel Pleasure (TP) and Mode Pleasure (MP) are two important factors behind the mode choice of users, also identified as important in the profiles obtained through the market segmentation. In addition, residential location, Perceived Accessibility (PAC), and AFF (I like to drive) variables were also found significant in affecting the decision behind choosing any mode. In contrast to this Subjective Norms (SN), Personal Norms (PN) and pro-environment behaviour do not affect mode choice. The opposite of this is also reported by Ababio-Donkor *et al.*, (2020) who state that PN or pro-environmental attitudes influence the choice of transport mode where the individuals with pro-environmental attitude are likely to travel with sustainable travel modes. This identified discrepancy in behaviour might be due to different social and cultural context than Italy; indeed, Ababio-Donkor *et al.*, (2020) investigated the impact of perceptions and believes on the predicting power of transport mode choice model in Edinburgh, Scotland.

This finding shows that the preferences are the strong motivation for the population to select the mode instead of what is available because they prefer to use fast, reliable, flexible and less delayed mode, as also found by Gaborieau (2016) in the same study area. Trip chain (multimodal) was used by the majority of respondents. After trip chain analysis, car was used by most of respondents, showing the important of AFF variable in the model.

One limitation of this study is that it is based on the data of single-day travel. In future, data from multiple days on multimodal travel can be studied in line with the present study to define the trends on weekdays and weekends of multimodal travel, which is a typical limitation of TS as also reported by other researchers (Minal *et al.*, 2021).

Rystam's (1998) qualitative studies of mode choice show that changes in behaviour lead to changes in attitudes. Therefore, the continuous assessment of attitudes is also necessary to observe the impact of the policies targeted to sustainability. Moreover, as for demographics, the attitudes and public perceptions of the population are constantly changing. The attitudes towards mobility have shifted across generations, and these attitude shifts influence travellers' choices in different situations. There is limited information on these attitude changes and limited abilities to forecast attitude changes. A high priority is related to improve methods for measuring and forecasting changes in attitudes and public perceptions. For example, the change in attitudes towards driving among young people was not a shift that was widely expected before it happened. These attitudinal shifts lead to a different travel behaviour among younger cohorts. Tracking and understanding public attitudes and their influence on travel behaviour would improve the anticipation of impacts of such shifts, as also suggested by Martin *et al.* (2016).

According to Nilsson (1998), attitudes' value for predicting actual behaviour is poor, because they are collected through interviews or questionnaires. The same problem also applies to Stated Preference interviews. It is important when asking questions on attitudes to base them as far as possible on the individual's experience which should be the focus of future studies using interviews or questionnaires.

A limitation of the study is about the sample representativeness of the population. This inconsistency between population and sample is due to the survey administration: it did reach very well some targets (workers in Torino from any sectors of study area and university students), but it failed towards other people, like retired people, unemployed, housewife, etc. Indeed, a so large sample on attitudes about transport is very rare, even unique in academic context to carry out very profitable results.

Finally, the study presents a roadmap for future research. As other studies show (Dieleman *et al.*, 2002; Racca and Ratledge, 2004; Schwanen and Mokhtarian, 2005; Ewing and Cervero, 2010; Böcker *et al.*, 2013; Böcker *et al.*, 2017; Helbich, 2017), mode choice is also affected by different individual and household characteristics, built environment, weather conditions, and trip characteristics. The further research can incorporate these other characteristics together with preferences and attitudes in the mode choice modelling to see their effect in the living environment.

The mode choice modelling allows to suggest the following practical policy implications:

- improving the multimodal transport systems that focus more on PT and active modes by improving the access, egress, waiting and transfer time that could be helpful in maintaining for long run this habit;
- attractive advertisements, tours organized by car manufacturers, motors show, and racing should not be widely allowed to stop the reinforcement of self-identity with an industrial product that bears a heavy responsibility for climate change. Even, if possible, these kinds of events should be replaced by events promoting sustainable mobility by creating affective advertisements and awareness campaigns of active modes;
- even if the attraction towards car is found stronger, the users can still be diverted towards more sustainable modes if the policy makers and transport planners work on more user-oriented services and infrastructure;
- the focus should be the user, to understand how they perceive the transport services, and what the users really want. Together with the regular monitoring of the PT service quality,

the monitoring of users' satisfaction should be periodically made to know the actual users' needs;
- improvement of PT facilities alone will not result in an increased mode share of PT. Introduction of policies which restrict the use of private vehicles like congestion charging, parking pricing etc., are also needed to reduce the dependency of people on private vehicles and shift them to improved PT systems.

Regarding future research, advances in information technology are opening new ways to measure mobility patterns more comprehensively. These transformative trends are reshaping how we think transport policy, operations, and planning. The emerging methodologies and new forms of data that show significant potential to improve the understanding of travel behaviour need to be investigated in the future. As changing socio-demographics have influenced travel in the United States, rapidly evolving technology has similarly played a notable role in shaping travel choices (Martin *et al.*, 2016). Although in understanding various travel data sources, we identified that the new techniques for travel data collection mainly limited to socio demographic and spatial information. Therefore, despite the cheapness, wider availability, and dynamic nature of data collection, the new tools cannot completely replace the TS which can collect comparatively travel information relating to all aspects. As one of the disadvantages of the advanced technology is that they cannot touch the emotions of humans, they are not very useful for investigating behavioural aspects. Nonetheless, the findings of this research can also be applied to experiment if apps can be used for TS.

As methodologies and datasets evolve to adapt to changing technology, they hold promise for understanding travel behaviour and mobility patterns. A major step forward has been the harnessing of real-time data to observe and analyse revealed travel choices. Gaps remain in translating metropolitan/statewide surveys for local level transport planning, or keeping the data updated for long-term infrastructure planning. Moreover, emerging datasets, such as real-time GPS data, are often cumbersome to manage and analyse. Future research can leverage these datasets, but will need to overcome institutional and technological barriers, such as data sharing, data accuracy, cyber security, and privacy (Martin *et al.*, 2016).

References

Ababio-Donkor, A., Saleh, W. and Fonzone, A. (2020). The role of personal norms in the choice of mode for commuting. *Research in Transportation Economics*, 83, p. 100966. doi: 10.1016/j.retrec.2020.100966.

Abou-zeid, M. *et al.* (2011). Attitudes and Value of Time Heterogeneity, *Annual Meeting of the Transportation Research Board (TRB) Compendium of Papers*, pp. 1–27.

Adolfsson, A., Ackerman, M. and Brownstein, N. C. (2019). To cluster, or not to cluster: An analysis of clusterability methods. *Pattern Recognition*. doi: 10.1016/j.patcog.2018.10.026.

Ajzen, I., & Cote, N. G. (2008). Attitudes and the Prediction of Behavior. In W. D. Crano, & R. Prislin (Eds.), *Attitudes and Attitude Change* (pp. 289-311). New York, NY: Psychology Press.

Albano, R., & Molino, D. (2013). Misurazione di variabili latenti. Torino: Celid.

Anable, J. (2005). “Complacent Car Addicts” or “Aspiring Environmentalists”? Identifying travel behaviour segments using attitude theory. *Transport Policy*, 12(1), pp. 65–78. doi: 10.1016/j.tranpol.2004.11.004.

Anastasi, G. *et al.* (2013). Urban and social sensing for sustainable mobility in smart cities. In *2013 Sustainable Internet and ICT for Sustainability, SustainIT 2013*. doi: 10.1109/SustainIT.2013.6685198.

Anda, C., Erath, A. and Fourie, P. J. (2017). Transport modelling in the age of big data. *International Journal of Urban Sciences*, 21(sup1), pp. 19–42. doi: 10.1080/12265934.2017.1281150.

Andersen, E. B. (1977). Sufficient statistics and latent trait models. *Psychometrika*, 42(1), pp. 69–81. doi: 10.1007/BF02293746.

Andrich, D. (1978). A rating scale formulation for ordered response categories. *Psychometrika*, 43(4), pp. 561–573. doi: 10.1007/BF02293814.

De Angelis, M., Mantecchini, L. and Pietrantoni, L. (2021). A Cluster Analysis of University Commuters: Attitudes, Personal Norms and Constraints, and Travel Satisfaction. *International Journal of Environmental Research and Public Health*, 18(9), p. 4592. doi: 10.3390/ijerph18094592.

Arbuthnot, J. (1977). The Roles of Attitudinal and Personality Variables in the Prediction of Environmental Behavior and Knowledge. *Environment and Behavior*, 9(2), pp. 217–232. doi: 10.1177/001391657792004.

Arnold, O. *et al.* (2018). Capturing the Environmental Impact of Individual Lifestyles: Evidence of the Criterion Validity of the General Ecological Behavior Scale. *Environment and Behavior*, 50(3), pp. 350–372. doi: 10.1177/0013916517701796.

Arrindell, W. A. and van der Ende, J. (1985). An Empirical Test of the Utility of the Observations-To-Variables Ratio in Factor and Components Analysis. *Applied Psychological Measurement*, 9(2), pp. 165–178. doi: 10.1177/014662168500900205.

Atasoy, B., Glerum, A. and Bierlaire, M. (2013). Attitudes towards mode choice in Switzerland. *disP - The Planning Review*, 49(2), pp. 101–117. doi: 10.1080/02513625.2013.827518.

Axelrod, L. J. and Lehman, D. R. (1993). Responding to environmental concerns: What factors guide individual action?. *Journal of Environmental Psychology*, 13(2), pp. 149–159. doi: 10.1016/S0272-4944(05)80147-1.

Baldassare, M. and Katz, C. (1992). The Personal Threat of Environmental Problems as Predictor of Environmental Practices. *Environment and Behavior*, 24(5), pp. 602–616. doi: 10.1177/0013916592245002.

Barry, J. J. *et al.* (2002). Origin and destination estimation in New York City with automated fare system data. *Transportation Research Record*. doi: 10.3141/1817-24.

Barry, J. J., Freimer, R. and Slavin, H. (2009). Use of entry-only automatic fare collection data to estimate linked transit trips in New York city. *Transportation Research Record*. doi: 10.3141/2112-07.

Bartlett, M. S. (1950). Tests of Significance in factor analysis. *British Journal of Statistical Psychology*, 3(2), pp. 77–85. doi: 10.1111/j.2044-8317.1950.tb00285.x.

Beecroft, M. and Pangbourne, K. (2015). Future prospects for personal security in travel by public transport. *Transportation Planning and Technology*, 38(1), pp. 131–148. doi: 10.1080/03081060.2014.976980.

von Behren, S. *et al.* (2018). Bringing Travel Behavior and Attitudes Together: an Integrated Survey Approach for Clustering Urban Mobility Types. *Transportatio Reseach Record*.

Beirão, G. and Sarsfield Cabral, J. A. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy*, 14(6), pp. 478–489. doi: 10.1016/j.tranpol.2007.04.009.

Ben-Akiva, M. *et al.* (1999). Extended Framework for Modeling Choice Behavior. *Marketing Letters*, 10(3), pp. 187–203. doi: 10.1023/A:1008046730291.

Ben-Akiva, M. *et al.* (2002). Hybrid Choice Models: Progress and Challenges. *Marketing Letters*, 13(3), pp. 163–175. doi: 10.1023/A:1020254301302.

Berger, M. and Platzer, M. (2015). Field evaluation of the smartphone-based travel behaviour data collection app "smartMo"'. in *Transportation Research Procedia*. doi: 10.1016/j.trpro.2015.12.023.

Bhatnagar, A. and Ghose, S. (2004). A latent class segmentation analysis of e-shoppers. *Journal of Business Research*. doi: 10.1016/S0148-2963(02)00357-0.

Bielby, W. T. and Hauser, R. M. (1977). Structural Equation Models. *Annual Review of Sociology*, 3(1), pp. 137–161. doi: 10.1146/annurev.so.03.080177.001033.

Birch, M. W. (1964). The Detection of Partial Association, I: The 2 × 2 Case. *Journal of the Royal Statistical Society: Series B (Methodological)*, 26(2), pp. 313–324. doi: 10.1111/j.2517-6161.1964.tb00564.x.

Birenboim, A. and Shoval, N. (2016). Mobility research in the age of the smartphone. *Annals of the American Association of Geographers*. doi: 10.1080/00045608.2015.1100058.

Böcker, L., van Amen, P. and Helbich, M. (2017). Elderly travel frequencies and transport mode choices in Greater Rotterdam, the Netherlands. *Transportation*, 44(4), pp. 831–852. doi: 10.1007/s11116-016-9680-z.

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(1), pp. 71–91. doi: 10.1080/01441647.2012.747114.

Bollen, K. A. (1989). Structural Equations with Latent Variables. Hoboken, NJ, USA: John Wiley & Sons, Inc. Available at: http://doi.wiley.com/10.1002/9781118619179.

Bond, T. G. and Fox, C. M. (2003). Applying the Rasch Model: Fundamental Measurement in the Human Sciences. *Journal of Educational Measurement*, 40(2), pp. 185–187. doi: 10.1111/j.1745-3984.2003.tb01103.x.

Bond, T. G. and Fox, C. M. (2007). Applying the Rasch Model: Fundamental Measurement in the Human Sciences. Second Edition. *Psychology Press*. doi: 10.4324/9781410614575.

