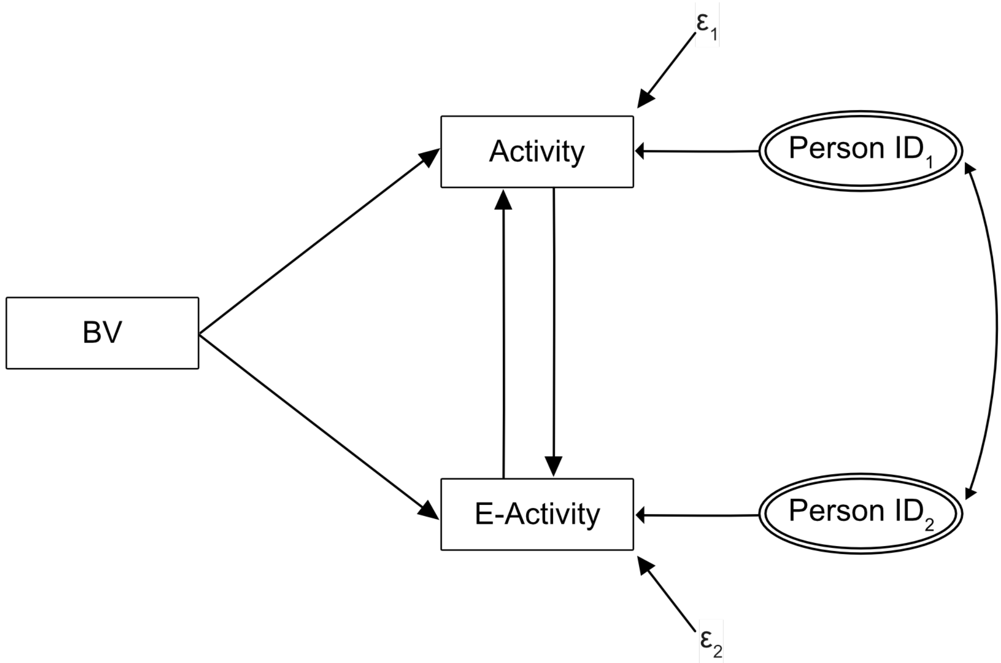

The Interdependencies between Travel Behaviour and ICT Use in Zurich: Using SEM

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Assistance: Basil Schmid

Master thesis
Institute for Transport Planning and Systems **July 2016**

Institut für Verkehrsplanung und Transportsysteme
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Acknowledgement

I would like to thank Basil Schmid for his help during the whole process of working on my Master Thesis. His inputs and understanding of the matter were crucial for me. Additionally, Prof. Dr. Kay W. Axhausen did push me in the right direction during our monthly meetings. This has been a great help. Milos Balac is also to be mentioned, since with his expertise it was possible to gather additional information about the population using his routing algorithm.

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Acronyms

AIC Akaike Information Criterion

AICc Akaike Information Criterion with small sample size correction

ICT Information and Communications Technologies

MATSim Multi-Agent Transport Simulation

ML Maximum Likelihood

MZ Mikrozensus 2010

QML Quasi Maximum Likelihood

SEM Structural Equation Modelling

RMSEA Root Mean Square Error of Approximation

Master thesis

The Interdependencies between Travel Behaviour and ICT Use in Zurich: Using SEM

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Abstract

In recent years people became more aware of the possibilities given by the internet and related technologies. Shopping online or communicating through these new devices is now broadly accepted. This work is an attempt to find interdependencies between Information and Communications Technologies (ICT) usage and travel behaviour. In other words, do online activities influence travel behaviour on a daily basis? A Structural Equation Modelling (SEM) approach has been employed. Due to its capabilities among others to estimate several relationships at once, it was deemed a valuable tool. The data used has been collected in the «Post-Car-World» study, an interdisciplinary project trying to find out how people react to changed boundary conditions (e.g. increased travel costs) in their daily life and also for long-term decisions. To use the data, it had to be cleaned, validated and aggregated. Numerous models have been estimated, including the activities of either all types or just specific purposes (e.g. leisure, shopping). These models consisted in relating out-of-home activities with online activities of the same purpose. The findings in this work indicate a relationship between online and out-of-home activities and also their durations. These interdependencies are different according the observed purpose. Shopping for long term goods (e.g. furniture, jewellery) decreases the number of online shopping activities whereas in the other direction the effect is opposite. The day of the observation has a significant influence on the number of activities and their durations both online and offline.

Keywords
SEM, ICT vs. out-of-home activities, Zurich, travel behavior

Preferred citation style

Fuchs, P.A. (2016) The Interdependencies between Travel Behaviour and ICT Use in Zurich: Using SEM, Master thesis, Institute for Transport Planning and Systems, ETH Zurich, Zurich.

Masterarbeit

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Zusammenfassung

Die Menschen nutzen die Möglichkeiten immer intensiver, die sich ihnen durch das Internet und ähnliche Technologien bieten: Online einzukaufen oder mit elektronischen Geräten zu kommunizieren, sind in der heutigen Zeit selbstverständlich. Diese Arbeit versucht, Zusammenhänge zwischen der Nutzung von Informationstechnologie und dem Reiseverhalten der Menschen zu finden. Ein Ziel war, herauszufinden, ob und wie Online-Aktivitäten unser tägliches Reiseverhalten beeinflussen. Dazu wurde ein Strukturgleichungsmodell-Ansatz angewandt. Dieser ist ideal, weil er die Fähigkeit hat, simultan verschiedene Beziehungen zu schätzen. Die benötigten Daten stammen aus der «Post-Car-World»-Studie. Bei diesem interdisziplinären Projekt wurde versucht herauszufinden, wie Menschen auf geänderte Rahmenbedingungen (wie z.B. erhöhte Reisekosten) in ihrem täglichen Leben kurz- und langfristig reagieren. Um die Daten zu nutzen, mussten sie zuerst bereinigt, validiert und aggregiert werden. Verschiedenste Modelle wurden geschätzt, wobei auch nach Zweck unterschieden wurde (z.B. Freizeit, Einkaufen). Diese Modelle setzen ausser Haus- und Online-Aktivitäten vom gleichen Zweck in Relation. Die Schätzungsergebnisse dieser Arbeit zeigen, dass eine Beziehung zwischen ausser Haus- und Online-Aktivitäten besteht. Jedoch unterscheiden sie sich nach beobachtetem Zweck. Einkaufen für Produkte wie Möbel oder Schmuck vermindert die Anzahl Online-Shopping-Aktivitäten, wobei in entgegengesetzter Richtung der Effekt umgekehrt ist. Der Wochentag, an dem beobachtet wurde, hat ebenfalls einen signifikanten Einfluss auf die Aktivitätsanzahl und deren Dauer.

Schlüsselwörter

SEM, online vs. ausser Haus Aktivitäten, Zürich, Reiseverhalten

Bevorzugter Zitierstil

Fuchs, P.A. (2016) The Interdependencies between Travel Behaviour and ICT Use in Zurich: Using SEM, Masterarbeit, Institut für Verkehrsplanung und Transportsysteme, ETH Zürich, Zürich.

1 Introduction

In recent years, people have started to use Information and Communications Technologies (ICT) with an increasing rate. They got used to gather information and started to accomplish an increasing number of tasks with these new tools and possibilities (e.g. shopping online or communicating electronically). Since these new activities are time-consuming and in some ways challenge established daily plans, they must be considered in travel behaviour research. Furthermore, possible interdependencies between ICT usage and other daily activities (i.e. with travel behaviour) should be investigated. In what way does the usage of ICT influence the pattern of daily activities and vice versa? Do they modify, generate or replace some part of the people's daily travel? Finding answers to these questions is the main goal of this work.

A model is implemented to estimate these effects. It is able to treat panel structure as well as interactions between several dependent variables. To do so a Structural Equation Modelling (SEM) approach has been employed, due to its ability to treat exogenous and endogenous variables simultaneously and that total, direct and indirect effects can be investigated at the same time (Golob, 2003). It is a main part of SEM to find covariances and therefore correlations. This could raise questions like: Is the amount of shopping trips influenced by the number of online shopping-activities or is there an effect in the opposite direction? SEM are consequently a valuable tool to use in this work.

The data used to answer these questions has been collected as part of the «Post-Car-World» study (e.g. Schmid and Axhausen (2015); Schmid et al. (2016a,b,c); for additional information see also http://postcarworld.epfl.ch/). This is an interdisciplinary project of the Eidgenössische Technische Hochschule Zürich (ETHZ), the École Polytechnique Fédérale de Lausanne (EPFL) and the Università della Svizzera Italiana (USI), Lugano. The main goal of this project is to find out how individuals react and rearrange their daily schedule to changing generalized transport costs (Weis, 2012) (i.e. through restricted car usage or other policy changes). Both short and long term reactions are observed using stated and revealed preference data. Thus the conclusions of this work will contribute to that project. The region studied is the metropolitan area of Zurich in Switzerland.

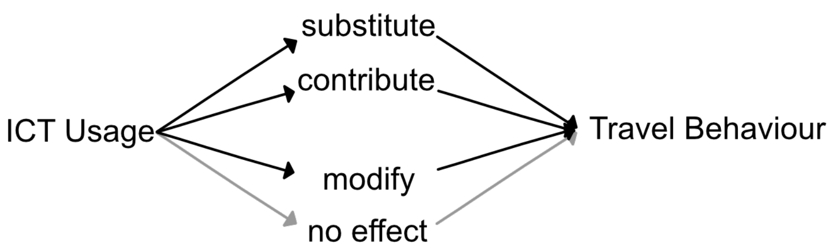
The following work is structured as follows: The first part (section 2) consists of a literature review, section 3 treats the SEM-Theory in more detail as well as some implications for the model structure. The following section (4) shows how the data has been collected as well as processed and validated including some descriptive statistics. Section 5 describes the modelling approach (i.e. the main hypotheses formulated and how it was proceeded to get the answers for these). Section 6 shows which models were estimated and gives an overview of the estimation outcomes, section 7 gives an interpretation and finally in section 8 conclusions are drawn. Finally, a brief outline of future research is given in section 9.

2 Literature Review

In order to see what has already been found on interdependencies of ICT with travel behaviour a literature review is presented here. There is more literature on the effects of online shopping on in-store shopping than for leisure activities. This is quite understandable, since understanding peoples shopping behaviour possibly increases benefits for a company. On the other hand, only some parts of all leisure activities are priced and therefore, the willingness to investigate leisure behaviour is rather small. So in the beginning the review is only about shopping (see section 2.1) and then in the end some sources on leisure are discussed in section 2.2.

A review of ICT usage and its possible influence on travel behaviour was made by Salomon (1986). He states that the relationship between ICT and travel behaviour is not unidirectional and there could be three different types of interactions. Either the ICT use substitutes, enhances or complements travel behaviour as shown in Figure 1. Additionally, he indicates that a modification of behaviour is more likely than a substitution. The concept of these three interactions is then further investigated by Mokhtarian (2003). She states that a lot of recent short term studies have found a substitution effect through the use of ICT, but these studies are incomplete and miss subtle effects (i.e. indirect or long-term effects) because in her opinion it is evident that there is no substitution effect. Furthermore, it is stated that there is a relation between ICT and travel behaviour but it is not clear in what way. Though, it could be coincidental that both (mobility and ICT-usage) are increasing in recent years.

Figure 1: Four different types of interactions between ICT and travel behaviour.



Source: Salomon (1986)

Using a representative study of the adult Swiss population of 1999, Axhausen et al. (2000) were able to identify relations between car ownership, PT trips, socio-demographic variables and PT ticket ownership (e.g. season ticket or half-fare card). The conducted study included socio-demographic information as well as the respondents annual mileage and the number of PT trips during one week. The main findings were the dominant influence of car ownership on the other observed variables.

Simma (2000) used Austrian travel data from 1992 with 330'000 respondents. The dataset included information about the household and its members as well as their travel diaries. She then used this data to find relationships between out-of-home activities, residential location and travel behaviour. The employment of men and women is the most important factor influencing travel behaviour.

Due to the lack of existing literature on effects of weekdays onto other weekdays, Simma and Axhausen (2001) tested for these effects. They used the *MOBIdrive* data to observe such effects (Axhausen et al., 2002). In their SEM model different socio-demographic variables are used to describe mobility on a certain day as well as all the other weekdays. They conclude that there is a difference of behaviour according to the observed day. In other words, there is a significant difference between weekday and weekend travel behaviour. Also according to them socio-demographic variables do not have a substantial impact on a persons travel behaviour.

2.1 Shopping

The different ways of shopping (online or in-store) are scrutinised by Mokhtarian (2004), but there seems to be no clear conclusion. Each of them has its specific benefits as well as drawbacks. Furthermore, it is hypothesised that waiting for a purchased good to be delivered is monetarily equivalent to making a trip and buy it immediately. Additionally, she states that it becomes more and more difficult to really count shopping activities because the emergence of ICT has made it possible to fragment the shopping process. It is possible to get information about the product online, touch the product in the shop, compare different shops online and then buy it online or at the cheapest shop. So it is challenging to measure the effects but its worth the effort to better understand the shopping process and it impacts on transportation. Table 1 presents a few relationships found by other authors in their work.