Boone, W. J., Staver, J. R. and Yale, M. S. (2014). Rasch Analysis in the Human Sciences. Dordrecht: Springer Netherlands. doi: 10.1007/978-94-007-6857-4.

Boone, W. J., Townsend, J. S. and Staver, J. R. (2016). Utilizing Multifaceted Rasch Measurement Through FACETS to Evaluate Science Education Data Sets Composed of Judges, Respondents, and Rating Scale Items: An Exemplar Utilizing the Elementary Science Teaching Analysis Matrix Instrument. *Science Education*, 100(2), pp. 221–238. doi: 10.1002/sce.21210.

Borsellino, R., Zahnow, R. and Corcoran, J. (2018). Not all those who Wander are lost: exploring human mobility using a smartphone application. *Australian Geographer*. doi: 10.1080/00049182.2018.1451215.

Bouwman, H. *et al.* (2013). Opportunities and problems with automated data collection via smartphones. *Mobile Media and Communication*. doi: 10.1177/2050157912464492.

Boyle, D. K. (1998). Passenger Counting Technologies and Procedures. *Transit Cooperative Research Program (TCRP) Synthesis 29*, published by Transportation Research Board, Washington.

Brann, K. L. *et al.* (2021). Development of the School Mental Health Self-Efficacy Teacher Survey Using Rasch Analysis. *Journal of Psychoeducational Assessment*, 39(2), pp. 197–211. doi: 10.1177/0734282920947504.

Bravo, Y. *et al.* (2016). Smart Mobility by Optimizing the Traffic Lights: A New Tool for Traffic Control Centers. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 147–156. doi: 10.1007/978-3-319-39595-1_15.

Brock, G. *et al.* (2008). ClValid: An R package for cluster validation. *Journal of Statistical Software*. doi: 10.18637/jss.v025.i04.

Broll, G. *et al.* (2012). Tripzoom: An app to improve your mobility behavior. in *Proceedings of the 11th International Conference on Mobile and Ubiquitous Multimedia, MUM 2012*. doi: 10.1145/2406367.2406436.

Browne, M. W. (1984). Asymptotically distribution-free methods for the analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology*, 37(1), pp. 62–83. doi: 10.1111/j.2044-8317.1984.tb00789.x.

C Stern, P. (2000). Toward a coherent theory of environmentally significant behaviour. *Journal of Social Issues*, 56(3), pp. 407–424. Available at: 10.1111/0022-4537.00175.

Campbell, D. T. (1963). Social Attitudes and Other Acquired Behavioral Dispositions. In S. Koch, *Psychology: A study of a science. Study II. Empirical substructure and relations with other sciences. Vol. 6. Investigations of man as socius: Their place in psychology and the social sciences* (pp. 94–172). McGraw-Hill. https://doi.org/10.1037/10590-003

Campbell, J. M. (1983). Ambient Stressors. *Environment and Behavior*, 15(3), pp. 355–380. doi: 10.1177/0013916583153005.

Cardoso, N., Madureira, J. and Pereira, N. (2016). Smartphone-based transport mode detection for elderly care. In *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services, Healthcom 2016*. doi: 10.1109/HealthCom.2016.7749465.

Carrion, C. *et al.* (2014). Evaluating FMS: A preliminary comparison with a traditional travel survey. In *Transportation Research Board 93rd Annual Meeting*.

Cattell, R. B. and Jaspers, J. (1967). A general plasmode (No. 30-10-5-2) for factor analytic exercises and research. *Multivariate Behavioral Research Monographs*, 67(3), p. 211.

Cellina, F. *et al.* (2013). Using Smartphones to Profile Mobility Patterns in a Living Lab for the Transition to E-mobility. In *IFIP Advances in Information and Communication Technology*. doi: 10.1007/978-3-642-41151-9_15.

Cellina, F. *et al.* (2018). Outcomes of a smart city living lab prompting low-carbon mobility patterns by a mobile app. In *Proceedings of the 18th Swiss Transport Research Conference*.

Cellina, F., Martin, R. and Rudel, R. (2016). GoEco! - A Set of Smartphone Apps Supporting the Transition Towards Sustainable Mobility Patterns. In *Change - IT (Workshop at ICT4S 2016)*, pp. 1–9.

Charrad, M. *et al.* (2014). Nbclust: An R package for determining the relevant number of clusters in a data set. *Journal of Statistical Software*. doi: 10.18637/jss.v061.i06.

Chen, J. and Li, S. (2017). Mode Choice Model for Public Transport with Categorized Latent Variables. *Mathematical Problems in Engineering*, 2017, pp. 1–11. doi: 10.1155/2017/7861945.

Chen, K. H., Liu, H. H. and Chang, F. H. (2013). Essential customer service factors and the segmentation of older visitors within wellness tourism based on hot springs hotels. *International Journal of Hospitality Management*. doi: 10.1016/j.ijhm.2013.05.013.

Clark, A. *et al.* (2017). Detailed Mapping of Tools and Applications for Travel Surveys. Technical report.

Cohen, L. (1979). Approximate expressions for parameter estimates in the Rasch model. *British Journal of Mathematical and Statistical Psychology*, 32(1), pp. 113–120. doi: 10.1111/j.2044-8317.1979.tb00756.x.

Comrey, A. L. and Lee, H. B. (1992). A First Course in Factor Analysis. Psychology Press. doi: 10.4324/9781315827506.

Cornet, Y. *et al.* (2019). Worthwhile Travel Time: Design Challenges of Capturing the User Experience by Smartphone. In *2019 Smart Cities Symposium Prague, SCSP 2019 - Proceedings*. doi: 10.1109/SCSP.2019.8805706.

Costello, A. B. and Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research and Evaluation*, 10(7), pp. 1–9. doi: 10.7275/jyj1-4868.

Cui, A. (2006). Bus Passenger Origin-Destination Matrix Estimation Using Automated Data Collection Systems. Master Thesis. Massachusetts Institute of Technology.

D'Agostino, R. and Pearson, E. S. (1973). Tests for departure from normality. Empirical results for the distributions of b2 and √b1. *Biometrika*. doi: 10.2307/2335012.

Dahlstrand, U. and Biel, A. (1997). Pro-Environmental Habits: Propensity Levels in Behavioral Change1. *Journal of Applied Social Psychology*, 27(7), pp. 588–601. doi: 10.1111/j.1559-1816.1997.tb00650.x.

Daniel Mcfadden (1973). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, pp. 105–142.

Devika, R., Harikrishna, M. and Anjaneyulu, M. V. L. R. (2020). Influence of psychological factors in mode choice decision making: A structural equation modeling approach. *Transportation Research Procedia*, 48, pp. 2821–2830. doi: 10.1016/j.trpro.2020.08.236.

Díaz, E. and Koutra, C. (2013). Evaluation of the persuasive features of hotel chains websites: A latent class segmentation analysis. *International Journal of Hospitality Management*. doi: 10.1016/j.ijhm.2012.11.009.

Dieleman, F. M., Dijst, M. and Burghouwt, G. (2002). Urban Form and Travel Behaviour: Micro-level Household Attributes and Residential Context. *Urban Studies*, 39(3), pp. 507–527. doi: 10.1080/00420980220112801.

Dilek, E. and Ayozen, Y. E. (2016). Smart Mobility in Istanbul with ``IBB CepTrafik''. In *NOMS 2016 - 2016 IEEE/IFIP Network Operationss and Management Symposium*.

Distefano, C., Zhu, M. and Mindrila, D. (2009). Understanding and Using Factor Scores: Considerations for the Applied Researcher. *Practical Assessment, Research & Evaluation*, 14(20), pp. 1–11.

Dow, J. K. and Endersby, J. W. (2004). Multinomial probit and multinomial logit: a comparison of choice models for voting research. *Electoral Studies*, 23(1), pp. 107–122. doi: 10.1016/S0261-3794(03)00040-4.

Duboz, A. (2018). The intention to use real-time multimodal information to change travel behaviour: the use of psychosocial variables for the market. PhD Thesis. Politecnico di Torino, Italy.

Duncan, P. W. *et al.* (2003). Rasch analysis of a new stroke-specific outcome scale: The stroke impact scale. *Archives of Physical Medicine and Rehabilitation*, 84(7), pp. 950–963. doi: 10.1016/S0003-9993(03)00035-2.

Duxbury, B. (2012). Planning for the Olympics : A Transportation SWOT Analysis of Vancouver.

Dziuban, C. D. and Shirkey, E. C. (1974). When is a correlation matrix appropriate for factor analysis? Some decision rules. *Psychological Bulletin*, 81(6), pp. 358–361. doi: 10.1037/h0036316.

Espino, R., Román, C. and De Ortúzar, J. D. (2006). Analysing Demand for Suburban Trips: A Mixed RP/SP Model with Latent Variables and Interaction Effects. *Transportation*, 33(3), pp. 241–261. doi: 10.1007/s11116-005-2299-0.

Everitt, B. S. (1975). Multivariate Analysis: The Need for Data, and other Problems. *British Journal of Psychiatry*, 126(3), pp. 237–240. doi: 10.1192/bjp.126.3.237.

Ewing, R. and Cervero, R. (2010). Travel and the Built Environment: A meta analysis. *Journal of the American Planning Association*, 76(3), pp. 265–294. doi: 10.1080/01944361003766766.

Fabrigar, L. R. *et al.* (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3), pp. 272–299. doi: 10.1037/1082-989X.4.3.272.

Fabrigar, L. R. and Wegener, D. T. (2012). Requirements for and decisions in choosing exploratory factor common analysis. In *Understanding Statistics : Exploratory Factor Analysis*. Oxford ; New York : Oxford University Press.

Fallah-Shorshani, M. *et al.* (2018). Evaluating the Impact of Neighborhood Characteristics on Differences between Residential and Mobility-Based Exposures to Outdoor Air Pollution. *Environmental Science and Technology*. doi: 10.1021/acs.est.8b02260.

Fan, Y. *et al.* (2012). Smartphone-Based Travel Experience Sampling and Behavior Intervention among Young Adults. Technical Report. Intelligent Transportation Systems Institute, Center for Transportation Studies, University of Minnesota.

Fayers, P. (2004). Item Response Theory for Psychologists. *Quality of Life Research*, 13(3), pp. 715–716. doi: 10.1023/B:QURE.0000021503.45367.f2.

Fernandes, B. *et al.* (2015). Mobile application for automatic accident detection and multimodal alert. In *IEEE Vehicular Technology Conference*. doi: 10.1109/VTCSpring.2015.7145935.

Field, A. P. (2000). Discovering Statistics Using SPSS for Windows, Advanced Techniques for the Beginner. *Sage Publications.*

Fornell, C. and Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), pp. 39–50. doi: 10.1177/002224378101800104.

Frank, L. *et al.* (2007). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, 35(1), pp. 37–54. doi: 10.1007/s11116-007-9136-6.

Fransson, N. and Tommy, G. (1999). Environmental concern: Conceptual definitions, measurement methods, and research findings. *Journal of Environmental Psychology*, 19(4), pp. 369–382. doi: 10.1006/jevp.1999.0141.

Fridgen, C. (1994). Human disposition toward hazards: Testing the environmental appraisal inventory. *Journal of Environmental Psychology*. doi: 10.1016/S0272-4944(05)80164-1.

Froehlich, J. *et al.* (2009). UbiGreen: Investigating a mobile tool for tracking and supporting green transportation habits. In *Conference on Human Factors in Computing Systems - Proceedings*. doi: 10.1145/1518701.1518861.

Gaborieau (2016). Evaluation of the potential modal shift induced by the use of a real time multimodal navigator: psycho-social study of travel behaviour and attitudes. PhD Thesis. Politecnico di Torino, Italy.

Gaborieau, J.-B. and Pronello, C. (2021). Validation of a unidimensional and probabilistic measurement scale for pro-environmental behaviour by travellers. *Transportation*. Springer US, 48(2), pp. 555–593. doi: 10.1007/s11116-019-10068-w.

Gabrielli, S. *et al.* (2013). Designing Motivational Features for Sustainable Urban Mobility. In *Conference on Human Factors in Computing Systems - Proceedings*. doi: 10.1145/2468356.2468617.

Gagnon Thompson, S. C. and Barton, M. A. (1994). Ecocentric and anthropocentric attitudes toward the environment. *Journal of Environmental Psychology*, 14(2), pp. 149–157. doi: 10.1016/S0272-4944(05)80168-9.

Gal-Tzur, A. *et al.* (2014). The potential of social media in delivering transport policy goals. *Transport Policy*. doi: 10.1016/j.tranpol.2014.01.007.

Gamba, R. J. and Oskamp, S. (1994). Factors Influencing Community Residents’ Participation in Commingled Curbside Recycling Programs. *Environment and Behavior*, 26(5), pp. 587–612. doi: 10.1177/0013916594265001.

Gärling, T., Gillholm, R. and Gärling, A. (1998). Reintroducing attitude theory in travel behavior research: The validity of an interactive interview procedure to predict car use. *Transportation*, 25(2), pp. 129–146. doi: 10.1023/A:1005004311776.

Garside, J. (2011). Harold Goddijn: TomTom’s founder needs his business to turn the corner. *The Guardian*.

Gatersleben, B. and Appleton, K. M. (2007). Contemplating cycling to work: Attitudes and perceptions in different stages of change. *Transportation Research Part A: Policy and Practice*, 41(4), pp. 302–312. doi: 10.1016/j.tra.2006.09.002.

Gatersleben, B., Steg, L. and Vlek, C. (2002). Measurement and Determinants of Environmentally Significant Consumer Behavior. *Environment and Behavior*, 34(3), pp. 335–362. doi: 10.1177/0013916502034003004.

Gebresselassie, M. and Sanchez, T. (2018). “Smart” Tools for Socially Sustainable Transport: A Review of Mobility Apps. *Urban Science*, 2(2), p. 45. doi: 10.3390/urbansci2020045.

Geurs, K. T. *et al.* (2015). Automatic trip and mode detection with move smarter: First results from the Dutch Mobile Mobility Panel. In *Transportation Research Procedia*. doi: 10.1016/j.trpro.2015.12.022.

Gifford, R., Kormos, C. and McIntyre, A. (2011). Behavioral dimensions of climate change: drivers, responses, barriers, and interventions. *WIREs Climate Change*, 2(6), pp. 801–827. doi: 10.1002/wcc.143.

Gliem, J. A. and Gliem R. R. (2003). Calculating, Interpreting, and Reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales. In *2003 Midwest Research to Practice Conference in Adult, Continuing, and Community Education*, pp. 82–88.

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological*, 37(1), pp. 1–25. doi: 10.1016/S0191-2615(01)00046-7.

Gorsuch, R. L. (1983). Factor Analysis. Hillsdale, Michigan, USA: NJ, Erlbaum.

Grice, J. W. (2001). A comparison of factor scores under conditions of factor obliquity. *Psychological Methods*, 6(1), pp. 67–83. doi: 10.1037/1082-989X.6.1.67.

Guilford, J. P. (1957). Fundamental Statistics in Psychology and Education. *Science Education*, 41(3), pp. 244–244. doi: 10.1002/sce.3730410357.

Guo, X. *et al.* (2013). Optimal pricing strategy based on market segmentation for service products using online reservation systems: An application to hotel rooms. *International Journal of Hospitality Management*. doi: 10.1016/j.ijhm.2013.07.001.

Gustarini, M. *et al.* (2014). UnCrowdTPG: Assuring the experience of public transportation users. In *International Conference on Wireless and Mobile Computing, Networking and Communications*. doi: 10.1109/WiMOB.2014.6962141.

Hagenauer, J. and Helbich, M. (2017). A comparative study of machine learning classifiers for modeling travel mode choice. *Expert Systems with Applications*, 78, pp. 273–282. doi: 10.1016/j.eswa.2017.01.057.

Hair, J. F. *et al.* (2010). Multivariate Data Analysis: A Global Perspective. 7th Edition, Pearson Education, Upper Saddle River.

Hamidi, Z. and Zhao, C. (2020). Shaping sustainable travel behaviour: Attitude, skills, and access all matter. *Transportation Research Part D: Transport and Environment*, 88, p. 102566. doi: 10.1016/j.trd.2020.102566.

Hartigan, A. and Wong, M. A. (1979). A K-Means Clustering Algorithm. *Journal of the Royal Statistical Society*. doi: 10.2307/2346830.

Haustein, S. (2021). What role does free-floating car sharing play for changes in car ownership? Evidence from longitudinal survey data and population segments in Copenhagen. *Travel Behaviour and Society*, 24, pp. 181–194. doi: 10.1016/j.tbs.2021.04.003.

Helbich, M. (2017). Children's school commuting in the Netherlands: Does it matter how urban form is incorporated in mode choice models?'. *International Journal of Sustainable Transportation*, 11(7), pp. 507–517. doi: 10.1080/15568318.2016.1275892.

Heller, B. W., Mazumdar, S. and Ciravegna, F. (2018). Large Scale, Long-Term, High Granularity Measurement of Active Travel Using Smartphones Apps. *Proceedings*. doi: 10.3390/proceedings2060293.

Henze, N. and Zirkler, B. (1990). A class of invariant consistent tests for multivariate normality. *Communications in Statistics - Theory and Methods*. doi: 10.1080/03610929008830400.

Hergesell, A. (2014). Exploring the Relationship between General Environmental Behaviour and Holiday Transport Mode Choice. In *BEST EN Think Tank XIV: Politics, Politics, Policy and Governance in Sustainable Tourism*, pp. 142–149.

Hergesell, A. (2017). Environmental commitment in holiday transport mode choice. *International Journal of Culture, Tourism and Hospitality Research*, 11(1), pp. 67–80. doi: 10.1108/IJCTHR-09-2015-0118.

Hilbert, M. (2013). Big Data for Development: From Information to Knowledge Societies. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2205145.

Hines, J. M., Hungerford, H. R. and Tomera, A. N. (1987). Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis. *The Journal of Environmental Education*, 18(2), pp. 1–8. doi: 10.1080/00958964.1987.9943482.

Hinkin, T. R. (1995). A Review of Scale Development Practices in the Study of Organizations. *Journal of Management*, 21(5), pp. 967–988. doi: 10.1177/014920639502100509.

Hinkin, T. R. (1998). A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires. *Organizational Research Methods*, 1(1), pp. 104–121. doi: 10.1177/109442819800100106.

Holland, P. W. and Thayer, D. T. (1988). Differential Item Performance and the Mantel–Haenszel Procedure. In Wainer, H. and Braun, H. I. (eds) *Test Validity*. 1st Editio. Lawrence Erlbaum Associates, Inc, pp. 129–145. doi: 10.4324/9780203056905-19.

Horn, B. and Huang, W. (2016). Comparison of Segmentation Approaches. In *Decision Analyst*.

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, 30(2), pp. 179–185. doi: 10.1007/BF02289447.

Howard, G. S. (2000). Adapting human lifestyles for the 21st century. *American Psychologist*, 55(5), pp. 509–515. doi: 10.1037/0003-066X.55.5.509.

Howard, M. C. (2016). A Review of Exploratory Factor Analysis Decisions and Overview of Current Practices: What We Are Doing and How Can We Improve?. *International Journal of Human-Computer Interaction*, 32(1), pp. 51–62. doi: 10.1080/10447318.2015.1087664.

Hoyle, R. H. (1995). The structural equation modeling approach: Basic concepts and fundamental issues. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 1–15). Sage Publications, Inc.

Humphreys, L. G. and Montanelli, R. G. (1975). An Investigation of the Parallel Analysis Criterion for Determining the Number of Common Factors. *Multivariate Behavioral Research*, 10(2), pp. 193–205. doi: 10.1207/s15327906mbr1002_5.

Hung, M. (2017). Leading the IoT - Gartner Insights on How to Lead in a Connected World. *Gartner*. doi: 10.1038/sj.emboj.7600210.

Icek, A. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 50(2), pp. 179–211.

Ilahi, A. *et al.* (2021). Understanding travel and mode choice with emerging modes; a pooled SP and RP model in Greater Jakarta, Indonesia. *Transportation Research Part A: Policy and Practice*, 150, pp. 398–422. doi: 10.1016/j.tra.2021.06.023.

Ilahi, A., Belgiawan, P. F. and Axhausen, K. W. (2020). Influence of pricing on mode choice decision integrated with latent variable. In *Mapping the Travel Behavior Genome*. Elsevier, pp. 125–143. doi: 10.1016/B978-0-12-817340-4.00008-5.

Jariyasunant, J. *et al.* (2012). The Quantified Traveler : Using personal travel data to promote sustainable transport behavior. In *91st Annual Meeting Transportation Research Board*.

Jochem, P. *et al.* (2020). Does free-floating carsharing reduce private vehicle ownership? The case of SHARE NOW in European cities. *Transportation Research Part A: Policy and Practice*, 141, pp. 373–395. doi: 10.1016/j.tra.2020.09.016.

Johansson, M. V., Heldt, T. and Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice*, 40(6), pp. 507–525. doi: 10.1016/j.tra.2005.09.001.

Johnson, S. C. (1967). Hierarchical clustering schemes. *Psychometrika*. doi: 10.1007/BF02289588.

Jylhä, A. *et al.* (2013). Matkahupi: A persuasive mobile application for sustainable mobility. In *UbiComp 2013 Adjunct - Adjunct Publication of the 2013 ACM Conference on Ubiquitous Computing*. doi: 10.1145/2494091.2494164.

Kagerbauer, M. *et al.* (2015). Household travel survey of intermodal trips - Approach, challenges and comparison. In *Transportation Research Procedia*. doi: 10.1016/j.trpro.2015.12.028.

Kaiser, F. G. *et al.* (1999). Ecological Behavior, Environmental Attitude, and Feelings of Responsibility for the Environment. *European Psychologist*, 4(2), pp. 59–74. doi: 10.1027//1016-9040.4.2.59.

Kaiser, F. G. and Biel, A. (2000). Assessing General Ecological Behavior: A Cross-Cultural Comparison between Switzerland and Sweden. *European Journal of Psychological Assessment*, 16(1), pp. 44–52. doi: 10.1027//1015-5759.16.1.44.

Kaiser, F. G. and Wilson, M. (2000). Assessing People's General Ecological Behavior: A Cross-Cultural Measure1. *Journal of Applied Social Psychology*, 30(5), pp. 952–978. doi: 10.1111/j.1559-1816.2000.tb02505.x.

Kaiser, H. F. (1970). A second generation little jiffy. *Psychometrika*, 35(4), pp. 401–415. doi: 10.1007/BF02291817.

Kallgren, C. A. and Wood, W. (1986). Access to attitude-relevant information in memory as a determinant of attitude-behavior consistency. *Journal of Experimental Social Psychology*. doi: 10.1016/0022-1031(86)90018-1.

Kim, S. H., Mokhtarian, P. L. and Circella, G. (2020). How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. *Transportation Research Part F: Traffic Psychology and Behaviour*, 70, pp. 68–80. doi: 10.1016/j.trf.2020.02.012.

Kismiantini *et al.* (2014). Analyzing the Factors of Job Satisfaction in a Mexican Hospital with Binary Indicators by Confirmatory Factor Analysis. *International Journal of Business and Management*, 9(8), pp. 61–83. doi: 10.5539/ijbm.v9n8p61.

Kitchin, R. (2014). The real-time city? Big data and smart urbanism. *GeoJournal*. doi: 10.1007/s10708-013-9516-8.

Kline, P. (1994). A general description of factor analysis. *An easy guide to factor analysis*, pp. 1–14.

Koppelman, F. S. and Pas, E. I. (1980). Travel-choice behaviour: models of perceptions, feelings, preferences, and choice. *Transportation Research Record*, (765), pp. 26–33.

Krause, D. (1993). Environmental Consciousness. *Environment and Behavior*, 25(1), pp. 126–142. doi: 10.1177/0013916593251007.

Krueger, R., Rashidi, T. H. and Vij, A. (2020). X vs. Y: an analysis of intergenerational differences in transport mode use among young adults. *Transportation*, 47(5), pp. 2203–2231. doi: 10.1007/s11116-019-10009-7.

de Kruijf, J. *et al.* (2018). Evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands. *Journal of Transport & Health*, 10, pp. 74–83. doi: 10.1016/j.jth.2018.06.003.

Krygsman, S., Dijst, M. and Arentze, T. (2004). Multimodal public transport: an analysis of travel time elements and the interconnectivity ratio. *Transport Policy*, 11(3), pp. 265–275. doi: 10.1016/j.tranpol.2003.12.001.

Kuhnimhof, T. *et al.* (2012). Travel trends among young adults in Germany: Increasing multimodality and declining car use for men. *Journal of Transport Geography*. doi: 10.1016/j.jtrangeo.2012.04.018.

Kupek, E. (2005). Log-Linear Transformation of Binary Variables: A Suitable Input for SEM. *Structural Equation Modeling: A Multidisciplinary Journal*, 12(1), pp. 28–40. doi: 10.1207/s15328007sem1201_2.

Kupek, E. (2006). Beyond logistic regression: structural equations modelling for binary variables and its application to investigating unobserved confounders. *BMC Medical Research Methodology*, 6(1), p. 13. doi: 10.1186/1471-2288-6-13.

Lawson, R. G. and Jurs, P. C. (1990). New Index for Clustering Tendency and Its Application to Chemical Problems. *Journal of Chemical Information and Computer Sciences*. doi: 10.1021/ci00065a010.

Leeming, F. C. *et al.* (1993). Outcome Research in Environmental Education: A Critical Review. *The Journal of Environmental Education*, 24(4), pp. 8–21. doi: 10.1080/00958964.1993.9943504.

Li, C.-Y. *et al.* (2018). Linking Existing Instruments to Develop an Activity of Daily Living Item Bank. *Evaluation & the Health Professions*, 41(1), pp. 25–43. doi: 10.1177/0163278716676873.

Li, T. *et al.* (2018). Smart card data mining of public transport destination: A literature review. *Information (Switzerland)*. doi: 10.3390/info9010018.

Li, Z. (2015). A Power Formula for the Mantel–Haenszel Test for Differential Item Functioning. *Applied Psychological Measurement*, 39(5), pp. 373–388. doi: 10.1177/0146621614568805.