Gould and Golob (1997) looked at data of an American study of 1994, which included roughly 7'000 people in 3'800 households. These people conducted a two day travel and activity diary and gave information about their households. An activity was only recorded if it was longer than 30 minutes. They found that people working from home spend more time on shopping activities than others. They hypothesised that additional electronic home shopping technologies will influence travel behaviour significantly.

Table 1: This table contains a not exclusive list of observed relationships by other authors. The estimated signs shown are direct effects which are highly significant.

Author	Explanatory Variable	Dependent Variable	Estimated Sign
Axhausen et al. (2000)	Being male	PT trips	negative
	Income (Thousand CHF)	PT trips	negative
Bagley and Mokhtarian (2001)	Being female	log(vehicle miles)	negative
	# Vehicles[2]	log(vehicle miles)	positive
	# Vehicles[2]	log(PT miles)	negative
Farag et al. (2007)	Frequency of in-store shopping	Online buying	positive
	Frequency of in-store shopping	Shopping duration per trip	negative
	Being female	Frequency of in-store shopping	positive
	Age (continuous)	Frequency of in-store shopping	negative
	Income (three categories)	Frequency of in-store shopping	positive
	# Vehicles (0, 1, >1)	Frequency of in-store shopping	negative
Ferrell (2004)	# Vehicles	Shopping trips per household	positive
	Home shopping activities	Shopping trips per household	positive
Ferrell (2005)	Being employed	Shopping trips per person	positive
Gould and Golob (1997)	Age (continuous)	Shopping trips per person	positive
	# Vehicles	Shopping trips per person	positive
Simma (2000)	Car availability (women only)	Shopping trips per person	positive
	Car availability (women only)	Other trips per person	positive
Simma and Axhausen (2001)	Being male	Walk, PT trips	negative
	Being male	Car trips	positive
	Being employed	Walk trips	negative
	Being employed	Car trips	positive
Wang and Yuk (2007)	# Trips	ICT-Experience	positive
	Being employed	# Trips	positive
	Age (continuous)	# Leisure activities	positive

Ferrell (2004) used the San Francisco Bay Area Travel Survey for 2000 (BATS 2000) which is an activity survey conducted with nearly 15'000 inhabitants (Metropolitan Transporation Comission, 2000) to observe for relationships between ICT use and travel behaviour. He has found evidence that shopping from home (by internet, catalogue or television) increases trip-chaining and the amount of shopping trips. Moreover, he states that people with a high accessibility are more likely to chain their trips during one day. Though, these effects could be due to the fact that trip-chaining and home-based shopping both are efficiency tools, meaning either one of those actions increases the utility of one's daily schedule. But no significant relationship between home-based and in-store shopping has been found. Ferrell (2005) worked with the same data but finds different results. He concludes that this is because he looked into the personal diary and not into the aggregated household as in his previous study. He found that people who shop from their home take less time to travel for shopping and make fewer and shorter trips.

Another topic is discussed by Weltevreden (2007). He also lists diverse studies about the impact of online on in-store shopping and vice versa. He concludes that if one looks at shopping behaviour it is crucial to differentiate between different goods, because the effects he found depend on the nature of the good. He conducted an online questionnaire with more than 3'000 participants, who claimed to shop at least once a year in a city in the Netherlands. It asked about the frequency of online shopping as well as what they have bought during the last year. People purchase mainly products of long term use. He states that longitudinal data is of higher importance than cross-sectional data because one needs to evaluate the behaviour over time to see the long term effects.

Farag et al. (2007) write about the concept of task oriented or leisure oriented shopping. For one person the shopping trip is mandatory (e.g. food or groceries) and for another person it is a relaxing activity (e.g. clothing or jewellery). He used data collected by him from Utrecht and some surrounding municipalities in the centre of the Netherlands. It is also crucial to define online shopping properly, because the definition varies between different researchers. There are different parts which could be included like gathering information, comparing products and shops or buying (which is always included). He concludes that online shopping does not lead to fewer shopping trips, but accessibility and internet connection play a large role in the amount of online shopping activities, because urban residents with a fast internet connection shop more online. Accessibility in this context means: The more shopping possibilities are within a certain range the higher the accessibility. He has also found a negative correlation between accessibility and the amount of online shopping activities.

The concept of «three interactions» is then dealt by Cao (2010), who compares different studies about the observed impact of online shopping on travel behaviour and groups them by interaction.

The studies range from 2005 to 2009 (including (Ferrell, 2004, 2005; Weltevreden, 2007; Farag et al., 2007)). A majority of the studies find that there is a contributing effect, but there are also substituting effects, which is contradicting the others. Another comparison was whether these studies found if people in a rural or urban residential location shop more online (according to the two hypotheses of Anderson et al. (2003)). These are: the innovation-diffusion hypothesis (through more innovation diffusion there is more online shopping) and the efficiency hypothesis (people with low shopping accessibility are more likely to shop online out of efficiency reasons). But also within this comparison there are some contradicting results. Furthermore, a study by Wang and Yuk (2007) (in Hong Kong) leads to the conclusion that use of ICT leads to an increase in travel demand.

Hsiao (2009) criticises the lack of existing literature on which factors influence the choice between in-store and online shopping. With data from a stated preference survey conducted in large book stores in Taiwan in the year 2002, he observed that avoiding a shopping trip to buy a book is monetarily more beneficial than waiting for the same book after purchasing it online. So he is contradicting Mokhtarian (2004) by saying that waiting for a good is not monetarily equivalent to travel to the book store. Despite the fact that he is only looking at costs and times and excludes other factors which could influence the choice, he seems confident about his results.

Laghaei et al. (2015) state that home shopping increases the amount of traffic due to the increase of delivery trucks and additional personal trips. These are possible because of gained free time through avoiding shopping trips. They mention that because of the increase in traffic the pollution level in their research area (Newark) did increase over time. A different article tells that shopping online is not sparing the environment from emissions unless one purchases more than 25 articles (Newcastle University, 2010). Therefore, the individuals environmental concerns should be considered in the models.

According the gender related effects, Dholakia (2009) found that women feel still more responsible to go shopping than men. She used data from 1'600 US households of which she selected responses from married couples (wife and husband). Similar effects have been observed by Alreck and Settle (2002a), by interviewing 300 men and 300 women in the United States about their perception of different shopping possibilities (online, catalogue or in-store). According to them, women tend to shop more often than men, either in-store or by a catalogue. Both genders spend an equal amount of time shopping online. The attitude towards shopping is also significantly higher from a female participant. Furthermore, Alreck and Settle (2002b) report that people assume they would save time by shopping online or over a catalogue, but rarely use these tools to actually save time. For this study they interviewed about 1'800 American citizens between 20 and 60 years of age. Bagley and Mokhtarian (2001) conclude that socio-demographic variables have only little impact on travel behaviour. Furthermore, they state that residential location factors should be included in a SEM and reasonable restrictions have to be made before running a model. In that way SEM would be a good way to observe what interdependencies are in the dataset.

2.2 Leisure

Leisure activities are often accounted for insufficiently according to Schlich et al. (2003a). The goal of their project was to find key drivers of leisure related mode and destination choice. They state that it is crucial to know what exact leisure activity is done, since there are large differences between daily, weekend or vacation leisure activities. Also the planning of such activities is different depending on the activity. So if one asks for leisure activities one should ask as broad as possible. Major influences on the amount of activities have the available free space at home (garden or second living place) or the residential location. People with more available space tend to stay more at home for leisure whereas urban people are more active outside their homes. Also the social network of a person has a substantial effect on their leisure activities. But the main factor affecting leisure activity duration and location is the travelled distance. According to Schlich et al. (2003b) the attractiveness of a location decreases largely with distance travelled to it. But both studies only looked at skiing, hiking and visiting friends and relatives as leisure activities in Switzerland.

Ren and Kwan (2009) address the complexity of either ICT use or its impacts on travel behaviour. They used data from the activity-Internet diary survey in the Columbus metropolitan area from 2003 and 2004. It involved socio-demographic as well as a two day physical and internet diary. They discuss hidden features of internet usage which are not obvious. Therefore, one should break the total amount of activities into fragments to check for interesting effects. They also look at gender related effects. For example, leisure internet usage by men reduces the travel demand for leisure activities. On the other hand women increase online maintenance activities and decrease real life activities. They differentiate between replacement of physical activities and time competition as a reason for online activities.

3 Theory

This section gives a theoretical background to use SEM. Section 3.1 handles the theory of Structural Equation Modelling (SEM) and in the following sections the Maximum Likelihood (ML) estimation (3.2), clustering of standard errors (3.3), random effects (3.4) and goodness of fit indices (3.5) are also described.

3.1 Structural Equation Modelling

SEM modelling is a tool to simultaneously estimate several relationships between different variables. The idea of a SEM is to minimize the difference between the sample covariance matrix (Σ) and the estimated covariance matrix ($\Sigma(\theta)$). This can be formulated as $\Sigma = \Sigma(\theta)$ (Bollen, 1989; Mueller, 1996; Kline, 2011). It is a more general way of describing relationships, hence other models can be treated as special cases of SEM. Golob (2003) lists several advantages of SEM, which are among others: Simultaneous treatment of endogenous and exogenous variables, handling latent variables, separation of specification and measurement errors, tests for a whole model at once and handling non-normal data. It is though very common to ignore assumptions of normality (Bagley and Mokhtarian, 2001). A data set fulfils these assumptions if the variables follow a normal distribution.

Exogenous variables are variables which have a descriptive character. This means they are measured and not influenced by others (e.g. age or sex), or in other words independent. Endogenous variables on the other hand are variables which are influenced by exogenous variables. Therefore, they are dependent on other variables (e.g. the number of trips is dependent on the car availability, assuming the car availability is exogenous). A latent variable is a special kind of variable, a hypothetical construct (Kepplinger and Habermeier (1998); e.g. attitudes and perceptions). A latent variable is measured, but not directly observable. Interdependencies which would not be observable without it, can therefore be described. However, in this work no latent variable approach is used. Attitudes are assumed to be exogenous in the model, using predicted factor scores resulting from a factor analysis.

A SEM is built out of two separate parts: the measurement model and the structural model. The structural model (defined in Equation 1) is used to describe the relationship between latent (unobserved) variables as random variables with measurement errors. But if there are no latent variables (as in this work) it also represents the relationships between the observed variables. On the other hand the measurement model represents the relationship between the latent variable and the observed variable. In this work only the structural model is used because the observed behaviour on each diary entry is of interest without any latent variables.

$$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta \tag{1}$$

Where:

η: $m \times 1$ vector of endogenous variables
$\mathbf{B}$: $m \times m$ coefficient matrix of endogenous variables
ξ: $n \times 1$ matrix of exogenous variables
$\mathbf{\Gamma}$: $m \times n$ coefficient matrix of exogenous variables
ζ: $m \times 1$ vector of disturbances

So the (m) endogenous variables are a function of m endogenous variables multiplied by the coefficient matrix $\mathbf{B}$ and n exogenous variables multiplied by the coefficient matrix $\mathbf{\Gamma}$ and the disturbances ζ. The values on the diagonal of $\mathbf{B}$ are zero because no variable can explain itself directly. Additionally, there are the matrices $\boldsymbol{\phi}$ and $\boldsymbol{\psi}$ which are the covariance matrices of ξ and ζ respectively. The researcher then decides which entry in $\mathbf{B}$, $\mathbf{\Gamma}$ or $\boldsymbol{\phi}$ should be estimated. In other words, what relation is hypothesised to exist and which estimate (or relationship between two variables) is set to be zero or to a certain constant (Bollen, 1989; Simma and Axhausen, 2001). It is therefore more a confirmatory method than an exploratory, since all the relations are pre-set by the researcher (Golob, 2003).

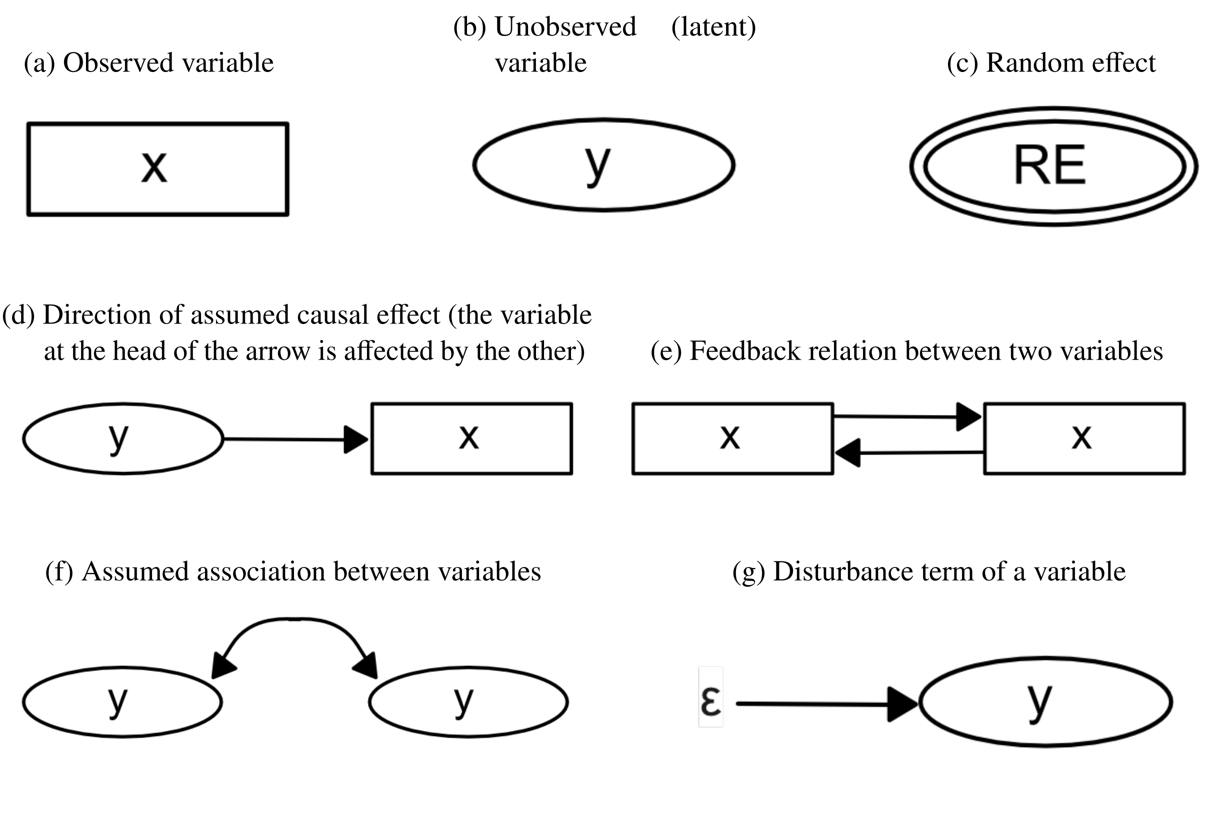
According to Muthén (1989) a big issue in research with SEM is the false treatment of data as homogeneous. The so called unobserved heterogeneity has to be accounted for (Jedidi et al., 1997). A way to do so is through random effects, which is further discussed in section 3.4. One should never forget the great importance of the model specification. It has to be avoided to do post-hoc adaptations of the model. Because by doing so the data is fitted to the model and not vice versa. If in further research other data is used in the same model, it could fail to fit (Golob, 2003).

It is important to keep in mind that a model does not give causal results, but an explaining variable "helps to predict" another variable (Iacobucci, 2009). She also gives a good insight of how to use and illustrate SEM. Furthermore, Iacobucci (2010) provides more information of which fit indices to use when estimating a model and assessing its fit. In addition, she states that ML estimation is the best and most robust estimation method (see section 3.2). On the other hand, Fabrigar et al. (2010) mention that it is important to look at fit indices but they do not agree every time and therefore it is at least as important to look at the estimates and if their magnitudes lie within a reasonable range.

3.1.1 Path Analysis

In SEM it is a consensus that one illustrates a model as a path diagram, which was initially used by Wright (1918, 1921). Bollen (1989) proposes the following structure illustrated in Figure 2. This way of illustrating models is a good way to simply show what the model actually means without any formulas or equations. Relations can be estimated between observed and latent variables in both directions. Error terms could also be estimated for observed variables. Simple models with only a few estimated parameters are easily described by formulas, but the more complicated a model gets the better suited the graphical representation's. An example of a model in form of equations and path diagram is shown in the subsequent section (see Figure 3 and Equations 2 and 3).

Figure 2: Description of all elements of the path analysis.



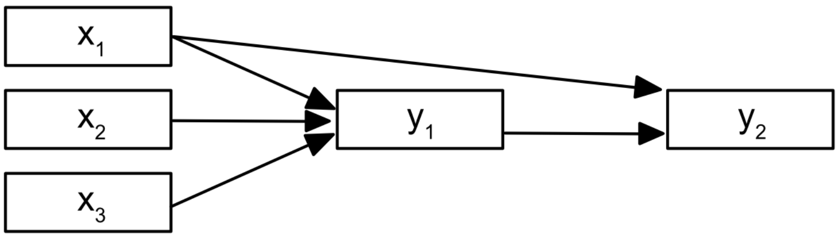
Source: Bollen (1989); Stata Press (2013)

3.1.2 Total, Direct and Indirect Effects

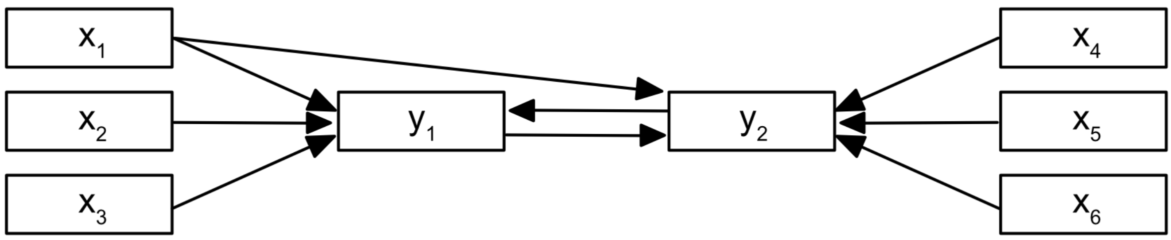
The resulting estimates of SEM models can be reported in the form of direct, indirect or total effects. Direct effects are the estimates themselves (the arrows in the path model), whereas indirect effects are the multiplied effects along the path (see Figure 3). This means if an explanatory variable (x_2) has no direct effect on an explained variable (y_2) but has one on another variable (y_1) with a direct effect on (y_2), those two direct effects are multiplied and are the indirect effect. Total effects are the sum of the indirect and direct effects (Bollen, 1987, 1989).

Figure 3: This Figure shows a recursive model (a) and a non-recursive model (b) whereas the arrows signify estimated parameters β_i between endogenous variables (y_i) and λ_{ji} between an exogenous (x_j) and an endogenous variable (y_i).

(a)



(b)



Source: (Stata Press, 2013)

Recursive Model, Figure 3(a)

$$
\begin{aligned}
y_1 &= \alpha_1 + \lambda_{11}x_1 + \lambda_{21}x_2 + \lambda_{31}x_3 + \varepsilon_1 \\
y_2 &= \alpha_2 + \lambda_{12}x_1 + \beta_1 y_1 + \varepsilon_2
\end{aligned}
\tag{2}
$$

Non-Recursive Model, Figure 3(b)

$$\begin{aligned} y_1 &= \alpha_1 + \lambda_{11}x_1 + \lambda_{21}x_2 + \lambda_{31}x_3+ && \beta_2 y_2+\varepsilon_1 \\ y_2 &= \alpha_2 + \lambda_{12}x_1 + \lambda_{42}x_4 + \lambda_{52}x_5 + \lambda_{62}x_6+ && \beta_1 y_1+\varepsilon_2 \end{aligned} \tag{3}$$

SEM models are grouped into two different kinds of models: Recursive models and non-recursive models. Figure 3 shows these two model types graphically whereas equations 2 and 3 show the formulated models. The formulated models lack the information about the assumed relationship between the different variables. Path diagrams do not miss this information, because a missing arrow signifies an assumed estimate of zero (Bollen, 1989). In a recursive model the matrix **B** is lower triangular and $\boldsymbol{\psi}$ diagonal. The difference between recursive models and non recursive models is very confusing if one adds the calculation of their total effects. Recursive models are unidirectional and therefore total effects are computable recursively. This implies for example that the direct effects of x_1 on y_2 is λ_{12}, the indirect $\lambda_{11}\beta_1$ and hence the total effects $\lambda_{12} + \lambda_{11}\beta_1$. Non-recursive models include a feedback loop whereas recursive models do not. A loop signifies that the total effects of y_1 on y_2 are influenced by y_2. In other words, the explained variable (y_2) explains itself by explaining its explanatory variable (y_1). The same example as for the recursive model has direct effects of λ_{12} and indirect effects of $\lambda_{11}\beta_1 + \lambda_{11}\beta_1\beta_2\beta_1 + \lambda_{11}\beta_1(\beta_2\beta_1)^2$... and so on. Therefore, in non recursive models, the total effects are calculated recursively but not in a sense that the model is recursive (Stata Press, 2013). Because of the recursive calculation of the indirect effects of a non-recursive model, they converge only if the absolute estimates are smaller than one. Otherwise the indirect and total effects would go towards infinity. Hence the indirect and total effects can only be calculated if the eigenvalues of **B** lie inside the unit circle (Bollen, 1987; Stata Press, 2013).

3.2 Maximum Likelihood Estimation

The ML estimation method is used because it is relatively robust against violations of the assumption of normality (Golob, 2003). In *STATA 14.1* this estimation method is available and its main assumptions are that all the response variables are independent and identically distributed across the estimation sample (Stata Press, 2013). Because of clustering (see section 3.3) a Quasi Maximum Likelihood (QML) estimation is used. It does not maximize the logarithm of the likelihood function, but a more simple approximation of it. This method balances the standard errors in order to handle non-normality (Stata Press, 2013).

3.3 Clustering

Since several observations are made by the same person and every person does have its own weekly plan, all the observations of one person are possibly related to one another. Therefore, the variance of the estimates could be correlated in the observation-set of one participant. To account for this instability the variables are clustered in *STATA 14.1*. This means that the standard errors are allowed to be heteroscedastic and the estimates are allowed to be correlated in the observation-set of one person. Having said that, the standard errors are not allowed to be correlated between those clusters. This leads to a more robust estimation of the errors. Furthermore, clustering inhibits the user from the possibility of using other than Gaussian response variables with an identity link function. Though, because of a non-recursive model used in this case, this is no obstacle as non-recursive models only allow this combination as well. Gaussian response variable means that the assumed distribution of the estimated dependent variable is a normal distribution. In combination with a identity link function this implies a linear regression function of the response variable (Stata Press, 2013).

3.4 Random Effects

Likewise to the problems mentioned in the previous sections, there is unobserved heterogeneity in the dataset since observations of the same person could be correlated. Treating the data as homogeneous would be wrong, as mentioned previously. A parameter is introduced for each participant to account for this unobserved component of the estimates. To do so Muthén (1989) introduces a group-level and individual-level random component. For the purpose of this work only the individual-level random component is used, since no groups have been formed. Equation 4 illustrates this effect. The estimate of δ is fixed to be 1 because the product of δ_{id} and M_{id} is estimated together and there are numerous solutions to this (Stata Press, 2013; Drukker, 2014).

$$y = \alpha + \sum_{i=1}^{n} \beta_i \cdot x_i + \delta_{id} \cdot M_{id} + \varepsilon_y \tag{4}$$

Where:

y: Dependent variable
α: Intercept
n: Number of parameters
β_i: Estimate
x_i: Parameter value
δ_{id}: Estimate of random effect
M_{id}: Random effect for each person
ε_y: Error

By introducing this effect one has changed the model into a multilevel model, and there are two different levels of estimation (level 1 are all the observations, level 2 are all the individual participants). By introducing the aforementioned group-level random component one would gain another level (Rabe-Hesketh et al., 2004). They also propose another way of estimating such multilevel models with their generalized linear latent and mixed modelling (GLLAMM) framework.

3.5 Goodness of Fit

Comparing the established models is a crucial step in finding the best model to work with later. To do so, indices to measure the goodness of fit have to be found. The basic parameter to assess the goodness of fit would be the χ^2-statistics which tests if the observed sample is well represented by the estimated model or not. It has though some drawbacks because with a larger amount of observations the test is most of the times significant. The result is therefore overestimated. Other indices take this into account better. Well known and broadly accepted indices are the Akaike Information Criterion (AIC) and its improvement, the Akaike Information Criterion with small sample size correction (AICc). They are though only useful to compare models for better fit and not if the fit of the model is sufficient. Therefore, another indices has to be found. A valuable candidate is the Root Mean Square Error of Approximation (RMSEA). Those indices are further discussed in this section.

3.5.1 AIC and AICc

The AIC is a comparative measure of fit, which means that it only gives an information if a model is better than another one but it says nothing about the model fit. It was proposed initially by Akaike (1973) and is given in equation 5. The addition of the χ^2-statistics is taken from Bollen (1989, p. 279). This addition is needed to calculate the RMSEA afterwards. For models with many degrees of freedom the AIC has to be adapted to penalize free parameters even more and also to account for small sample sizes. These changes are given in equation 6. The AIC is calculated by *STATA 14.1* whereas the AICc has to be computed manually afterwards.

$$AIC = 2 \cdot k - ln(L) = \chi^2 - 2 \cdot df \tag{5}$$

$$AICc = AIC + \frac{2 \cdot df \cdot (df + 1)}{n - df - 1} \tag{6}$$

Where:

k: Number of estimated parameters
L: logLikelihood of the model
df: Degrees of freedom in the model
n: Sample size (in this work the number of participants)
χ^2: χ^2-Statistics

3.5.2 RMSEA

Since the χ^2-Value is almost every time significant in models with many degrees of freedom, it has to be accounted for. Therefore, the RMSEA can be used as an alternative. It is an absolute measure of fit which ranges from 0 to positive infinity. This means that with this indicator one is able to compare different models according to their fit on to the dataset. Additionally, it is possible to say whether a model fits the data just by looking at this index. It is calculated according to equation 7. This measure encompasses the parameter estimates as well as the population covariance matrix. It depends also on the number of variables used in the model (Browne and Cudeck, 1992). A perfect fit is achieved with a RMSEA of 0, whereas the larger the value the poorer the fit. There is no clarity about where the best cut off point is, but the consensus is that a model with a RMSEA > 0.1 indicates poor model fit (Chen et al., 2008). Because *STATA 14.1* does not calculate it by default one is obliged to do it manually. The

RMSEA is calculated according equation 7 with the χ^2-Value of equation 5.

$$RMSEA = \sqrt{\frac{\chi^2 - df}{df \cdot (N-1)}} \tag{7}$$

Where:

χ^2: χ^2-Statistics
df: Degrees of freedom of the model
N: Number of observations

4 Methodology

The dataset used is mainly described in Schmid et al. (2016b). More about the data collection is presented in section 4.1. In section 4.2 it is briefly described how the data used has been obtained and cleaned. The prepared data is explained in more detail in section 4.3 and validated in section 4.4. Additionally, the factor analysis for the attitudes used is described in section 4.5 and in section 4.6, some descriptive statistics are presented.