Linacre, J. M. (1994). Sample Size and Item Calibration or Person Measure Stability. *Rasch Measurement Transactions*, 7(4), p. 328. Available at: http://www.rasch.org/rmt/rmt74m.htm.

Linacre, J. M. (1999). Investigating rating scale category utility. *Journal of outcome measurement*, 3(2), pp. 103–22. Available at: http://www.ncbi.nlm.nih.gov/pubmed/10204322.

Linacre, J. M. (2002). Optimizing rating scale category effectiveness. *Journal of applied measurement*, 3(1), pp. 85–106. Available at: http://www.ncbi.nlm.nih.gov/pubmed/11997586.

Linacre J. M., 2009. Unidimensional models in a multidimensional world. Rasch Measurement Trans- actions, 23(2), 1209.

Linacre, M. (2011). Practical Rasch Measurement - Further Topics. doi: https://www.winsteps.com/a/winsteps-tutorial-further-4.pdf.

Linacre, J. M., 2012. A user's guide to Winsteps Ministeps Rasch-model computer programs [version 3.74.0]. Retrieved from http://www.winsteps.com/winsteps.htm.

Linacre, J. M., 2008. The Expected Value of a point-Biserial (or Similar) Correlation, Rasch Measurement Transactions, 22(1): 1154.

Linacre, M. (2012). Winsteps Tutorial 4 Mike Linacre , instructor – June 2012 A. Differential Test Functioning (DTF)', June, pp. 1–22.

Lunz, M. E. (2010). Using The Very Useful Wright Map. *Measurement Research Associates Test Insights*. Available at: http://www.rasch.org/mra/mra-01-10.htm.

Van Der Maaten, L. and Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*. 9(2605), pp. 2579-2605

Maddalena, E. *et al.* (2019). Hybrid human machine workflows for mobility management. In *The Web Conference 2019 - Companion of the World Wide Web Conference, WWW 2019*. doi: 10.1145/3308560.3317056.

Magdolen, M. *et al.* (2021). Mobility Styles and Car Ownership—Potentials for a Sustainable Urban Transport. *Sustainability*, 13(5), p. 2968. doi: 10.3390/su13052968.

Maia, A. G. *et al.* (2020). The Motives Behind Transport Mode Choice: a Study with University Students in Brazil. *Ambiente & Sociedade*, 23, pp. 1–20. doi: 10.1590/1809-4422asoc20170188r4vu2020l5ao.

Maloney, M. P. and Ward, M. P. (1973). Ecology: Let's hear from the people: An objective scale for the measurement of ecological attitudes and knowledge. *American Psychologist*, 28(7), pp. 583–586. doi: 10.1037/h0034936.

Mannor, S. *et al.* (2011). K-Means Clustering. In *Encyclopedia of Machine Learning*. doi: 10.1007/978-0-387-30164-8_425.

Mantel, N. and Haenszel, W. (1959). Statistical Aspects of the Analysis of Data From Retrospective Studies of Disease. *JNCI: Journal of the National Cancer Institute*, 22(4), pp. 719–748. doi: 10.1093/jnci/22.4.719.

Manyika, J. *et al.* (2011). Big data: The next frontier for innovation, competition and productivity. *McKinsey Global Institute*.

Manzoni, V. *et al.* (2011). Transportation mode identification and real-time CO2 emission estimation using smartphones: How CO2GO works. Technical Report.

March, R. (1997). Diversity in Asian outbound travel industries: A comparison between Indonesia, Thailand, Taiwan, South Korea and Japan. *International Journal of Hospitality Management*. doi: 10.1016/s0278-4319(97)00009-1.

Marsh, H. W., Hau, K.-T. and Wen, Z. (2004). In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indexes and Dangers in Overgeneralizing Hu and Bentler's (1999) Findings. *Structural Equation Modeling: A Multidisciplinary Journal*, 11(3), pp. 320–341. doi: 10.1207/s15328007sem1103_2.

Martin, E. *et al.* (2016). Understanding Travel Behavior: Research Scan. Technical Report. U.S. Department of Transportation. Federal Highway Administration.

Martinková, P. *et al.* (2017). Checking Equity: Why Differential Item Functioning Analysis Should Be a Routine Part of Developing Conceptual Assessments. *CBE—Life Sciences Education*. Edited by R. Nehm, 16(2). doi: 10.1187/cbe.16-10-0307.

Marutho, D. *et al.* (2018). The Determination of Cluster Number at k-Mean Using Elbow Method and Purity Evaluation on Headline News. In *Proceedings - 2018 International Seminar on Application for Technology of Information and Communication: Creative Technology for Human Life, iSemantic 2018*. doi: 10.1109/ISEMANTIC.2018.8549751.

Masters, G. N. (1982). A rasch model for partial credit scoring. *Psychometrika*, 47(2), pp. 149–174. doi: 10.1007/BF02296272.

Matthies, E., Kuhn, S. and Klöckner, C. A. (2002). Travel mode choice of women: The result of limitation, ecological norm, or weak habit?'. *Environment and Behavior*, 34(2), pp. 163–177. doi: 10.1177/0013916502034002001.

Mattioli, G. and Colleoni, M. (2016). Transport Disadvantage, Car Dependence and Urban Form. In *Research for Development*, pp. 171–190. doi: 10.1007/978-3-319-22578-4_10.

McCreary, L. L. *et al.* (2013). Using the Rasch Measurement Model in Psychometric Analysis of the Family Effectiveness Measure. *Nursing Research*, 62(3), pp. 149–159. doi: 10.1097/NNR.0b013e31828eafe6.

McDonald John H. (2014). *A handbook of biological statistics*.

McDonald, R. P. (1981). The dimensionality of tests and items. *British Journal of Mathematical and Statistical Psychology*, 34(1), pp. 100–117. doi: 10.1111/j.2044-8317.1981.tb00621.x.

McFadden, D. (1986). The Choice Theory Approach to Market Research. *Marketing Science*, 5(4), pp. 275–297. doi: 10.1287/mksc.5.4.275.

Midden, C. J. H., Kaiser, F. G. and Teddy McCalley, L. (2007). Technology's Four Roles in Understanding Individuals' Conservation of Natural Resources. *Journal of Social Issues*, 63(1), pp. 155–174. doi: 10.1111/j.1540-4560.2007.00501.x.

Miller, A. and Dishon, S. (2006). Health-related Quality of Life in Multiple Sclerosis: The Impact of Disability, Gender and Employment Status. *Quality of Life Research*, 15(2), pp. 259–271. doi: 10.1007/s11136-005-0891-6.

Minal, RaviSekhar, C. and Madhu, E. (2021). Multimodal travel choice determinants in context of travel time reliability. *Proceedings of the Institution of Civil Engineers - Transport*, pp. 1–10. doi: 10.1680/jtran.20.00091.

Moraes, C., Carrigan, M. and Szmigin, I. (2012). The coherence of inconsistencies: Attitude–behaviour gaps and new consumption communities. *Journal of Marketing Management*, 28(1–2), pp. 103–128. doi: 10.1080/0267257X.2011.615482.

Mosenia, A. *et al.* (2018). PinMe: Tracking a smartphone user around the world. *IEEE Transactions on Multi-Scale Computing Systems*. doi: 10.1109/TMSCS.2017.2751462.

Mun, M. *et al.* (2009). PEIR, the personal environmental impact report, as a platform for participatory sensing systems research. In *MobiSys'09 - Proceedings of the 7th ACM International Conference on Mobile Systems, Applications, and Services*. doi: 10.1145/1555816.1555823.

Munizaga, M. *et al.* (2014). Validating travel behavior estimated from smartcard data. *Transportation Research Part C: Emerging Technologies*. doi: 10.1016/j.trc.2014.03.008.

Munizaga, M. A. and Palma, C. (2012). Estimation of a disaggregate multimodal public transport Origin-Destination matrix from passive smartcard data from Santiago, Chile. *Transportation Research Part C: Emerging Technologies*. doi: 10.1016/j.trc.2012.01.007.

Nilsson, M. and Küller, R. (2000). Travel behaviour and environmental concern. *Transportation Research Part D: Transport and Environment*, 5(3), pp. 211–234. doi: 10.1016/S1361-9209(99)00034-6.

Norman, G., & Streiner, D. (2014). Biostatistics: The Bare Essentials. Shelton, USA: People's Medical Publishing House (PMPH).

Novicevic, M. M. *et al.* (2004). Dual-perspective SWOT: a synthesis of marketing intelligence and planning. *Marketing Intelligence & Planning*, 22(1), pp. 84–94. doi: 10.1108/02634500410516931.

Nunes, A. A., Dias, T. G. and Falcão E Cunha, J. (2016). Passenger journey destination estimation from automated fare collection system data using spatial validation. *IEEE Transactions on Intelligent Transportation Systems*. doi: 10.1109/TITS.2015.2464335.

Nunnally, J.C. (1978) Psychometric Theory. 2nd Edition, McGraw-Hill, New York.

O'Connor, J. *et al.* (2016). The Development of the Stereotypical Attitudes in HPE Scale. *Australian Journal of Teacher Education*, 41(7), pp. 70–87. doi: 10.14221/ajte.2016v41n7.5.

Operti, V. (2019). Travellers' Preferences and Attitudes to understand Travel Behaviour and define Market Segmentation. PhD Thesis. Politecnico di Torino, Italy.

Oskamp, S. and Stern, P. (1987). Managing scarce environmental resources. In *Handbook of environmental psychology*, pp. 1044–1088.

Otto, S., Kaiser, F. G. and Arnold, O. (2014). The Critical Challenge of Climate Change for Psychology: Preventing rebound and promoting more individual irrationality. *European Psychologist*, 19(2), pp. 96–106. doi: 10.1027/1016-9040/a000182.

Pallant, J. F. and Tennant, A. (2007). An introduction to the Rasch measurement model: An example using the Hospital Anxiety and Depression Scale (HADS). *British Journal of Clinical Psychology*, 46(1), pp. 1–18. doi: 10.1348/014466506X96931.

Pas, E. I. and Huber, J. C. (1992). Market segmentation analysis of potential inter-city rail travelers. *Transportation*, 19(2), pp. 177–196. doi: 10.1007/BF02132837.

Patterson, Z. *et al.* (2019). Itinerum: The open smartphone travel survey platform. *SoftwareX*. doi: 10.1016/j.softx.2019.04.002.

Patterson, Z. and Fitzsimmons, K. (2016). DataMobile: Smartphone travel survey experiment. *Transportation Research Record*. doi: 10.3141/2594-07.

Pelletier, M. P., Trépanier, M. and Morency, C. (2011). Smart card data use in public transit: A literature review. *Transportation Research Part C: Emerging Technologies*. doi: 10.1016/j.trc.2010.12.003.

Piccolo, D. (2000). Statistica. Bologna: Il Mulino.

Pickett, G. M., Kangun, N. and Grove, S. J. (1993). Is There a General Conserving Consumer? A Public Policy Concern. *Journal of Public Policy & Marketing*, 12(2), pp. 234–243. doi: 10.1177/074391569101200208.

Pinjari, A. R. *et al.* (2007). Modeling residential sorting effects to understand the impact of the built environment on commute mode choice. *Transportation*, 34(5), pp. 557–573. doi: 10.1007/s11116-007-9127-7.

Pizam, A. and Calantone, R. (1987). Beyond psychographics - values as determinants of tourist behavior. *International Journal of Hospitality Management*. doi: 10.1016/0278-4319(87)90052-1.

Planinic, M. *et al.* (2019). Rasch analysis in physics education research: Why measurement matters. *Physical Review Physics Education Research*, 15(2), p. 020111. doi: 10.1103/PhysRevPhysEducRes.15.020111.

Prelipcean, A. C., Gidófalvi, G. and Susilo, Y. O. (2018). MEILI: A travel diary collection, annotation and automation system. *Computers, Environment and Urban Systems*. doi: 10.1016/j.compenvurbsys.2018.01.011.

Pronello, C. and Camusso, C. (2011). Travellers' profiles definition using statistical multivariate analysis of attitudinal variables. *Journal of Transport Geography*, 19(6), pp. 1294–1308. doi: 10.1016/j.jtrangeo.2011.06.009.

Pronello, C. and Gaborieau, J.-B. (2018). Engaging in Pro-Environment Travel Behaviour Research from a Psycho-Social Perspective: A Review of Behavioural Variables and Theories. *Sustainability*, 10(7), p. 2412. doi: 10.3390/su10072412.

Pronello, C. and Kumawat, P. (2021). Smartphone Applications Developed to Collect Mobility Data: A Review and SWOT Analysis. In *Advances in Intelligent Systems and Computing*, pp. 449–467. doi: 10.1007/978-3-030-55187-2_35.

Pronello, C., Longhi, D. and Gaborieau, J. B. (2018). Smart card data mining to analyze mobility patterns in suburban areas. *Sustainability (Switzerland)*, 10(10), pp. 1–21. doi: 10.3390/su10103489.

Puglisi, S. *et al.* (2016). Mobilitapp: Analysing mobility data of citizens in the metropolitan area of Barcelona. In *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*. doi: 10.1007/978-3-319-47063-4_23.