4.1 Data Collection

The study began with a pretest during winter 2014 and covers the canton of Zurich. In this pretest not only the used data was collected but additionally Schmid and Axhausen (2015) tested different incentives and if the work load was appropriate. The first wave of the main study took place in summer 2015 and the second wave followed in autumn 2015. The third wave is currently in its completion. More information about participation and the survey procedure can be found in (Schmid and Axhausen, 2015; Schmid et al., 2016a,b,c). The study is structured as follows:

1. A randomly selected respondent receives an invitation letter for the study.
2. All of these selected people are then called by telephone to ask if they want to participate or not. If a person is reached, some questions about their household are asked.
3. All the participants receive a personal questionnaire, an online diary and a travel diary. For each household a questionnaire about the household is also distributed.
4. After sending back the filled out questionnaire the participants received another set of questionnaires with individual stated choice and attitudinal questions.
5. Finally a personal interview is conducted with one or more members of the household. This interview contains an additional set of stated adaptation experiments.

4.2 Data Preparation

The initial data set contained 9’829 trips made by 373 persons. These people wrote down their daily travel in a diary (see Figure 12 in section A). This diary asked about the main mode of transportation as well as the departure-time, arrival-time, type of activity, costs for the trip and other information. With this data, it was possible to evaluate how long an activity lasted and for which purpose. For the same week another questionnaire has been distributed to collect data about the respondents' online behaviour (see Figure 13 in section A). The preparation, merging and aggregation of the different datasets has been conducted in *R*.

The dataset included several inconsistencies like negative or zero travel and activity times, missing information about trip purposes or much too long travel durations. These inconsistencies were marked as «suspicious» entries. A first step was to find the sources of these problems. Hence, it was crucial to look at the data and if necessary compare the entries with the questionnaire filled out by the participants. The first thing noticed which caused problems was that some trips ended after midnight and therefore negative travel times arose. Since the weekday stays the same in the data set, a later time is subtracted from an earlier time. Thus, the only solution was to go through every entry which was marked «suspicious» and correct it appropriately.

For all cases where the activity time was zero the activity time was set to one minute and that one of the following activity was shortened by one minute. This seemed to be the straight forward solution for this problem. All the starting- and arrival times involved were adapted as well. Negative travel times with an arrival within two hours after midnight were recalculated whereas all the others were checked manually because a travel time of more than two hours seemed suspicious. Afterwards, all the other «suspicious» travel times were checked and corrected according to the travel diary. The next step was to go through all entries with a negative activity time. Usually the problem was that the day was typed in wrong and therefore the following activity started before the marked activity ended. Through checking for all these errors another problem surfaced. Somehow the order of the trips has been messed up and a lot of arrival-, departure- and activity-times were wrong. This had been corrected also manually by consulting the travel diary. To finalize the data, it was checked whether filling in some missing trip purposes or wrong purposes (only found if a «suspicious» value was near it) was possible. To get better values of travel times and distances another file had to be created. It contained all the departure and arrival addresses as well as the departure time. In this file several addresses were corrected manually according to the travel diary to facilitate the following steps. Afterwards, this file was routed by an algorithm using a Multi-Agent Transport Simulation (MATSim) for walking, bike and PT trips and *GoogleMaps* for car trips (Horni et al., 2016; Alphabet Inc., 2016). The results obtained were then reordered like the aforementioned data frame and then merged with it. The routing algorithm has some issues which are described further in the following list:

- If an address is not properly added to the data frame it could happen that a location is wrongly identified and the trip does not end where it is supposed to.
- If a location is not defined exactly it may occur that two locations are identified for the same address. Evidently this could lead to a wrong result.
- Sometimes there is no information about the departure or arrival address. Therefore, routing is not possible.
- If a trip is very short, MATSim is not able to route it. Some walking trips are not long enough to be routed and sometimes a short PT connection is not routed as well.
- MATSim is apparently not always able to route PT trips which are done during the night with special night lines.
- A lot of these trips have an identical departure and arrival address. This results in a trip with zero length and duration. This is for example the case if a participant went for a walk with his dog.

This issues lead to a count of missing routings of approximately 600 out of 9'829. To overcome some of these problems all the erroneous entries were checked and corrected where possible, again using *GoogleMaps* (Alphabet Inc., 2016). About 50 % of these trips were corrected likewise. The ones left had either missing addresses or had the issue of the same departure as arrival address. Furthermore, it was tested if there is a big difference between the routed travel time and the travel time which was given by the respondents. All entries in which this relation was different by a factor of two where also checked again and properly adjusted. This means if the given travel time was apparently wrong it was corrected (as well as the according start and arrival time and the activity duration). This subset contained about 250 trips.

For the remaining incorrect trips there would be the possibility of using the travel times and distances given by the respondents. But doing so, one would assume that all the guessed travel times and distances are correct. So it was decided to only do this for trips like promenade, walking with the dog, jogging, hiking or riding the bicycle. Therefore, only walking or biking trips with the identical start and arrival location were adapted likewise. The amount of missing travel durations and distances had been reduced to approximately 150. Aggregating the rest would have included too many assumptions and was therefore omitted.

It was chosen to aggregate the data over one whole day. Because the questionnaire concerning the online behaviour of the respondents asked only about the summed number of activities and their duration over the whole day. In total 93 days are missing the whole information about the participants daily travel schedule, as some of the missing trips were observed at the same day. Because of the absent travel information these days are not used in the models.

4.3 Overview of Variables

In the models several different variables are used. These are not always straight forward and are therefore explained in Table 2. Nevertheless, some variables need some additional clarification. Counting as it_tool are: Desktop PC, smartphone, tablet and laptop. The GA and ZVV ticket were chosen because if one owns either of them no single tickets are required (in the relevant region). It was assumed that this has the biggest effect on travel decisions. The respondents had to tell in which personal income category they belong to. Since it makes more sense to work with the actual income, it has been chosen to take the mid-point of each income category as an approximation to the real income. In this table the variables it_tool, hh_veh, hh_velo and pt are considered endogenous. This means they cannot be used as a describing variable at the beginning of the modelling process (further discussion section 5).

Table 3 gives an overview of the dependent variables used. The number of trips, the online activities and the activity duration both out-of-home and online are directly obtained from the questionnaire. The other variables concerning the trip length and travel time were calculated as aforementioned. For out-of-home activities the following purposes exist: Leisure, shopping (both long and short term separately), working, service and official activities. All activities are further explained in Table 4. On the other hand the online activities have other purposes also described in Table 4. It has to be stated that for the first two purposes (leisure, shopping) the amount of different activities of each category is counted and for all the others there is only a dummy to indicate whether activities of this type were done during the day.

Table 2: Overview of the describing variables used in the models.

Variable code	Definition	Classification
sex	Sex of the participant	dummy
age	Age of the participant	continuous
education	High level of education through university or Fachhochschule degree	dummy
income	Monthly personal income (interpolated mean of category in thousand CHF)	continuous
working	Employment status, whether the participant is working or not	dummy
working_h	Weekly working hours	continuous
car_avail	Whether a car is always available or not	dummy
pt	Participant owns GA or ZVV ticket	dummy
res_rur	Rural residential location	dummy
res_int	Intermediate residential location	dummy
res_cit	Urban residential location	dummy
hh_size	Number of household members	continuous
hh_children	Number of household members under 18 years of age	continuous
hh_veh	Number of motorised vehicles	continuous
hh_velo	Number of bicycles	continuous
it_tool	Number of different IT tools	continuous
attitudes	see section 4.5	continuous

Table 3: Overview of the endogenous variables used in the models.

Variable code	Definition
tot_trips	Total amount of trips during one day
purpose_trips	Total amount of trips during one day for a given purpose
tot_trav_dur	Total daily travel duration
purpose_trav_dur	Total daily travel duration for a given purpose
tot_act_dur	Total daily activity duration
purpose_act_dur	Total daily activity duration for a given purpose
tot_km_trav	Total daily kilometres travelled
purpose_km_trav	Total daily kilometres travelled for a given purpose
tot_onl_act	Total amount of different online activities during one day
onlpurpuse_onl_act	Total amount of different online activities during one day for a given purpose
tot_onl_dur	Total daily online activity duration
onlpurpose_onl_dur	Total daily online activity duration for a given purpose

Table 4: Description of purposes for out-of-home and online activities

Out-of-home Purpose	Description
Leisure	Personal Meetings and visits, going to the cinema or theatre, sports, restaurant, bar, club etc.
Short Term Shopping	Food, drinks, cleaning supplies, medicine, cigarettes etc.
Long Term Shopping	Clothing, electronic equipment, furniture, books etc.
Working	Work related activites or education
Service	Barber, visit to a M.D., optometry etc.
Official	Authority, postal services, garage etc.
Online Purpose	**Description**
Leisure	Watching TV, listening to music, gaming etc.
Shopping	Clothing, electronic equipment, furniture, books, food, tickets etc.
E-Banking	E-Banking and related activities
Social Networking	Facebook, twitter or others
Information gathering	Planing the holidays, compare prices, reading blogs or tutorials etc.
Communications	Non work related communication like SMS, calling on the phone, WhatsApp etc.

4.4 Validation

The prepared dataset consists of 339 participants in 224 households. This dataset is compared to the Mikrozensus 2010 (MZ) for the region of Zürich to see if the sample is representative for the whole population in the region. Clearly the sample is too small to be really representative but it can give an insight into possible over-representations (Schmid et al., 2016c). The MZ is a questionnaire conducted by the Swiss federal statistics office every five years. It consists of a travel diary and socio-demographic statistics on a household level (Bundesamt für Statistik (BFS), 2012).

This comparison is shown up in Table 5. It is striking that the data set has a strong bias towards well educated, high earning couples with kids and an age in the range of 36 to 65 years. Another difference can be seen in the attitude towards PT usage. The amount of half-fare cards and GA owners is much higher in this sample than in the MZ as is the amount of bicycles per household. Additionally, the car availability is much lower for the sample than for the population. On the other hand the number of cars per household is similarly distributed as in the MZ. An explanation for the smaller car availability could be that a majority of participants is living in the city centre whereas in the population, more people live in the agglomeration. Another reason for this discrepancy could be the aforementioned high education or income level of the sample. Overall the affinity towards private car usage seems to be lower than in a representative sample. These characteristics have been observed before at the IVT (Schmid et al., 2016c). The results of the models (see section 6) are therefore to be taken with precaution, since the sample is not fully representative.

4.5 Factor Analysis

Together with the stated choice experiments a substantial number of attitudinal questions were asked that are related to modal preferences and the mindset about the internet. A set of predefined questions based on the *MOBIdrive* protocol (Axhausen et al., 2002) were used. This questionnaire using 4-point-Likert-scales includes statements about:

1. Shopping behaviour and attitudes
2. Car ownership and environmental concerns
3. Affinity towards public transport
4. Walk and bike opportunities
5. Hypothetical transport modes

Table 5: Descriptive statistics: Mikrozensus 2010 (MZ) (canton of Zürich) vs. Dataset

Variable	Value	MZ [%]	Dataset [%]
Household size	1	31.6	18.7
	2	37.4	31.3
	≥3	31.0	50.0
Household income	Not reported	24.1	5.7
	< 4'000 CHF	14.9	4.9
	4'000 - 6'000 CHF	17.5	3.3
	6'000 - 8'000 CHF	14.5	13.0
	8'000 - 10'000 CHF	10.6	11.4
	> 10'000 CHF	18.4	61.8
Household type	Single-person household	31.6	18.7
	Couple without kids	33.0	25.2
	Couple with kids	26.6	48.0
	Single-parent household	5.8	4.5
	Living community	3.1	3.7
Area of living	City centre	38.9	50.0
	Agglomeration	54.8	43.1
	Rural	6.3	6.9
Number of cars	0	24.5	27.6
	1	49.1	55.3
	2	21.7	13.8
	> 2	4.6	3.3
Number of bikes	0	30.1	11.8
	1	21.3	16.3
	2	22.2	18.7
	> 2	26.4	53.3
Sex	Female	54.3	50.4
	Male	45.7	49.6
Age	18 - 35 years	20.7	10.5
	36 - 50 years	29.4	37.9
	51 - 65 years	27.4	46.8
	66 - 80 years	22.5	4.8
Education	Low	17.0	14.7
	Medium	56.9	22.3
	High	26.1	63.0
Seasontickets	None	36.4	11.0
	Half-fare card	53.2	72.9
	GA	10.4	16.1
Car availability	Never	7.3	59.0
	Sometimes	18.5	26.3
	Always	74.2	14.7

Source: Schmid and Axhausen (2015); Schmid et al. (2016c); Bundesamt für Statistik (BFS) (2012)

Out of these 80 statements 30 were chosen for subsequent analysis, as they are hypothesised to affect both travel and online behaviour.

This data has a large dimensionality and therefore, an exploratory factor analysis has been done. Hence the data was reduced to the most crucial parts and sources of covariance and noise of measurement were removed. *STATA 14.1* was used to undertake this task before entering the data into the models. Three latent variables were retained which consist of highly related elements. To find these the factor-Eigenvalue plot, a parallel analysis and a latent-root-criterion (Hayton et al., 2004) were used. The major dimensions of variability is explained by these three variables (explained variance = 32 %).

The factor loadings reported in Table 6 can be interpreted as the weight of their influence on the factor. This means the higher (in absolute values) the loading the better the representation of the described factor. This factor structure is sensible and statistically robust (acceptable goodness-of-fit measures for factor reliability and correlations structure) and suggests the subsequent classification

1. The environmental sensitivity factor (*ENVISENSI*) indicates high positive loadings on statements concerning a reduction of car usage through higher prices and regulations. Additionally the loadings are positive for statements in favour of pedestrians, bike riders and PT users.
2. The conservative anti technologies factor (*ANTIONLTECH*) exhibits by strong aversion against new things like autonomous vehicles (i.e. everything should stay as it is). The loadings are high on statements about distrust towards the internet.
3. The car lover factor (*CARLOVE*) is characterized by endorsement of car usage, pleasure of driving and reluctance of other means of transportation.

Bartlett's method has been used to calculate individual factor scores to construct these three attitudinal variables for following analyses (Bartlett, 1947). Normalized (mean ≈ 0; standard deviation ≈ 1) and unbiased maximum likelihood estimates of the "true" factor scores has been used. This analysis has been done by Basil Schmid following the same procedure mentioned in (Schmid et al., 2016a) with additional items.

4.6 Descriptive Statistics

This section consist in describing the variables used in the models. Table 7 shows all the explanatory variables. They are categorised person specific and household specific variables. Both categories include dummy and continuous variables. The dummies are explained by their

Table 6: Factor loadings for 30 selected attitude and value items

Questionnaire Item	ENVISENSI	ANTIONLTECH	CARLOVE
1. Often buying on the internet	-	**-0.6360**	-
2. E-shopping bears risks	-	0.4731	-
3. Do not like give away creditcard number	-	**0.6275**	-
4. Internet has more cons than pros	-	**0.5570**	-
5. E-shopping means no physical check	-	-	-
6. E-shopping simplifies comparison	-	**-0.5375**	-
7. Risk to get wrong product	-	0.4690	-
8. Social disadvantage without car	-	-	0.3923
9. Owning a car is a status symbol	-	-	**0.6271**
10. Decrease speed for lower pollution	**0.6288**	-	
11. Higher fuel price should subsidize PT	**0.7061**	-	
12. Car should be something particular	-	-	**0.6078**
13. Without car every day live unimaginable	**-0.5102**	-	-
14. Car driving is bad for the environment	**0.6581**	-	-
15. PT should get priority in the traffic	0.4238	-	-
16. Annoyed by meeting unpleasant people in PT	-	-	0.4133
17. PT is not flexible enough	-	-	0.4496
18. PT timetables are too complicated	-	-	**0.6039**
19. Too much noise and pollution for pedestrians	0.3952	-	-
20. Riding a bike is a feeling of freedom	0.4347	-	-
21. Riding a bike is the best travel mode	0.4631	-	-
22. Noise of car engines provides good feelings	-	-	0.4259
23. Could live without car	**0.6527**	-	-
24. Car-Sharing offer should be increased	**0.5206**	-	-
25. More investment in autonomous vehicles	-	-0.4505	-
26. Autonomous vehicles good alternative	-	-0.3818	-
27. Autonomous vehicles are scary	-	**0.5208**	-
28. Reduction in traffic by lowering immigration	-	0.3029	-
29. Zürich without cars is inconceivable	**-0.6311**	-	-
30. Everything should remain as it is	-	0.3151	-

Estimation method: Maximum likelihood
Rotation method: Orthogonal varimax
Variance explained: 32 %. Cronbach's Alpha: 0.79
Kaiser-Meyer-Olkin measure of sampling adequacy: 0.83
LR test: 3 factors vs. saturated: $p < 0.00$
Number of subjects: 339; Subject-to-Item ratio: 3.39

$- = |loading| < 0.3$. $Bold = |loading| > 0.5$

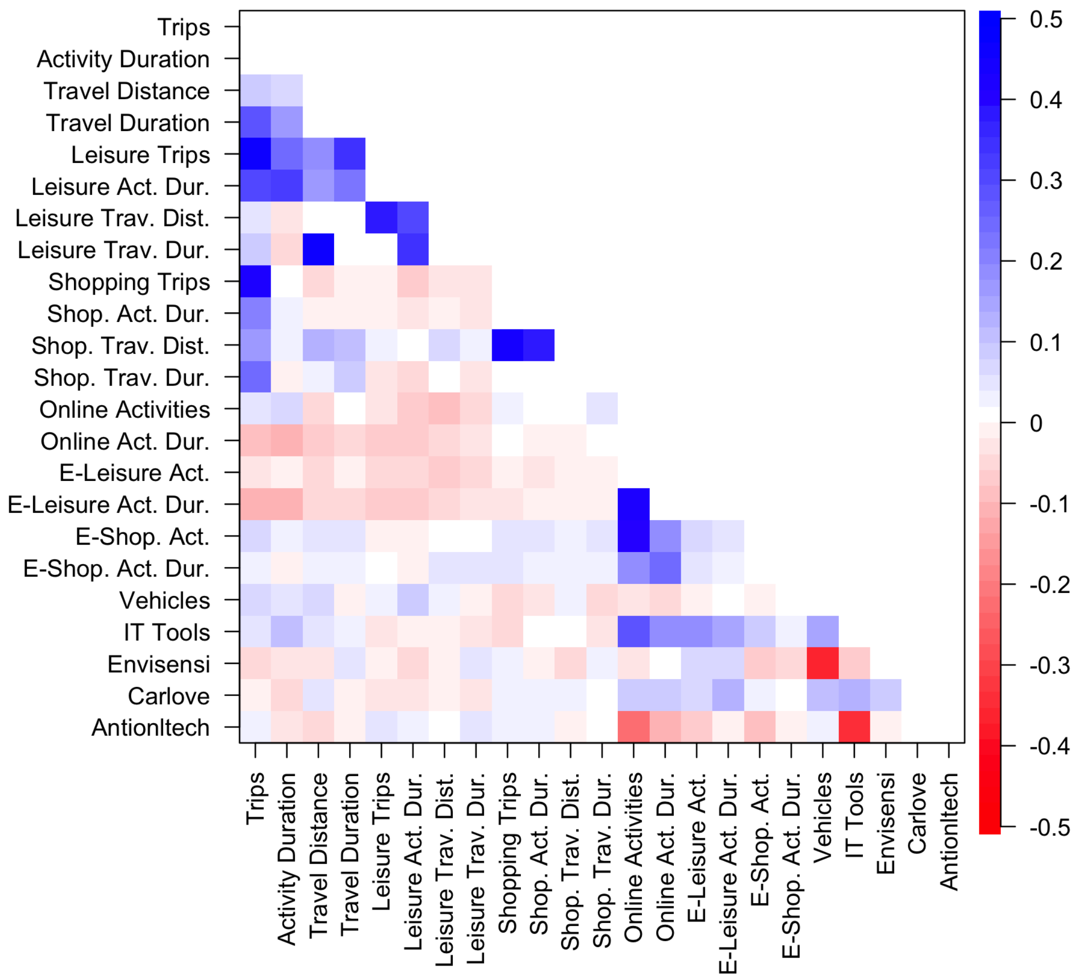
Table 7: Summary of explanatory variables (336 persons in 225 households)

Person Specific				Household Specific			
Variable	Amount	Percentage		Variable	Amount	Percentage	
Sex				Residential Location			
female	173	51.5 %		rural	15	6.7 %	
male	163	48.5 %		agglomeration	98	43.6 %	
Education				urban	112	49.8 %	
high	137	40.8 %					
low	199	59.2 %					
Working							
employed	309	91.9 %		Variable	Mean	Median	Max.
unemployed	27	8.0 %		Household size	2.72	2	6
Car Availability				# Children	0.68	0	4
always	194	57.7 %		# Vehicles	1.17	1	5
not always	142	42.3 %		# Bicycles	2.89	3	10
PT							
always	176	52.4 %					
not always	160	47.6 %					
Variable	Mean	Median	Max.				
Age	48.42	50	77				
Income	7'406	6'650	40'000				
# IT Tools	2.74	3	4				
Working Hours	30.41	36	59				

share and the continuous variables by their mean, median and maximum value. Respondents seem to be well educated and employed. More than half of the people have no children which goes along with the fact that about half of the households are either single ore two-person households. Keeping that in mind it is surprising that the median household owns three bicycles. Therefore, on average a person has slightly more than one bicycle. An explanation for this could be the fact that most of the participants households lie within the metropolitan area of Zurich, where bicycles are more present than in other (rural) locations. Therefore, in a metropolitan area one would assume more bicycles than elsewhere. These values are slightly different to those in Table 5 since three persons are not considered in the following work, due to incomplete diaries.

Figure 4 shows the correlations between the key variables used in the models whereas both online and out-of-home activities are divided into leisure and shopping activities. This plot shows that the attitude variables (see section 4.5) represent the mindset of the participant rather well. Especially the *ANTIONLTECH* and the *ENVISENSI* factors show substantially high correlations with other variables that are expected to be correlated (e.g. negative correlation

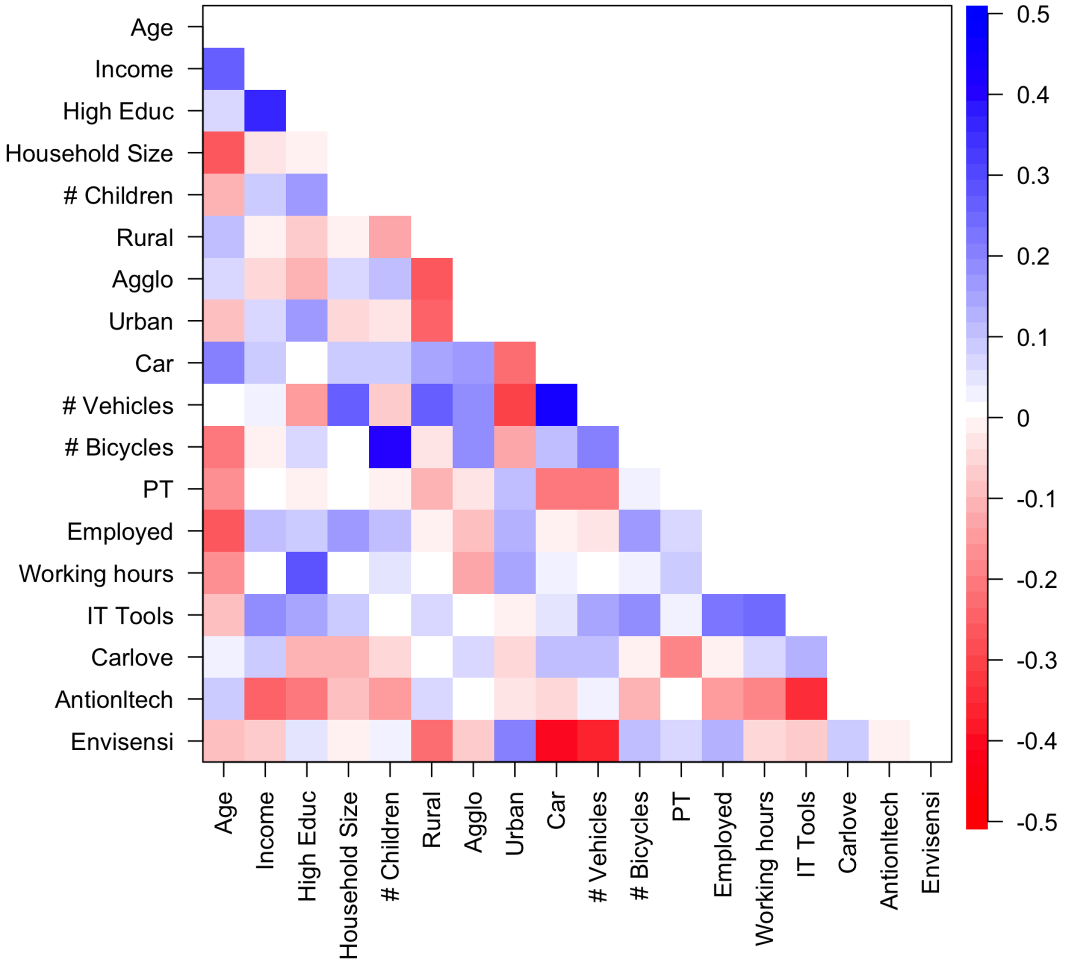
Figure 4: Correlation plot of key variables with endogenous explanatory variables and attitudes. The prefix "E-" signifies online related activities (336 Participants).



of *ANTIONLTECH* with the number of different online activities and IT tools). The duration of online and out-of-home activities are negatively correlated, which seems reasonable since they are exclusive to each other. Nevertheless, the number of trips and the associated activity durations are positively correlated with the number of online activities. The correlation between offline and online activities and their durations are not strong according to this picture.