Racca, D. P. and Ratledge, E. C. (2004). Factors That Affect and:or Can Alter Mode Choice. Project Report. Center for Applied Demography & Survey Research

Rasch, G. (1961). Probabilistic Models for Some Intelligence and Attainment Tests. *Information and Control*, 4(4), p. 382. doi: 10.1016/S0019-9958(61)80061-2.

Reckase, M. D. (1979). Unifactor Latent Trait Models Applied to Multifactor Tests: Results and Implications. *Journal of Educational Statistics*, 4(3), pp. 207–230. doi: 10.3102/10769986004003207.

Rieser-Schüssler, N. and Axhausen, K. W. (2014). Self-tracing and reporting: State of the art in the capture of revealed behaviour. In *Handbook of Choice Modelling*. doi: 10.4337/9781781003152.00012.

Rosenblad, A. (2009). Applied Multivariate Statistics for the Social Sciences, Fifth Edition by James P. Stevens. *International Statistical Review*, 77(3), pp. 476–476. doi: 10.1111/j.1751-5823.2009.00095_13.x.

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*. doi: 10.1016/0377-0427(87)90125-7.

Ruxton, G. D., Wilkinson, D. M. and Neuhäuser, M. (2015). Advice on testing the null hypothesis that a sample is drawn from a normal distribution. *Animal Behaviour*, 107, pp. 249–252. doi: 10.1016/j.anbehav.2015.07.006.

Schade, W. and Rothengatter, W. (2011). Economic Aspects of Sustainable Mobility. *Brussels, © European Parliament, 2011.*

Scheuneman, J. D. and Bleistein, C. A. (1989). A Consumer's Guide to Statistics for Identifying Differential Item Functioning. *Applied Measurement in Education*, 2(3), pp. 255–275. doi: 10.1207/s15324818ame0203_6.

Schmidt, F. N. and Gifford, R. (1989). A dispositional approach to hazard perception: Preliminary development of the environmental appraisal inventory. *Journal of Environmental Psychology*, 9(1), pp. 57–67. doi: 10.1016/S0272-4944(89)80026-X.

Schmitt, N. and Stuits, D. M. (1985). Factors Defined by Negatively Keyed Items: The Result of Careless Respondents?. *Applied Psychological Measurement*, 9(4), pp. 367–373. doi: 10.1177/014662168500900405.

Schwanen, T. and Mokhtarian, P. L. (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?. *Journal of Transport Geography*, 13(1), pp. 83–99. doi: 10.1016/j.jtrangeo.2004.11.001.

Schwartz, S. H. (1978). Temporal instability as a moderator of the attitude-behavior relationship. *Journal of Personality and Social Psychology*, 36(7), pp. 715–724. doi: 10.1037/0022-3514.36.7.715.

Scott, D. and Willits, F. K. (1994). Environmental Attitudes and Behavior. *Environment and Behavior*, 26(2), pp. 239–260. doi: 10.1177/001391659402600206.

Scott, N. W. *et al.* (2009). A simulation study provided sample size guidance for differential item functioning (DIF) studies using short scales. *Journal of Clinical Epidemiology*, 62(3), pp. 288–295. doi: 10.1016/j.jclinepi.2008.06.003.

Sekhar, C. R. (2014). Mode choice analysis: the data, the models and future ahead. *International Journal for Traffic and Transport Engineering*, 4(3), pp. 269–285. doi: 10.7708/ijtte.2014.4(3).03.

Seong, T.-J. (1990). Sensitivity of Marginal Maximum Likelihood Estimation of Item and Ability Parameters to the Characteristics of the Prior Ability Distributions. *Applied Psychological Measurement*, 14(3), pp. 299–311. doi: 10.1177/014662169001400307.

Shankari, K. *et al.* (2018). E-mission: An open-source, smartphone platform for collecting human travel data. *Transportation Research Record*. doi: 10.1177/0361198118770167.

Shapiro and Wilk, M. B. (2015). The Shapiro-Wilk And Related Tests For Normality.

Sheeran, P. (2002). Intention—Behavior Relations: A Conceptual and Empirical Review. *European Review of Social Psychology*, 12(1), pp. 1–36. doi: 10.1080/14792772143000003.

Shin, D. *et al.* (2015). Urban sensing: Using smartphones for transportation mode classification. *Computers, Environment and Urban Systems*. doi: 10.1016/j.compenvurbsys.2014.07.011.

Siuhi, S. and Mwakalonge, J. (2016). Opportunities and challenges of smart mobile applications in transportation. *Journal of Traffic and Transportation Engineering (English Edition)*. doi: 10.1016/j.jtte.2016.11.001.

Sottile, E., Piras, F. and Meloni, I. (2020). Panel approach: travel behavior and psycho-attitudinal factors evolution. In *Mapping the Travel Behavior Genome*, pp. 167–186.

Steg, L., Dreijerink, L. and Abrahamse, W. (2005). Factors influencing the acceptability of energy policies: A test of VBN theory. *Journal of Environmental Psychology*, 25(4), pp. 415–425. doi: 10.1016/j.jenvp.2005.08.003.

Steg, L. and Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. *Journal of Environmental Psychology*, 29(3), pp. 309–317. doi: 10.1016/j.jenvp.2008.10.004.

Stelmack, J. *et al.* (2004). Use of Rasch person-item map in exploratory data analysis: A clinical perspective. *The Journal of Rehabilitation Research and Development*, 41(2), p. 233. doi: 10.1682/JRRD.2004.02.0233.

Stone, C. A. (1992). Recovery of Marginal Maximum Likelihood Estimates in the Two-Parameter Logistic Response Model: An Evaluation of MULTILOG. *Applied Psychological Measurement*, 16(1), pp. 1–16. doi: 10.1177/014662169201600101.

Swim, J. K., Clayton, S. and Howard, G. S. (2011). Human behavioral contributions to climate change: Psychological and contextual drivers. *American Psychologist*, 66(4), pp. 251–264. doi: 10.1037/a0023472.

Teeuw, W. B., Koolwaaij, J. and Peddemors, A. (2012). User behaviour captured by mobile phones. In *Communications in Computer and Information Science*. doi: 10.1007/978-3-642-31479-7_15.

Tennant, A. and Conaghan, P. G. (2007). The Rasch measurement model in rheumatology: What is it and why use it? When should it be applied, and what should one look for in a Rasch paper?. *Arthritis & Rheumatism*, 57(8), pp. 1358–1362. doi: 10.1002/art.23108.

Thakuriah, P. (2001). Urban Transportation Planning: A Decision-Oriented Approach. *Journal of Transportation Engineering*. doi: 10.1061/(asce)0733-947x(2001)127:5(454).

Theodoridis, S. and Konstantinos, K. (2009). Pattern Recognition (Fourth Edition).

Thomas, T. *et al.* (2018). Automatic Trip Detection with the Dutch Mobile Mobility Panel: Towards Reliable Multiple-Week Trip Registration for Large Samples. *Journal of Urban Technology*. doi: 10.1080/10630732.2018.1471874.

Torre-Bastida, A. I. *et al.* (2018). Big Data for transportation and mobility: Recent advances, trends and challenges. *IET Intelligent Transport Systems*. doi: 10.1049/iet-its.2018.5188.

Triandis, H. C. (1980). Values, attitudes, and interpersonal behavior. *Nebraska Symposium on Motivation.*, 27, pp. 195–259. Available at: http://www.ncbi.nlm.nih.gov/pubmed/7242748.

Tucker, L. R. and MacCallum, R. C. (1997). Exploratory Factor Analysis.

Uluman, M. and Dogan, D. (2016). Comparison of Factor Score Computation Methods In Factor Analysis. *Australian Journal of Basic and Applied Sciences*, 10(8), pp. 143–151.

Vlassenroot, S. *et al.* (2015). The use of smartphone applications in the collection of travel behaviour data. *International Journal of Intelligent Transportation Systems Research*. doi: 10.1007/s13177-013-0076-6.

De Vos, J. and Witlox, F. (2016). Do people live in urban neighbourhoods because they do not like to travel? Analysing an alternative residential self-selection hypothesis. *Travel Behaviour and Society*, 4, pp. 29–39. doi: 10.1016/j.tbs.2015.12.002.

Walker, J. and Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, 43(3), pp. 303–343. doi: 10.1016/S0165-4896(02)00023-9.

Wang, W., Attanucci, J. P. and Wilson, N. H. M. (2011). Bus passenger origin-destination estimation and related analyses using Automated Data Collection Systems. *Journal of Public Transportation*. doi: 10.5038/2375-0901.14.4.7.

Watkins, M. W. (2018). Exploratory Factor Analysis: A Guide to Best Practice. *Journal of Black Psychology*, 44(3), pp. 219–246. doi: 10.1177/0095798418771807.

Weber, A. M. *et al.* (2014). My places diary - Automatic place and transportation- Mode detection. In *MobiQuitous 2014 - 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*. doi: 10.4108/icst.mobiquitous.2014.257992.

Wee, B. Van, Holwerda, H. and Baren, R. Van (2003). Preferences for Modes , Residential Location and Travel Behaviour : the Relevance for Land-Use Impacts on Mobility. *European Journal of Transport and Infrastructure Research*, 2(3/4), pp. 305–316.

van Wee, B., De Vos, J. and Maat, K. (2019). Impacts of the built environment and travel behaviour on attitudes: Theories underpinning the reverse causality hypothesis. *Journal of Transport Geography*, 80, p. 102540. doi: 10.1016/j.jtrangeo.2019.102540.

Weigel, R. H. (1977). Ideological and Demographic Correlates of Proecology Behavior. *The Journal of Social Psychology*, 103(1), pp. 39–47. doi: 10.1080/00224545.1977.9713294.

West, S. G., Finch, J. F., and Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). Sage Publications, Inc.

Westfall, P., and Henning, K.S.S. (2013). Understanding Advanced Statistical Methods (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/b14398

Whipple, J., Arensman, W. and Boler, M. S. (2009). A public safety application of GPS-enabled smartphones and the android operating system. In *2009 IEEE International Conference on Systems, Man and Cybernetics*. IEEE, pp. 2059–2061. doi: 10.1109/ICSMC.2009.5346390.

Williams, J. S. and Child, D. (1974). The Essentials of Factor Analysis. *Contemporary Sociology*, 3(5), p. 411. doi: 10.2307/2061984.

Wind, S. A. & Hua, C., 2021. Rasch Measurement Theory analysis in R: Illustrations and practical guidance for researchers and practitioners. Chapman & Hall/CRC The R Series.

Wolins, L., Wright, B. D. and Rasch, G. (1982). Probabilistic Models for some Intelligence and Attainment Tests. *Journal of the American Statistical Association*, 77(377), p. 220. doi: 10.2307/2287805.

Wright, B., Mok, M. M. C. and Hatari, N., Widiyatmoko, A., P. (2004). An Overview of the Family of Rasch Measurement Models. *Unnes Science Education Journal*, 5(2), pp. 1–24.

Wright, B. and Panchapakesan, N. (1969). A Procedure for Sample-Free Item Analysis. *Educational and Psychological Measurement*, 29(1), pp. 23–48. doi: 10.1177/001316446902900102.

Xie, C., Lu, J. and Parkany, E. (2003). Work Travel Mode Choice Modeling with Data Mining: Decision Trees and Neural Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 1854(1), pp. 50–61. doi: 10.3141/1854-06.

Yen, K. *et al.* (2012). Deployment Support and Data Collection for Caltrans TSI Travel Behavior Survey Using the GPS-ATD. Technical Report. California Department of Transportation.

Yen, W. M. (1984). Effects of Local Item Dependence on the Fit and Equating Performance of the Three-Parameter Logistic Model. *Applied Psychological Measurement*, 8(2), pp. 125–145. doi: 10.1177/014662168400800201.

Yen, W. M. (1993). Scaling Performance Assessments: Strategies for Managing Local Item Dependence. *Journal of Educational Measurement*, 30(3), pp. 187–213. doi: 10.1111/j.1745-3984.1993.tb00423.x.

Zenina, N. and Borisov, A. (2011). Transportation Mode Choice Analysis Based on Classification Methods. *Scientific Journal of Riga Technical University. Computer Sciences*, 45(1), pp. 49–53. doi: 10.2478/v10143-011-0041-2.

Zhang, R. H., Wu, X. G. and Chen, S. P. (2011). Public transportation trip OD matrix inference using IC card data and GPS information. In *ICCTP 2011: Towards Sustainable Transportation Systems - Proceedings of the 11th International Conference of Chinese Transportation Professionals*. doi: 10.1061/41186(421)57.

Zhao, J., Rahbee, A. and Wilson, N. H. M. (2007). Estimating a rail passenger trip origin-destination matrix using automatic data collection systems. *Computer-Aided Civil and Infrastructure Engineering*. doi: 10.1111/j.1467-8667.2007.00494.x.

Zhu, X., Hu, X. and Chiu, Y. C. (2013). Design of Driving Behavior Pattern Measurements Using Smartphone Global Positioning System Data. *International Journal of Transportation Science and Technology*. doi: 10.1260/2046-0430.2.4.269.

Zwick, R., Thayer, D. T. and Lewis, C. (1999). An Empirical Bayes Approach to Mantel-Haenszel DIF Analysis. *Journal of Educational Measurement*, 36(1), pp. 1–28. doi: 10.1111/j.1745-3984.1999.tb00543.x.