Figure 5 shows a correlation plot for all the explanatory variables. There are strong correlations between variables which one might expect (e.g. people with more cars in the household have an increased car availability). Again the attitude variables are fairly well representing behavioural aspects of the respondents. Other relations are not as expected in the previous section (e.g. the number of bicycles per household is negatively correlated with the urban

Figure 5: Correlation plot of exogenous and endogenous explanatory variables and attitudes (336 Participants).



residential location), which contradicts the assumption of higher bicycle ownership in urban locations. This correlogram gives also information about how the attitudes are related to other explanatory variables. Some are as expected like a higher score in *CARLOVE* leads to fewer PT season tickets or the *ENVISENSI* factor has a substantial (negative) correlation with the number of cars available and a positive correlation with an urban residential location.

5 Modelling Approach

Hypotheses have to be established next (in section 5.1). Furthermore, the proceedings of how to get a satisfactory and comprehensive result is given in section 5.2.

5.1 Hypotheses

The following hypotheses guide the modelling process. They sometimes try to match results of other researchers whereas some are relations one might expect by looking at the data.

H_1: Shopping online contributes to in-store shopping. The number of shopping trips a day increases by the number of online shopping activities.

H_2: Long term shopping is affected stronger than short term shopping. The influence of online shopping on long term shopping trips is larger than on short term shopping trips, as people buy more long term products online (Weltevreden, 2007).

H_3: Socio-demographic variables have a small influence on the travel behaviour or ICT usage, as suggested by Bagley and Mokhtarian (2001).

H_4: Residential location has an influence on ICT as mentioned by Anderson et al. (2003).

- $H_{4.1}$: Urban people shop more online because the technology is more diffused and accepted in the cities than outside (innovation-diffusion hypothesis).
- $H_{4.2}$: Rural people shop more online because their benefit of it is higher as their shopping distances are higher (efficiency hypothesis).

H_5: In contrast to the effect described in H_1, leisure activities are substitutes for each other. This means that the effects are negative from both sides.

H_6: Working people with many working hours a week tend to shop more often online.

H_7: People with a high environmental sensitivity shop less. This includes online and instore shopping as well, since both produce pollutions and therefore those people minimise their shopping activities (Newcastle University, 2010).

H_8: The effects of weekends diverge from the effects during the week as found by Simma and Axhausen (2001).

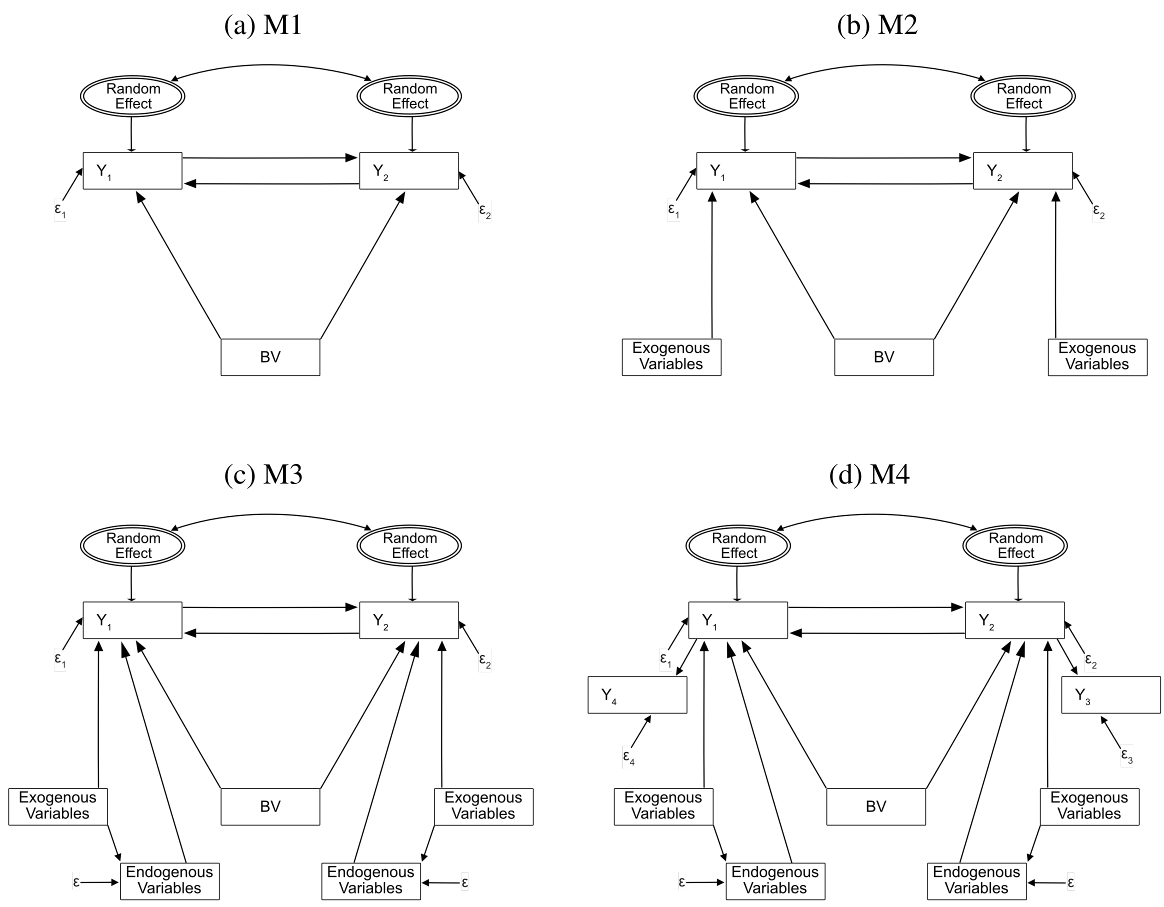
H_9: As stated by Dholakia (2009), women tend to shop more than men. Therefore, the gender effect on the amount of shopping trips is expected to be substantial.

H_{10}: A higher factor score in *ANTIONLTECH* leads to more trips in general as they have a positive correlation (see Figure 4).

5.2 Model structure

To test the aforementioned hypotheses a comprehensible procedure had to be established. The first step was to test how the different key variables were best described in a linear regression model. This model included random effects for each person as they have a deviating behaviour from one another. This leads to a certain set of descriptive variables for each key variable, which are listed in Table 3. Afterwards, the modelling according to the structures pictured in Figure 6 has been executed. This process is more an exploratory procedure than a confirmatory analysis (Golob, 2003). Nevertheless, this way of standardising the procedure is favoured because of its understandability. These models are all non-recursive and therefore not all indirect (and total) effects are computable (see Section 3.1).

Figure 6: Modelling Structures for SEM with all submodels



The first model (*M1*) consists only of the interactions between the two key variables, their random effects variables and the describing effect of the base variables (BV). These consist of dummies for the respective wave, the day and one for the second week. This is because in the pretest the respondents were asked to write the diary for two weeks. This model is pictured in Figure 6(a). Not all models estimated for this configuration did obtain reasonable results. Therefore, only the ones with a reasonable outcome are listed in the following section (see Section 6).

The next step (*M2*) consisted in adding further exogenous variables to describe the key variables (see Figure 6(b)). Afterwards, also endogenous variables were included as explanatory variables in *M3*. These variables are also described by other exogenous variables whereas they are not affected by the pre existing model since the relationship is unidirectional from the newly introduced variable on the key variable. Figure 6(c) shows this model. This modelling sequence was done first for aggregated data of all purposes and then refined into leisure and shopping, which had also two subgroups for long term shopping and short term shopping.

Until this step the models are bivariate. To continue one would now try to make a bigger network with interactions between more key variables (*M4*). This is only done for a few groups of variables because there were convergence issues for some of them. This kind of model is pictured in Figure 6(d). The variables Y_3 and Y_4 could also be dependent on both key variables of the original pair (Y_1 and Y_2) at the same time. A loop between some or even all of these variables would also be possible.

6 Models Estimated

All the estimated models are presented in this chapter, which is structured in four parts. Section 6.1 handles in models treating aggregated information regardless of the purpose. Following in section 6.2 are the models for leisure activities. Lastly in sections 6.3, 6.4 and 6.5 are the models for both kinds of shopping combined and afterwards they are then separated into long term and short term shopping. In section 6.6 two models with an even more complicated structure are discussed. Only the models which did converge to a solution are described here. If the model had underwhelming estimation results or a really poor fit, they are discussed but the results are in the Appendix (see section B). Convergence issues were encountered during the whole estimation process. Either the model did converge to a solution but the results were non intuitive or incomplete or the QML estimation did not converge to a maximum value, which then lead to no solution at all. This could be because the coefficient matrix **B** has eigenvalues outside the unit circle (see section 3.1). The estimated models are presented in order of increasing complexity (i.e. *M1* - *M4*). Since the change of the model from *M3* to *M4* is not influencing the results of *M3* it was decided to just present the additional results.

6.1 All Purposes

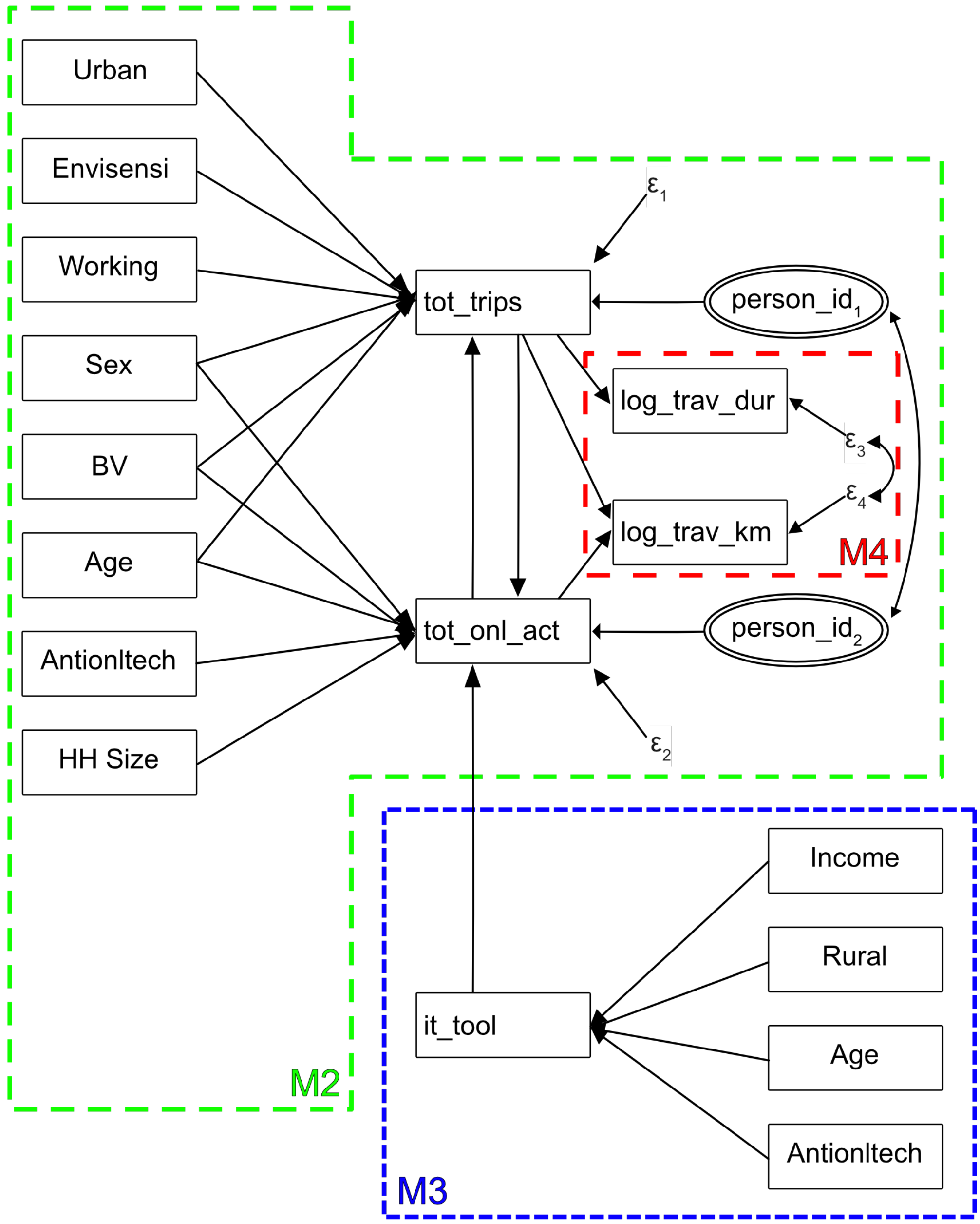
The section presents models concerning the total amount of trips and online activities first. Models which use the duration as key variable are discussed in the second subsection.

6.1.1 Activity vs. E-Activity

Figure 7 shows the path diagram of the estimated models *M2*, *M3* and *M4* for this pair of key variables. Model *M1* has been tested but the model did not converge to a reasonable result and is therefore not depicted. The variable it_tool has no constant because its distribution is assumed to follow an ordered logit distribution. So, in Table 9 the cut values are also shown. Ordered logit is a distribution which is used for dichotomous data. This means that owning one tool excludes the possibility of owning another number of tools. The cut values indicate if such a distribution is applicable (i.e. if they are significant, such a distribution can be used). Additionally, they inform where the boundaries are between two quantities (e.g. with a score for it_tool below or equal cut_1 one owns zero devices).

The resulting estimates of *M2* are listed in Table 8. It can be seen that the number of trips has a positive effect on the number of online activities. In the other direction the effect is negative

Figure 7: Out-of-home vs. online activities for all purposes



and has a larger scale. The weekday dummies are describing the number of online activities rather good (with a high significance). It seems that towards the end of the week, fewer online activities are undertaken. Furthermore, there is a distinct difference in the effects of different weekdays on the number of trips. The negative influence of weekends is highly significant. This seems reasonable since at the weekends, no work trips and on Sundays normally no shopping trips are made. Being male has a positive effect on both key variables. The RMSEA indicates a rather poor fit for *M2*.

Table 8: Results of the model "Out-of-home vs. online activities" (M2) for all purposes

Variable $tot\_trips \leftarrow$	Estimate	Std. Err.		Variable $tot\_onl\_act \leftarrow$	Estimate	Std. Err.	
tot_onl_act	-0.52	0.28	(.)	tot_trips	0.16	0.09	(.)
$wave_1$	-0.02	0.21		$wave_1$	-0.35	0.18	(.)
$wave_2$	0.21	0.18		$wave_2$	-0.15	0.18	
$tuesday$	-0.26	0.14	(.)	$tuesday$	-0.21	0.07	(∗∗)
$wednesday$	-0.13	0.16		$wednesday$	-0.33	0.07	(∗∗)
$thursday$	-0.13	0.18		$thursday$	-0.38	0.08	(∗∗)
$friday$	-0.15	0.19		$friday$	-0.48	0.08	(∗∗)
$saturday$	-0.56	0.28	(∗)	$saturday$	-0.78	0.08	(∗∗)
$sunday$	-2.12	0.26	(∗∗)	$sunday$	-0.50	0.18	(∗∗)
$week$	0.10	0.12		$week$	-0.17	0.09	(∗)
sex	0.33	0.18	(.)	sex	0.27	0.12	(∗)
age	-0.01	0.01		age	-0.03	0.01	(∗∗)
$working$	0.50	0.21	(∗)	$att\_antionltech$	-0.27	0.06	(∗∗)
$att\_envisensi$	-0.15	0.07	(∗)	hh_size	-0.14	0.05	(∗∗)
res_cit	0.18	0.14					
$cons.$	5.09	1.16	(∗∗)	$cons.$	4.11	0.42	(∗∗)
$var(RE_1)$	1.15	0.34					
$var(RE_2)$	0.96	0.09					
$cov(RE_1, RE_2)$	0.38	0.21	(.)				
$var(\varepsilon_1)$	3.06	0.30					
$var(\varepsilon_2)$	0.96	0.10					
$cor(RE_1, RE_2)$	0.36						
Goodness of fit (AICc; RMSEA)					18’499; 0.44		

Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1
2’623 Complete observations on 336 people

The fit of *M3* is slightly better, which can be seen in Table 9 but it is still not convincing, because the RMSEA is much higher than 0.1 The magnitude of the effects between number of trips and online activities has decreased by a factor of two. But the effects of weekend days on the trips has not changed that much. The added endogenous explanatory variable it_tool has a significant positive effect on the amount of online activities (i.e. possessing more such tools increases the amount of online activities). The variable hh_veh is not included because including it, would decrease the significance of many other variables in the model.

In Table 10 the additional results of *M4* are shown. The new variables are well described by the initial key variables. It is interesting that the number of online activities has a significant negative influence on the logarithm of the kilometres travelled for the out-of-home activities.

Table 9: Results of the model "Out-of-home vs. online activities" for all purposes (M3)

Variable tot_trips ←	Estimate	Std. Err.		Variable tot_onl_act ←	Estimate	Std. Err.	
tot_onl_act	-0.25	0.18		tot_trips	0.08	0.06	
$wave_1$	0.03	0.18		$wave_1$	-0.37	0.17	(*)
$wave_2$	0.23	0.16		$wave_2$	-0.17	0.17	
tuesday	-0.20	0.13		tuesday	-0.23	0.06	(**)
wednesday	-0.04	0.14		wednesday	-0.33	0.07	(**)
thursday	-0.03	0.15		thursday	-0.38	0.08	(**)
friday	-0.02	0.15		friday	-0.47	0.07	(**)
saturday	-0.34	0.20	(.)	saturday	-0.79	0.08	(**)
sunday	-1.91	0.19	(**)	sunday	-0.64	0.13	(**)
week	0.14	0.12		week	-0.16	0.09	(.)
age	-0.01	0.01		sex	0.23	0.11	(*)
sex	0.21	0.14		age	-0.03	0.01	(**)
working	0.48	0.19	(*)	att_antionltech	-0.20	0.05	(**)
att_envisensi	-0.14	0.06	(*)	hh_size	-0.14	0.05	(**)
res_cit	0.15	0.14		it_tool	0.30	0.07	(**)
cons.	4.01	0.78	(**)	cons.	3.56	0.38	(**)
	Estimate	**Std. Err.**		**Variable it_tool ←**	**Estimate**	**Std. Err.**	
$var(RE_1)$	0.94	0.15		income	0.04	0.02	(*)
$var(RE_2)$	0.88	0.08		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	0.18	0.14		age	-0.02	0.01	(*)
$var(\varepsilon_1)$	2.88	0.16		att_antionltech	-0.55	0.11	(**)
$var(\varepsilon_2)$	0.90	0.05		cut_1	-6.61	1.09	(**)
$cor(RE_1, RE_2)$	0.19			cut_2	-2.95	0.47	(**)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)						18'763; 0.37	
Significance codes: (**) <0.01, (*) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

Nevertheless, it is a small effect. The estimated constants are relatively big, which implies a small influence by the key variables. There is also a significant covariance between the error terms of the newly introduced variables. The RMSEA increased substantially, which indicates a poorer model fit than the previous model.

Table 10: Results of the model "Out-of-home vs. online activities" for all purposes (M4)

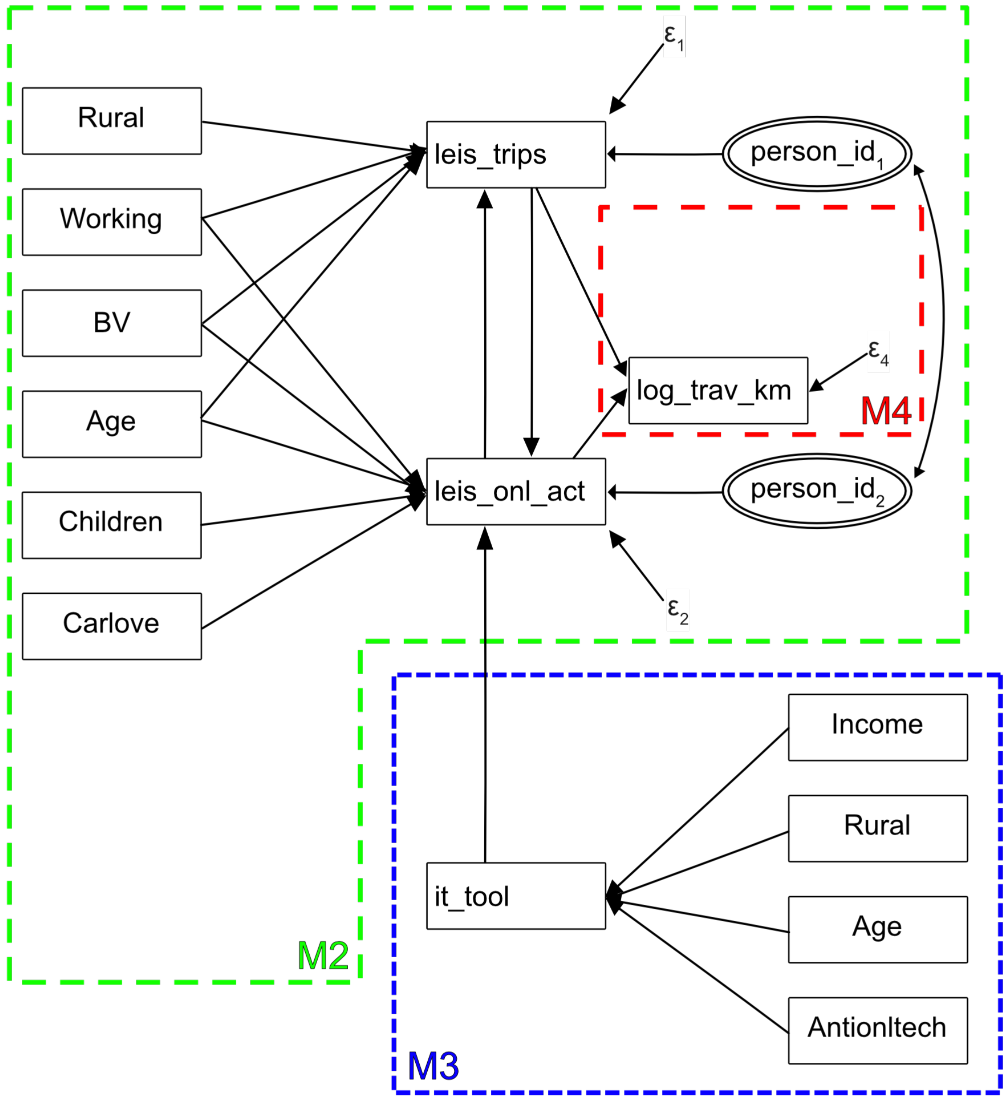
Variable							
$log\_tot\_km\_trav \leftarrow$	Estimate	Std. Err.			Estimate	Std. Err.	
tot_trips	0.14	0.02	(**)	$var(\varepsilon_{km})$	1.58	0.07	
tot_onl_act	-0.05	0.02	(**)	$var(\varepsilon_{dur})$	0.65	0.05	
$cons.$	2.58	0.10	(**)	$cov(\varepsilon_{km}, \varepsilon_{dur})$	0.82	0.04	(**)
$log\_tot\_trav\_dur \leftarrow$	Estimate	Std. Err.					
tot_trips	0.12	0.01	(**)				
$cons.$	3.66	0.05	(**)				
Goodness of fit (AICc; RMSEA)					36'268; 0.51		
Significance codes: (**) <0.01, (*) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

6.1.2 Activity vs. E-Activity Duration

Figure 14 shows the estimated models concerning the durations of both online and offline activities. The results of these estimations were not that impressive and are therefore to be found in the Section B.1. Nevertheless, some of the results are worth to discuss. Table 25 shows the results for *M1* and Table 26 for *M2*. The RMSEA of both of these models indicates a really poor fit (0.99 and 0.84 respectively), despite that in these models some effects of the weekends on the activity duration are noticeable. The time spent online influences the time spent out of home significantly (the estimate is -6.6), whereas the other way the effect is very small. The influences on out-of-home activity durations are much lower at weekends than during the week and the online activity duration is estimated to be higher at the weekends. Men tend to be about three hours a day more often outside their home than women. Age has also a significant negative effect on the out-of-home activity duration. This could be due to the estimated constant for these type of activities which is really high (~ 1'900 minutes).

Table 27 shows the results of *M3*. Despite that the model fit improved it is still a rather poor fit (0.78). The estimated constant is also higher but as well are the negative estimates for the out-of-home activity duration. The endogenous variable it_tool has a significant negative influence on the time spent online. This is rather surprising but the standard error is three times the absolute value of the estimated influence. Therefore, this value is to be taken with precaution.

Figure 8: Path diagram of the models *M2*, *M3* and *M4* for the key variable pair : Out-of-home vs. online leisure activities



6.2 Leisure

The estimated models considering only leisure related trips and activities are shown in this section. The first part consists of models with the number of activities each day and the second part presents the models where the according activity durations are brought in relationship.

6.2.1 Activity vs. E-Activity

The tested model for leisure activities is shown in Figure 8, again in the form of a path diagram. The same assumption about ordered logit apply here for the variable it_tool. The model *M1* did not converge to a reasonable result and is therefore not presented. Table 11 shows the results of *M2*. The effect of online activities on trips has a rather high magnitude, though it is not significant. Again the weekend has a significant influence on the number of undertaken trips. Contrary to the results in section 6.1, leisure trips are more often taken at the weekends, which seems reasonable since usually nobody is working on weekends and has free time to go somewhere for leisure purposes or to visit somebody. The fact that a participant is working has a negative influence on the amount of leisure trips he makes, but also this effect is not significant. The age has a significant effect on the amount of online activities. It seems rather small but since the average age of the population is about 50 years old, the effect is quite substantial. The fit of the model is better than the previous but still not in a range considered good (see section 3.5).

Table 12 shows the results of *M3*. The effects between the key variables disappeared, which is not surprising since their effect was not significant in the previous model. The effects of weekdays on the amount of trips became significant and shows a rather large influence of Friday, Saturday and Sunday. This seems again reasonable since at the weekends one tends to do more trips for leisure purposes. The fact that someone is working has now a significant negative influence on both key variables. The age of the participant stayed also at the same level of magnitude but got even more significant. The introduced endogenous variable *it_tool* has a significant positive (but rather small) effect on online leisure activities. But similarly to the effect of age it becomes more substantial with more such tools. The RMSEA indicates a worse fit than for *M2*.