Appendices

Appendix A – Variables set

Table A1: Extra 11 items in GEB-51 questionnaire Duboz (2018)

No.	Item description	Code
	Category 1 - Pro-social behaviour	
1	Sometimes, I host, for free, people I don't know (e.g., Couchsurfing)	CS8
	Category 4 - Ecologically aware consumerism	
2	Sometimes, I sell goods I don't use anymore	CE7
3	Sometimes, I buy second hands goods	CE8
4	Sometimes, I offer goods I don't use anymore	CE9
5	Sometimes, I accept goods already used from someone who doesn't use it anymore	CE10
6	Sometimes, I borrow goods I occasionally use, rather than buy them	CE11
7	Sometimes, I rent goods I occasionally use, rather than buy them	CE12
8	Sometimes, I lend goods I occasionally use	CE13
9	Sometimes, I rent for free to someone, goods I occasionally use	CE14
10	I eat less meat than years ago	CE15
	Category 6 - Environmental activism	
11	I boycott companies using OGM or pesticides	V5

Table A2: Initially selected 107 variables for clustering

No.	Label	Variable	Scale - Type
	Part A questionnaire		
Section 2 (Diary of most important trip) - Satisfaction about the most imp trip (q11)			
1	SatCheap	Expensive	1-Not at all to 6-very (6-point likert scale) - Interval
2	SatSpeed	Fast	
3	SatEco	Polluting	
4	SatSafe	Safe with respect to accidents	
5	SatSecure	Secure or towards personal assaults	
6	SatFlexibile	Flexible	
7	SatReliable	Affordable and (constant) compared to the duration of the journey	
8	SatComfort	Comfortable	
9	SatFreeTim	It leaves you free time for other activities while moving	
10	SatCaryObject	It can carry objects	
11	SatAccompany	Easy to pick up/accompany someone	
12	SatLikeMode	I like the mode of transport I use	
Section 3 (Integrated mobility) - Determinants of mode choice (q17)			

13	UseNoAlternativ	I have no other alternative (no train, bus, tram, metro, bicycle, car, etc.)	1-CD to 6-CA (6-point likert scale) - Interval
14	UseCheap	seems to me the cheapest way	
15	UseFast	seems to me the fastest way	
16	UseLeastPolutnt	seem to pollute much less	
17	UseLesAcident	Seem to have less accidents	
18	UseLesAgreson	I have far fewer risks to my personal safety (aggressions, slits, etc.) than alternatives	
19	UseLesDelay	Seem to have less delay	
20	UseWhyLike	I like the mode of transport I use	
21	UseWhyFelFre	I feel freer	
22	UseContctLndscp	I like the contact with the landscape that I have with	
23	UseArriveDest	There's no real reason: The important thing is to get to your destination	
Section 3 (Integrated mobility) – Parking condition for most frequent trip (q19)			
24	Parking_Origin_Availabilty	Availability of car parking near to the origin	1-CD to 6-CA (6-point likert scale) – Interval
25	Parking_Origin_Cost	Cost of car parking near to the origin	
26	Parking_Destin_Availabilty	Availability of car parking near to the destination	
27	Parking_Destin_Cost	Cost of car parking near to the destination	
Section 3 (Integrated mobility) – Activities in PT/car/Bike/Walk during most important trip (q20_SQ00)			
28	Work	I would work/study	1-Never to 6-Always (6-point likert scale) – Interval
29	Read	Read a newspaper/newspaper (also digital/online)	
30	SocialNetwrk	Navigate on social networks	
31	ListenMusic	I would listen to the radio and/or music	
32	WatchMovie	I'd watch a movie/video/TV series	
33	Relax	I would rest	
34	Think	I think/reflect	
35	Landscape	I'd look at the landscape	
36	Call	I'd call someone on the phone	
37	Chatting	I would write a message/chatting	
38	TalkFriend	I'd chat with travel companion	
39	TalkStranger	I'd chat with traveler I don't know	
Section 3 (Integrated mobility) – Activities in Autonomous Vehicle (AV) during most important trip (q20AV_SQ00)			
40	AV_Work	I would work/study in AV	1-Never to 6-Always (6-point likert scale) – Interval
41	AV_Read	Read a newspaper/newspaper (also digital/online) in AV	
42	AV_SocialNetwrk	Navigate on social networks in AV	
43	AV_ListenMusic	I would listen to the radio and/or music in AV	
44	AV_WatchMovie	I'd watch a movie/video/TV series in AV	
45	AV_Relax	I would rest in AV	
46	AV_Landscape	I'd look at the landscape in AV	
47	AV_Call	I'd call someone on the phone in AV	
48	AV_Chatting	I would write a message/chatting in AV	
49	AV_TalkFriend	I'd chat with travel companion in AV	

		Section 3 (Integrated mobility) – Perceived quality of PT services (q21)	
50	PT_LowerPrice	Importance of lower price of PT ticket	1-Not at all to 6-very (6-point likert scale) – Interval
51	PT_MoreSpeed	Importance of more speed of PT	
52	PT_MoreFreq	Importance of more frequency of PT	
53	PT_OnTime	Importance of more punctuality of PT	
54	PT_MoreComfort	Importance of more comfort of PT	
55	PT_More_eTicket	Importance of more e-ticket of PT	
56	PT_MoreIntegration	Importance of more integration of PT	
57	PT_MoreClean	Importance of more cleaning of PT	
58	PT_MoreSecurity	Importance of more security of PT	
		Section 4 (Mobility as a Service) – Willingness to purchase car for shred use (q31y)	
59	JoinGAS	Willingness to join in a fair buying group to purchase a car	1-Absolutely not to 6 Absolutely yes – Interval
		Section 4 (Mobility as a Service) – Willingness to using car pooling (q35y)	
60	CarPooling_Pax	Willingness to do car pooling, as driver	1-CD to 6-CA (6-point likert scale) – Interval
61	CarPooling_Driver	Willingness to do car-pooling, as passenger	
		Section 4 (Mobility as a Service) – Willingness to use mobility packages (q27)	
62	MobilityPackages	Willigness to use a Mobility Packages	1-Absolutely not to 6 Absolutely yes - Interval
		Section 4 (Mobility as a Service) – Preferences towards managing travel tickets (q39y)	
63	PaperTicket	Preference to paper ticket	1-Absolutely not to 6 Absolutely yes - Interval
64	SmartphoneTicket	Preference to load ticket on smartphone	
65	SmartCardTicket	Preference to load ticket on smartcard	
		Section 5 (Attitudes and preferences) - Attitudes towards car use (q38)	
66	LikeDriving	I like driving	1-CD to 6-CA (6-point likert scale) - Interval
67	CleanCar	I force my self to keep clean car	
68	ToBePassengerInCar	I prefer to be passenger	
69	ShareCarFriends	I like sharing car with friends	
70	ShareCarUnknown	I like sharing car with unknown	
71	DriveUnkownRoad	like driving along unknown road	
72	NoDriveBigCity	I avoid driving in big cities	
73	NoDriveNight	I avoid to drive during night	
74	DriveDrinkBeer	I drive also after I drank a pint of beer	
75	UsuallyPassenger	I often passenger of my friends/partner in car	
76	DriveSlower120	I usually drive less than 120 km/h in motorway	
		Section 5 (Attitudes and preferences) - GEB (q39)	
77	Heating	I turn off the heat at night	1-CD to 6-CA (6-point likert scale) - Interval
78	LaundryFull	I wait until I have a full load before doing my laundry	
79	OpenWindowWinter	In winter, I leave the windows wide open for long periods of time to let in fresh air	
80	LaundrySoftner	I use fabric softener with my laundry	
81	BioProducts	I always look to buy vegetables from biological agriculture	
82	SellOldItems	Sometimes, I sell goods I don’t use anymore	
83	BuySecondHand	Sometimes, I buy second hands goods	

84	GiveOutOld	Sometimes, I offer goods I don't use anymore	
85	LendItems	Sometimes, I rent for free to someone, goods I occasionally use	
86	EatLessMeat	I eat less meat than years ago	
87	CharityToHomeless	Sometimes I give money to panhandlers	
88	CharityToOrganisation	From time to time, I give money to charity	
89	GiveSeatElderly	If an elderly or disabled person enters a crowded PT vehicle, I offer him/her my seat	
90	CriminalRecords	If I were an employer, I would not hesitate to hire a person previously convicted of crime	
91	TravelWithoutTickets	Sometimes I ride public transport without paying a fare	
92	NotCareWaste	I put dead batteries in the garbage	
93	Recycling	I sort glass wastes for recycling	
94	ReuseShopBag	I re-use plastic bag from the groceries	
95	CannedDrinks	I sometimes buy beverage in cans	
96	ChatProEnvironment	I often talk with friends about problems related to the environment	
97	EnvOrganActivities	I am a member of an environmental organization	
98	ProEnvBehaviour	In the past, I have pointed out to someone his or her un-ecological behaviour	
99	SupportEnvOrganisation	I sometimes contribute financially to environmental organizations	
100	NoOGMProducts	I boycott companies using OGM or pesticides	
	Section 5 (Attitudes and preferences) – Attitudes towards travelling (q41)		
101	LikDiscNewPlace	I like to move around looking for new places	
102	LikDareTravl	I prefer adventurous travel	1-CD to 6-CA (6-point likert scale) - Interval
103	LikRechUnknDest	I'm willing to move to achieve unknown destinations	
104	LikTravlAltrntiv	I like to experiment with different travel alternatives to reach the same destination	
105	LikMovOutNeed	I move essentially out of necessity	
106	LikNoFarHom	I'd rather not stay too far from home	
107	LikThinkAlon	I move to be alone, reflect, think	

Table A3: List of variables used initially in the mode choice model

No.	Label	Variable	Scale-Type
	Part I questionnaire		
	Section 1 - Satisfaction about the most imp trip		
1	SatCheap	Expensive	1-Not at all to 6-very (6-point likert scale) - Interval
2	SatSpeed	Fast	
3	SatEco	Polluting	
4	SatSafe	Safe with respect to accidents	
5	SatSecure	Secure or towards personal assaults	
6	SatFlexibile	Flexible	
7	SatReliable	Affordable and (constant) compared to the duration of the journey	
8	SatComfort	Comfortable	

9	SatFreeTim	It leaves you free time for other activities while moving	
10	SatCaryObject	It can carry objects	
11	SatAccompany	Easy to pick up/accompany someone	
12	SatLikeMode	I like the mode of transport I use	
	Section 2 - Determinants of mode choice		
13	UseNoAlternativ	I have no other alternative (no train, bus, tram, metro, bicycle, car, etc.)	1-CD to 6-CA (6-point likert scale) - Interval
14	UseCheap	seems to me the cheapest way	
15	UseFast	seems to me the fastest way	
16	UseLeastPolutnt	seem to pollute much less	
17	UseLesAcident	Seem to have less accidents	
18	UseLesAgreson	I have far fewer risks to my personal safety (aggressions, slits, etc.) than alternatives	
19	UseLesDelay	Seem to have less delay	
20	UseWhyLike	I like the mode of transport I use	
21	UseWhyFelFre	I feel freer	
22	UseContctLndscp	I like the contact with the landscape that I have with	
23	UseArriveDest	There's no real reason: The important thing is to get to your destination	
13	UseNoAlternativ	I have no other alternative (no train, bus, tram, metro, bicycle, car, etc.)	
	Section 3 - Activities in PT/car/Bike/Walk		
24	Work	I would work/study	1-Never to 6-Always (6-point likert scale) - Interval
25	Read	Read a newspaper/newspaper (also digital/online)	
26	SocialNetwrk	Navigate on social networks	
27	ListenMusic	I would listen to the radio and/or music	
28	WatchMovie	I'd watch a movie/video/TV series	
29	Relax	I would rest	
30	Think	I think/reflect	
31	Landscape	I'd look at the landscape	
32	Call	I'd call someone on the phone	
33	Chatting	I would write a message/chatting	
34	TalkFriend	I'd chat with travel companion	
35	TalkStanger	I'd chat with traveler I don't know	
	Section 4 - Attitudes towards travelling		
36	LikDiscNewPlace	I like to move around looking for new places	1-CD to 6-CA (6-point likert scale) - Interval
37	LikDareTravl	I prefer adventurous travel	
38	LikRechUnknDest	I'm willing to move to achieve unknown destinations	
39	LikTravlAltrntiv	I like to experiment with different travel alternatives to reach the same destination	
40	LikMovOutNeed	I move essentially out of necessity	
41	LikNoFarHom	I'd rather not stray too far from home	
42	LikThinkAlon	I move to be alone, reflect, think	
	Part II questionnaire		
	Section 5 - Attitudes to transport and the environment		
43	CongWorsAirPollutn (AC2)	Congestion worsens air pollution	1-CD to 6-CA
44	ChoseModEnvImp (AR1)	I take into account the environmental impact to choose the means of transport	

45	PersResRedEnvImp (AR2, A2)	It is my personal responsibility to reduce the greenhouse gas emissions that cause climate change	(6-point likert scale) - Interval
46	PolcyEncourgEnvImp (SN1, Inn1)	I expect the policy to encourage me to reduce the environmental impact of my travels	
47	FamlyPresurEnvImp (SN2, Inn2)	I expect my family and friends to put pressure on meto see the environmental impact ofmy travels	
48	ProbNoisPollutn (PA1)	Noise pollution is a real problem for the city of Turin	
49	ProbAirPollutn (PA2)	Air pollution is a real problem for the city of Turin	
	Section 6 – Car travel attitude		
51	AFF	I like to drive	NA, 1-CD to 6-CA (6-point likert scale) - Interval
	Section7 – Personal details		
52	Home	Where do you live?	Trinomial

Appendix B – Supplementary statistical details

Table B1: Data types (dtypes) of variables used for mobility patterns analysis

S.No.	Variables	Initial dtypes	Pre-processed dtypes
1	Respondent unique ID	int64	int64
2	Date of filling survey	Object	datetime64[ns]
3	District_Origin	Object	Object
4	Region_Origin	Object	Object
5	Latitude_Origin	Object	float64
6	Longitude_Origin	float64	float64
7	Code_Origin	float64	float64
8	Departure_Time	Object	datetime64[ns]
9	Arrival_Time	Object	datetime64[ns]
10	Travel_Duration	float64	float64
11	Travel_Distance	float64	float64
12	Travel_Mode	int64	int64
13	Latitude_Destination	Object	float64
14	Longitude_ Destination	Object	float64
15	District_Destination	Object	Object
16	Region_Destination	Object	Object
17	Code_Destination	float64	float64
18	Travel_Purpose	int64	int64
Total	**18**	**3**	**4**

Table B2: Features with only missing values

S.No.	Features	Count
1	District_Origin	287
2	Code_Origin	287

3	Departure_Time	590
4	Arrival_Time	590
5	Travel_Distance	183
6	Latitude_Destination	181
7	Longitude_Destination	181
8	District_Destination	429
9	Region_Destination	140
Total	**9**	**3082**

Table B3: Columns excluded with missing values after data preprocessing

No.	variable	Missing rows
1	LikeDriving	274
2	CleanCar	433
3	ToBePassengerInCar	232
4	ShareCarFriends	302
5	ShareCarUnknown	1017
6	DriveUnkownRoad	362
7	NoDriveBigCity	437
8	NoDriveNight	356
9	DriveDrinkBeer	721
10	UsuallyPassenger	213
11	DriveSlower120	572

Table B4: Cluster and sample median of excluded variables

	4 clusters	**cluster/sample**	**5 clusters**	**cluster/sample**	**Sample**
No.	**Variables**	**median**	**Variables**	**Median**	**Std**
1	Parking_Origin_Cost	1.0,	Parking_Origin_Cost	1.0	1.7
2	WatchMovie	1.0	WatchMovie	1.0	0.63
3	TalkStranger	1.0	TalkStranger	1.0,	0.68
4	PT_MoreSpeed	5.0,	PT_MoreSpeed	5.0,	1.32
5	BioProducts	3.0,	BioProducts	3.0 (one 4)	1.43
6	CharityToOrganisation	3.0,	CharityToOrganisation	3.0 (one 4)	1.64
7	GiveSeatElderly	6.0,	GiveSeatElderly	6.0,	1.01
8	TravelWithoutTickets	1.0,	TravelWithoutTickets	1.0,	1.22
9	NotCareWaste	1.0,	NotCareWaste	1.0,	1.4
10	Recycling	6.0,	Recycling	6.0,	1.01
11	ReuseShopBag	6.0,	ReuseShopBag	6.0,	0.97
12	EnvOrganActivities	1.0,	EnvOrganActivities	1.0,	1.21
13	LikMovOutNeed	3.0,	LikMovOutNeed	3.0,	1.52
14	LikNoFarHom	2.0	LikNoFarHom	2.0,	1.36

Table B5: Within cluster medians

	Within cluster median					
variables	**1**	**2**	**3**	**4**	**5**	**6**
Parking_Origin_Cost	1	1	1	1	1	1

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

BioProducts	3	3	3	3	3	3
CharityToOrganisation	3	3	3	3	3	3

Table B6: Kruskal-Wallis and chi square test result of socio-eco and demographic variables

No.	Variables	Chi-Square	df	*p* value	Remark
1	Gender	21.108	15	.133	InSig.
2	Age	106.393	5	.000	Sig.
3	Handicap	2.835	5	.725	InSig
4	Occupation	148.402	55	.000	Sig
5	Household size	33.770	5	.000	Sig.
6	Kids in household	33.826	5	.000	Sig.
7	Owned cars	13.583	5	.018	Sig.
8	Household income	4.412	5	.492	InSig
9	Degree	15.967	5	.007	Sig

Table B7: Kruskal-Wallis and chi square test results of variables related to mobility patterns

No.	variables	Chi-Square	df	*p* value	Remark
1	Travel mode	85.125	55	.006	Sig.
2	Travel distance	13.805	5	.017	Sig.
3	Travel purpose	105.609	30	.000	Sig
4	Travel time	2.093	5	.836	InSig
5	frequency of most important trip	4.553	5	.473	InSig

Table B8: Approximate relationships between the person measures

PCA Contrast	Item Clusters	Pearson Correlation	Disattenuated Correlation	Cluster Sizes
1	1 - 3	0.0220	0.0587	8 – 13
1	1 - 2	0.0868	1.0000	8 – 5
1	2 - 3	0.4401	1.0000	5 – 13

Table B9: Largest standardized residual correlations used to identify dependent items

		Entry		Entry	
No.	Correlation	Number	Item	Number	Item
1	0.39	15	CE9	16	CE14
2	0.27	1	CS1	2	CS2
3	0.25	13	CE7	14	CE8
4	0.22	21	V2	23	V4
5	0.21	20	V1	22	V3
6	0.20	7	R5	18	RR1
7	0.15	8	AE4	9	AE5
8	0.14	12	CE6	24	V5
9	-0.21	19	RR2_REVC	20	V1
10	-0.18	16	CE14	19	RR2_REVC
11	-0.17	15	CE9	25	T1
12	-0.16	10	AE6_REVC	12	CE6

13	-0.14	23	V4	25	T1
14	-0.14	4	CS4	16	CE14
15	-0.14	15	CE9	19	RR2_REVC
16	-0.14	5	CS6_REVC	14	CE8
17	-0.14	11	CE1_REVC	15	CE9
18	-0.14	11	CE1_REVC	12	CE6
19	-0.14	16	CE14	24	V5
20	-0.13	16	CE14	25	T1

Table B10: DIF by gender based on MH statistics

Groups	Chi square	*p* value	Size CUMLOR	Item no.	Item
Female, Male	5.7312	0.02	0.18	1	CS1
Female, Male	5.7443	0.02	0.18	2	CS2
Female, Male	0.5940	0.44	-0.11	3	CS3
Female, Male	3.9364	0.05	-0.13	4	CS4
Female, Male	0.9691	0.32	0.11	5	CS6_REVC
Female, Male	3.5024	0.06	-0.19	6	R1_REVC
Female, Male	0.3538	0.55	-0.10	7	R5
Female, Male	3.8502	0.05	-0.15	8	AE4
Female, Male	0.7917	0.37	-0.11	9	AE5
Female, Male	0.1955	0.66	-0.03	10	AE6_REVC
Female, Male	0.1191	0.73	0.02	11	CE1_REVC
Female, Male	0.4621	0.50	0.05	12	CE6
Female, Male	3.2893	0.07	-0.14	13	CE7
Female, Male	12.2603	0.00	-0.26	14	CE8
Female, Male	62.5887	0.00	0.63	15	CE9
Female, Male	1.0495	0.31	0.08	16	CE14
Female, Male	12.0450	0.00	0.25	17	CE15
Female, Male	4.7658	0.03	0.34	18	RR1
Female, Male	5.6486	0.01	0.15	19	RR2_REVC
Female, Male	38.1454	0.00	-0.47	20	V1
Female, Male	9.7647	0.00	-0.41	21	V2
Female, Male	1.3151	0.25	-0.09	22	V3
Female, Male	3.7809	0.05	-0.21	23	V4
Female, Male	0.2093	0.65	0.04	24	V5
Female, Male	11.9880	0.00	-0.24	25	T1
Female, Male	17.0990	0.00	0.29	26	T2

Table B11: DIF by residential location based on MH statistics

Groups	Chi square	*p* value	Size CUMLOR	Item no.	Item
Urban, Rural	0.02	0.86	0.02	1	CS1
Urban, Suburban	1.34	0.24	0.13	1	CS1
Urban, Rural	6.29	0.01	0.21	2	CS2
Urban, Suburban	1.78	0.18	0.14	2	CS2
Urban, Rural	6.27	0.01	-0.41	3	CS3
Urban, Suburban	5.12	0.02	-0.42	3	CS3
Urban, Rural	2.05	0.15	0.11	4	CS4

Urban, Suburban	0.09	0.75	0.03	4	CS4
Urban, Rural	4.99	0.02	0.29	5	CS6_REVC
Urban, Suburban	0.42	0.51	0.10	5	CS6_REVC
Urban, Rural	1.21	0.26	0.13	6	R1_REVC
Urban, Suburban	2.97	0.08	0.26	6	R1_REVC
Urban, Rural	23.50	0.00	0.90	7	R5
Urban, Suburban	21.46	0.00	1.12	7	R5
Urban, Rural	0.02	0.87	0.02	8	AE4
Urban, Suburban	0.00	0.99	-0.01	8	AE4
Urban, Rural	0.11	0.73	-0.05	9	AE5
Urban, Suburban	0.06	0.79	-0.05	9	AE5
Urban, Rural	0.01	0.90	-0.01	10	AE6_REVC
Urban, Suburban	0.73	0.39	-0.09	10	AE6_REVC
Urban, Rural	0.43	0.50	0.05	11	CE1_REVC
Urban, Suburban	1.19	0.27	-0.10	11	CE1_REVC
Urban, Rural	7.69	0.00	0.24	12	CE6
Urban, Suburban	9.19	0.00	0.31	12	CE6
Urban, Rural	1.03	0.30	-0.09	13	CE7
Urban, Suburban	0.49	0.48	0.08	13	CE7
Urban, Rural	9.23	0.00	-0.25	14	CE8
Urban, Suburban	4.44	0.03	-0.22	14	CE8
Urban, Rural	1.57	0.20	-0.11	15	CE9
Urban, Suburban	0.49	0.48	0.08	15	CE9
Urban, Rural	10.34	0.00	-0.27	16	CE14
Urban, Suburban	0.29	0.58	-0.06	16	CE14
Urban, Rural	13.45	0.00	-0.30	17	CE15
Urban, Suburban	7.21	0.00	-0.27	17	CE15
Urban, Rural	0.06	0.79	0.06	18	RR1
Urban, Suburban	0.12	0.72	0.09	18	RR1
Urban, Rural	3.31	0.06	0.13	19	RR2_REVC
Urban, Suburban	0.00	0.97	0.01	19	RR2_REVC
Urban, Rural	17.81	0.00	-0.36	20	V1
Urban, Suburban	6.77	0.00	-0.27	20	V1
Urban, Rural	1.35	0.24	-0.18	21	V2
Urban, Suburban	0.77	0.37	0.16	21	V2
Urban, Rural	4.71	0.03	-0.18	22	V3
Urban, Suburban	1.90	0.16	-0.14	22	V3
Urban, Rural	0.04	0.82	-0.03	23	V4
Urban, Suburban	1.26	0.26	0.16	23	V4
Urban, Rural	0.05	0.80	0.03	24	V5
Urban, Suburban	1.21	0.26	0.13	24	V5
Urban, Rural	34.44	0.00	0.44	25	T1
Urban, Suburban	2.50	0.11	-0.16	25	T1
Urban, Rural	0.45	0.50	-0.06	26	T2
Urban, Suburban	0.05	0.81	0.03	26	T2

Table B12: Estimates of initial RSM item parameters, infit, outfit, and point biserial correlations (items ordered by increasing point measure correlation)

Entry No.	Total Score	Measure	Model S.E.	Infit		Outfit		Point-bis. Corr.		Exact Match (%)		Item
				MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	
4	15655	0.11	0.01	1.09	5.26	1.27	9.90	-0.01	0.41	23.7	20.1	CS4
10	18094	-0.14	0.01	1.03	1.67	1.18	8.44	0.09	0.39	25.7	21.0	AE6_revc
5	22688	-0.85	0.02	1.61	9.90	1.84	9.90	0.15	0.27	41.1	42.0	CS6_revc
25	13351	0.20	0.01	1.50	9.90	1.60	9.90	0.20	0.41	13.3	20.3	T1
19	15065	0.17	0.01	1.18	9.90	1.24	9.90	0.21	0.42	19.0	20.3	RR2_revc
6	22446	-0.79	0.02	1.80	9.90	1.96	9.90	0.23	0.28	34.8	38.3	R1_revc
11	14426	0.23	0.01	1.33	9.90	1.37	9.90	0.28	0.42	14.8	20.5	CE1_revc
26	12414	0.26	0.01	1.15	8.21	1.18	9.28	0.29	0.41	18.0	20.6	T2
18	23546	-1.12	0.02	1.39	8.41	1.21	4.48	0.34	0.23	69.8	64.2	RR1
7	23687	-1.18	0.02	1.67	9.90	1.36	7.15	0.35	0.22	76.6	68.2	R5
3	22705	-0.85	0.02	0.95	-1.37	0.88	-3.40	0.37	0.27	46.2	42.1	CS3
8	19060	-0.25	0.01	1.19	9.29	1.21	8.91	0.38	0.38	16.9	21.9	AE4
13	11785	0.50	0.01	0.98	-0.80	0.98	-0.99	0.39	0.41	24.1	22.7	CE7
9	21567	-0.61	0.01	0.84	-6.22	0.85	-5.24	0.39	0.31	36.0	29.4	AE5
14	12772	0.40	0.01	0.92	-4.82	0.92	-4.61	0.43	0.42	23.0	21.8	CE8
1	11782	0.50	0.01	0.92	-4.43	0.91	-4.48	0.43	0.41	24.9	22.7	CS1
21	7165	1.22	0.02	1.23	6.58	1.07	2.10	0.46	0.31	38.0	37.5	V2
16	15992	0.08	0.01	0.76	-9.90	0.76	-9.90	0.49	0.41	27.1	20.1	CE14
2	13542	0.32	0.01	0.86	-8.86	0.86	-8.06	0.49	0.42	22.8	21.1	CS2
15	18035	-0.13	0.01	0.79	-9.90	0.78	-9.90	0.51	0.39	24.4	20.9	CE9
12	13835	0.29	0.01	0.62	-9.90	0.62	-9.90	0.52	0.42	30.8	20.8	CE6
17	15533	0.12	0.01	0.98	-0.93	0.97	-1.69	0.52	0.41	18.1	20.1	CE15
22	16427	0.03	0.01	0.73	-9.90	0.73	-9.90	0.52	0.41	26.5	20.2	V3
24	11104	0.58	0.01	1.04	2.08	1.01	0.65	0.56	0.40	20.5	23.6	V5
23	8957	0.87	0.01	0.93	-2.75	0.85	-5.77	0.57	0.37	28.0	27.0	V4
20	16141	0.06	0.01	0.62	-9.90	0.61	-9.90	0.59	0.41	28.0	20.0	V1
Mean	16068.2	0.00	0.01	1.08	0.8	1.09	0.6	-	-	29.7	28.0	-
P.SD	4507.0	0.58	0.00	0.31	7.7	0.33	7.8	-	-	14.8	13.0	-

Politecnico di Torino - Castello del Valentino – Viale Mattioli 39, 10125 - Torino, Italia
Ph.D. in URBAN AND REGIONAL DEVELOPMENT
Ph: +39 011.090. 6439 /7460
dottorato.d.ist@polito.it - http://dottorato.polito.it/urb

Table B13: Largest standardized residual correlations used to identify dependent items in RSM

		Entry		Entry	
No.	**Correlation**	**Number**	**Item**	**Number**	**Item**
1	0.41	15	CE9	16	CE14
2	0.41	21	V2	2 3	V4
3	0.37	13	CE7	14	CE8
4	0.36	1	CS1	2	CS2
5	0.30	20	V1	22	V3
6	0.27	7	R5	18	RR1
7	0.23	23	V4	25	V5
8	0.22	20	V1	21	V2
9	0.20	2	CS2	23	V4
10	0.19	8	AE4	9	AE5
11	0.18	14	CE8	16	CE14
12	0.18	4	CS4	10	AE6_revc
13	0.18	12	CE6	24	V5
14	-0.23	19	RR2_revc	20	V1
15	-0.20	4	CS4	23	V4
16	-0.18	15	CE9	25	T1
17	-0.18	10	AE6_revc	23	V4
18	-0.18	4	CS4	24	V5
19	-0.18	16	CE14	24	V5
20	-0.17	5	CS6_revc	14	CE8

Table B14: DIF by gender based on M statistics

Groups	**Chi square**	***p* value**	**Size CUMLOR**	**Item no.**	**Item**
Female, Male	4.1033	0.04	0.12	1	CS1
Female, Male	5.9968	0.01	0.14	2	CS2
Female, Male	0.0046	0.95	0.00	3	CS3
Female, Male	1.6239	0.20	-0.07	4	CS4
Female, Male	2.1345	0.14	0.12	5	CS6_revc
Female, Male	0.9247	0.34	-0.09	6	R1_revc
Female, Male	0.1050	0.75	-0.03	7	R5
Female, Male	4.9820	0.03	-0.14	8	AE4
Female, Male	0.0010	0.98	0.00	9	AE5
Female, Male	4.3389	0.04	-0.12	10	AE6_revc
Female, Male	0.0020	0.96	0.00	11	CE1_revc
Female, Male	1.3887	0.24	0.07	12	CE6
Female, Male	4.9111	0.03	-0.13	13	CE7
Female, Male	17.4524	0.00	-0.24	14	CE8
Female, Male	96.2642	0.00	0.59	15	CE9
Female, Male	0.4292	0.51	0.04	16	CE14
Female, Male	20.1917	0.00	0.27	17	CE15
Female, Male	4.3687	0.04	0.19	18	RR1
Female, Male	3.6210	0.06	0.11	19	RR2_revc
Female, Male	46.1839	0.00	-0.40	20	V1

Female, Male	12.6097	0.00	-0.27	21	V2
Female, Male	3.1137	0.08	-0.10	22	V3
Female, Male	10.8447	0.00	-0.22	23	V4
Female, Male	0.3705	0.54	-0.04	24	V5
Female, Male	7.6759	0.04	-0.17	25	T1
Female, Male	19.5354	0.00	0.27	26	T2

Table B15: DIF by residential location based on M statistics

Groups	Chi square	*p* value	Size CUMLOR	Item no.	Item
Urban, Rural	0.05	0.83	0.01	1	CS1
Urban, Suburban	0.85	0.36	0.07	1	CS1
Urban, Rural	6.99	0.01	0.17	2	CS2
Urban, Suburban	0 .29	0.59	0.04	2	CS2
Urban, Rural	13.18	0.00	-0.30	3	CS3
Urban, Suburban	13.27	0.00	-0.35	3	CS3
Urban, Rural	3.36	0.07	0.12	4	CS4
Urban, Suburban	0.02	0.89	0.01	4	CS4
Urban, Rural	10.17	0.00	0.30	5	CS6_revc
Urban, Suburban	0.91	0.34	0.11	5	CS6_revc
Urban, Rural	0.69	0.40	0.09	6	R1_revc
Urban, Suburban	0.07	0.79	-0.03	6	R1_revc
Urban, Rural	17.87	0.00	0.52	7	R5
Urban, Suburban	8.79	0.00	0.45	7	R5
Urban, Rural	0.09	0.76	-0.02	8	AE4
Urban, Suburban	0.22	0.64	0.04	8	AE4
Urban, Rural	1.41	0.24	-0.09	9	AE5
Urban, Suburban	1.51	0.22	-0.11	9	AE5
Urban, Rural	0.46	0.49	-0.04	10	AE6_revc
Urban, Suburban	0.62	0.43	-0.06	10	AE6_revc
Urban, Rural	0.05	0.82	0.01	11	CE1_revc
Urban, Suburban	0.06	0.81	0.02	11	CE1_revc
Urban, Rural	8.29	0.00	0.19	12	CE6
Urban, Suburban	8.42	0.00	0.23	12	CE6
Urban, Rural	1.28	0.26	-0.08	13	CE7
Urban, Suburban	0.34	0.56	0.05	13	CE7
Urban, Rural	5.92	0.01	-0.16	14	CE8
Urban, Suburban	0.91	0.34	-0.08	14	CE8
Urban, Rural	0.01	0.91	-0.01	15	CE9
Urban, Suburban	1.10	0.29	0.09	15	CE9
Urban, Rural	9.12	0.00	-0.20	16	CE14
Urban, Suburban	0.87	0.35	-0.07	16	CE14
Urban, Rural	19.70	0.00	-0.29	17	CE15
Urban, Suburban	10.70	0.00	-0.27	17	CE15
Urban, Rural	0.55	0.46	0.07	18	RR1
Urban, Suburban	0.62	0.43	0.10	18	RR1
Urban, Rural	6.66	0.01	0.16	19	RR2_revc
Urban, Suburban	0.36	0.55	0.05	19	RR2_revc

Urban, Rural	22.36	0.00	-0.31	20	V1
Urban, Suburban	7.68	0.01	-0.22	20	V1
Urban, Rural	0.02	0.89	-0.01	21	V2
Urban, Suburban	2.44	0.12	0.16	21	V2
Urban, Rural	6.91	0.01	-0.17	22	V3
Urban, Suburban	0.21	0.64	-0.04	22	V3
Urban, Rural	0.33	0.57	-0.04	23	V4
Urban, Suburban	0.06	0.81	0.02	23	V4
Urban, Rural	1.67	0.19	-0.09	24	V5
Urban, Suburban	0.92	0.34	0.08	24	V5
Urban, Rural	36.28	0.00	0.41	25	T1
Urban, Suburban	0.94	0.33	-0.08	25	T1
Urban, Rural	0.66	0.42	0.06	26	T2
Urban, Suburban	1.45	0.23	0.10	26	T2

Table B16: DIF by age based on M statistics

Groups	Chi square	*p* value	Size CUMLOR	Item no.	Item
Old, Medium	31.28	0.00	-0.43	1	CS1
Old, Young	51.44	0.00	-0.52	1	CS1
Old, Medium	64.17	0.00	-0.61	2	CS2
Old, Young	99.99	0.00	-1.08	2	CS2
Old, Medium	2.29	0.13	-0.14	3	CS3
Old, Young	1.17	0.28	-0.10	3	CS3
Old, Medium	3.06	0.08	-0.13	4	CS4
Old, Young	0.14	0.71	-0.03	4	CS4
Old, Medium	75.31	0.00	-1.02	5	CS6_revc
Old, Young	99.99	0.00	-1.24	5	CS6_revc
Old, Medium	1.15	0.28	0.14	6	R1_revc
Old, Young	4.34	0.04	0.24	6	R1_revc
Old, Medium	2.98	0.08	0.27	7	R5
Old, Young	2.88	0.09	-0.22	7	R5
Old, Medium	0.23	0.63	0.04	8	AE4
Old, Young	12.03	0.00	-0.26	8	AE4
Old, Medium	18.39	0.00	0.38	9	AE5
Old, Young	37.89	0.00	0.51	9	AE5
Old, Medium	0.16	0.69	0.03	10	AE6_revc
Old, Young	9.90	0.00	-0.23	10	AE6_revc
Old, Medium	15.21	0.00	-0.29	11	CE1_revc
Old, Young	30.72	0.00	-0.39	11	CE1_revc
Old, Medium	0.66	0.42	0.06	12	CE6
Old, Young	8.32	0.00	0.21	12	CE6
Old, Medium	38.71	0.00	0.48	13	CE7
Old, Young	89.35	0.00	0.69	13	CE7
Old, Medium	92.97	0.00	0.75	14	CE8
Old, Young	99.99	0.00	1.05	14	CE8
Old, Medium	3.38	0.07	-0.15	15	CE9
Old, Young	7.75	0.01	-0.20	15	CE9

Old, Medium	44.02	0.00	0.52	16	CE14
Old, Young	99.99	0.00	0.92	16	CE14
Old, Medium	5.78	0.02	-0.18	17	CE15
Old, Young	88.57	0.00	-0.67	17	CE15
Old, Medium	1.03	0.31	-0.12	18	RR1
Old, Young	4.28	0.04	0.23	18	RR1
Old, Medium	0.22	0.64	-0.03	19	RR2_revc
Old, Young	0.01	0.93	0.01	19	RR2_revc
Old, Medium	4.87	0.03	0.17	20	V1
Old, Young	0.00	0.95	0.00	20	V1
Old, Medium	8.50	0.00	0.27	21	V2
Old, Young	8.42	0.00	0.26	21	V2
Old, Medium	87.94	0.00	0.75	22	V3
Old, Young	99.99	0.00	1.16	22	V3
Old, Medium	8.62	0.00	-0.25	23	V4
Old, Young	48.88	0.00	-0.56	23	V4
Old, Medium	39.76	0.00	-0.50	24	V5
Old, Young	99.99	0.00	-0.96	24	V5
Old, Medium	8.83	0.00	0.24	25	T1
Old, Young	80.18	0.00	0.68	25	T1
Old, Medium	10.76	0.00	-0.26	26	T2
Old, Young	14.19	0.00	0.29	26	T2

Table B17: Descriptive statistics of these 8 variables for EFA for SEM model

Variables	Mean	std. dev.	Variance	Skewness	Kurtosis	Communalities
SatSpeed	3.67	1.679	2.820	-0.069	-1.245	0.495
SatFlexible	3.91	1.756	3.082	-0.220	-1.312	0.553
SatReliable	3.85	1.613	2.601	-0.260	-1.109	0.568
UseLesDelay	3.70	1.853	3.435	-0.137	-1.447	0.524
LikDiscNewPlace	4.61	1.356	1.838	-0.680	-0.467	0.562
LikDareTravel	3.82	1.565	2.448	-0.166	-1.043	0.560
LikRechUnknDest	4.30	1.483	2.199	-0.490	-0.820	0.650
LikTravlAltrntiv	3.79	1.591	2.532	-0.127	-1.160	0.383