The additional estimation results of *M4* are shown in Table 13. The travelled distance is not included in the model, because it did not converge that way. All the estimates are significant whereas the constant still has a big effect on the travelled kilometres. But the influence of the number of trips has increased substantially. This is according to the expectations.

6.2.2 Activity vs. E-Activity Duration

In section B.2 all the results of the estimated models with the out-of-home and online leisure activity duration are shown. They are not in the main part because their fit was rather poor. Figure 15 illustrates the estimated models. Due to convergence issues no *M4* model has been estimated with this pair.

Table 11: Results of the model "Out-of-home vs. online leisure activities" (M2)

Variable $leis\_trips \leftarrow$	Estimate	Std. Err.		Variable $leis\_onl\_act \leftarrow$	Estimate	Std. Err.	
$leis\_onl\_act$	-1.03	1.56		$leis\_trips$	0.32	0.57	
$wave_1$	-0.04	0.18		$wave_1$	-0.10	0.11	
$wave_2$	-0.03	0.14		$wave_2$	-0.07	0.11	
$tuesday$	0.12	0.07		$tuesday$	0.00	0.06	
$wednesday$	0.09	0.06		$wednesday$	-0.04	0.07	
$thursday$	0.03	0.12		$thursday$	-0.10	0.07	
$friday$	0.23	0.14		$friday$	-0.18	0.18	
$saturday$	0.48	0.23	(∗)	$saturday$	-0.34	0.36	
$sunday$	0.34	0.09	(∗∗)	$sunday$	-0.16	0.22	
$week$	0.00	0.09		$week$	-0.05	0.06	
age	-0.02	0.02		age	-0.01	0.01	(∗)
$hh\_children$	-0.11	0.08		$hh\_children$	-0.01	0.05	
res_rur	-0.16	0.22		$working$	-0.21	0.20	
$working$	-0.44	0.42		$att\_carlove$	0.05	0.03	(.)
$cons.$	2.63	2.46		$cons.$	1.28	0.64	(∗)
$var(RE_1)$	0.47	1.04					
$var(RE_2)$	0.36	0.08					
$cov(RE_1, RE_2)$	0.29	0.47					
$var(\varepsilon_1)$	0.77	0.57					
$var(\varepsilon_2)$	0.28	0.25					
$cor(RE_1, RE_2)$	0.70						
Goodness of fit (AICc; RMSEA)					10'657; 0.34		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

Table 28 shows the estimation results of *M2*. The socio-demographic variables have a significant influence on both key variables. But their magnitude seems not high enough to really change the key variables. The days at the end of the week (Friday, Saturday and Sunday) have a significant positive effect on the time spent out-of-home for leisure activities. The model fit is also very poor (0.82).

Table 29 gives an overlook about the estimation results of *M3*. The fit did improve but is still on a poor level (0.76). The time spent online has a negative influence on the time spent out-of-home. In the other direction the effect is nearly zero. The aforementioned effects of the weekend and the socio-demographic variables did not change substantially.

Table 12: Results of the model "Out-of-home vs. online leisure activities" (M3)

Variable $leis\_trips \leftarrow$	Estimate	Std. Err.		Variable $leis\_onl\_act \leftarrow$	Estimate	Std. Err.	
$leis\_onl\_act$	-0.17	0.37		$leis\_trips$	0.01	0.13	
$wave_1$	0.04	0.09		$wave_1$	-0.11	0.10	
$wave_2$	0.03	0.07		$wave_2$	-0.07	0.09	
$tuesday$	0.09	0.05	(.)	$tuesday$	0.03	0.03	
$wednesday$	0.10	0.05	(∗)	$wednesday$	-0.01	0.03	
$thursday$	0.09	0.06		$thursday$	-0.07	0.04	(∗)
$friday$	0.30	0.06	(∗∗)	$friday$	-0.09	0.05	
$saturday$	0.60	0.08	(∗∗)	$saturday$	-0.15	0.09	
$sunday$	0.37	0.06	(∗∗)	$sunday$	-0.05	0.06	
$week$	0.03	0.06		$week$	-0.04	0.05	
age	-0.01	0.01		age	-0.01	0.00	(∗∗)
res_rur	-0.06	0.09		$hh\_children$	-0.02	0.07	
$working$	-0.24	0.14	(.)	$working$	-0.36	0.16	(∗)
$cons.$	1.19	0.61	(.)	$att\_carlove$	0.03	0.03	
				it_tool	0.14	0.03	(∗∗)
				$cons.$	1.26	0.28	(∗∗)
	Estimate	**Std. Err.**		**Variable $it\_tool \leftarrow$**	**Estimate**	**Std. Err.**	
$var(RE_1)$	0.16	0.04		$income$	0.04	0.02	(∗)
$var(RE_2)$	0.32	0.03		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	0.04	0.10		age	-0.02	0.01	(∗)
$var(\varepsilon_1)$	0.60	0.04		$att\_antionltech$	-0.55	0.11	(∗∗)
$var(\varepsilon_2)$	0.20	0.01		cut_1	-6.61	1.09	(∗∗)
$cor(RE_1, RE_2)$	0.17			cut_2	-2.95	0.47	(∗∗)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)						17’109; 0.39	
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

6.3 All Shopping Purposes

Both long term, short term shopping and the sum of both are discussed in the following sections. This is due to the fact that some effects may only be observed in models with more observations, hence the combined model. But since the reasons to shop for long term purpose are different from the reasons to shop for short term purpose, there are additional models to observe other effects.

Table 13: Results of the model "Out-of-home vs. online leisure activities" (M4)

Variable $log\_leis\_km\_trav \leftarrow$	Estimate	Std. Err.	
$leis\_trips$	0.64	0.10	(∗∗)
$leis\_onl\_act$	-0.13	0.07	(∗)
$cons.$	1.09	0.16	(∗∗)
$var(\varepsilon_{km})$	2.13	0.29	
Goodness of fit (AICc; RMSEA)	21’915; 0.42		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1			
2’623 Complete observations on 336 people			

6.3.1 Activity vs. E-Activity

Figure 9 shows the specified models for both kinds of shopping purposes. Table 14 shows the results for *M1* and *M2*. *M1* exhibits that the effects of weekends is significant on the amount of shopping trips. Evidently the effects of Sunday is negative and the one of Saturday is positive. Because on Saturday one has time to shop, as normally one is not working that day. Interestingly the effects of weekends is not much different from weekdays for online shopping. There is apparently no preference on which day one likes to shop online. The fit of *M1* is not that bad comparing it to the models of the previous sections.

In *M2* the effects between the key variables have increased in absolute terms. Online shopping activities have a positive influence on the amount of shopping trips whereas in the other direction the effect is negative. But again these effects are not significant and therefore have to be treated with precaution. The socio-demographic variables have a rather low impact on the amount of trips. Despite that income could have a bigger influence, since its magnitude ranges up to 40’000 with a mean at roughly 7’000 CHF a month. The fact that one lives in the urban area has a positive effect on the number of online shopping activities, although it is very small. Environmentally sensitive people have a tendency to buy more things in-store than online but also this effect is small. The model fit is better than the one for *M1* but still not good.

The estimation results of the model *M3* is summarised in Table 15. The endogenous variable *hh_veh* can be described rather good with the variables used. None of the endogenous explanatory variables has a significant influence on the key variables. Also the goodness of fit is worse than in the previous steps. The other effects, which were significant before, did not change much and their scale remained approximately constant.

Figure 9: Path diagram of the models *M2*, *M3* and *M4* for the key variable pair : Out-of-home vs. online shopping activities

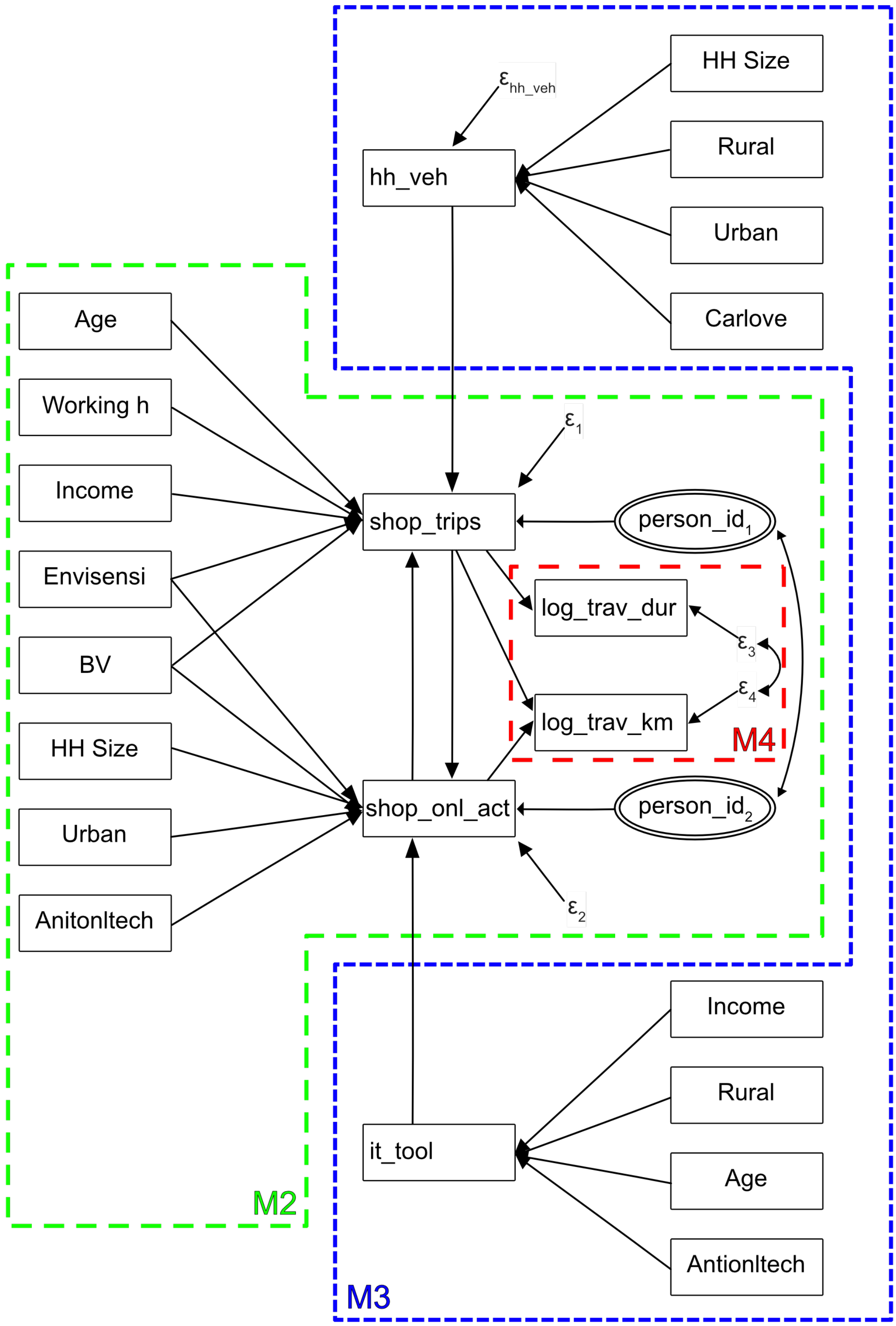


Table 14: Results of the model "Out-of-home vs. online shopping activities" (M1 and M2)

Variable	M1			M2		
$shop\_trips \leftarrow$	Estimate	Std. Err.		Estimate	Std. Err.	
$shop\_onl\_act$	0.11	0.29		0.53	0.40	
$wave_1$	0.02	0.04		0.04	0.05	
$wave_2$	-0.01	0.04		0.03	0.04	
$tuesday$	-0.07	0.04		-0.05	0.04	
$wednesday$	-0.04	0.04		-0.01	0.05	
$thursday$	-0.07	0.05		-0.05	0.05	
$friday$	0.00	0.05		0.03	0.05	
$saturday$	0.21	0.06	(∗∗)	0.24	0.06	(∗∗)
$sunday$	-0.30	0.05	(∗∗)	-0.26	0.05	(∗∗)
$week$	0.02	0.04		0.04	0.04	
age	-	-		0.00	0.00	(∗∗)
$working\_h$	-	-		0.00	0.00	
$income$	-	-		-0.01	0.00	(.)
$att\_envisensi$	-	-		0.03	0.02	
$cons.$	0.35	0.07	(∗∗)	0.15	0.13	
$shop\_onl\_act \leftarrow$	Estimate	Std. Err.		Estimate	Std. Err.	
$shop\_trips$	-0.03	0.11		-0.18	0.15	
$wave_1$	0.00	0.03		-0.02	0.03	
$wave_2$	0.01	0.03		-0.01	0.03	
$tuesday$	-0.04	0.03		-0.06	0.03	(.)
$wednesday$	-0.06	0.03	(.)	-0.06	0.03	(.)
$thursday$	-0.05	0.03		-0.06	0.03	(.)
$friday$	-0.08	0.03	(∗∗)	-0.08	0.03	(∗∗)
$saturday$	-0.07	0.03	(∗)	-0.04	0.04	
$sunday$	-0.12	0.05	(∗∗)	-0.16	0.05	(∗∗)
$week$	-0.03	0.03		-0.03	0.03	
hh_size	-	-		-0.02	0.01	(.)
$att\_envisensi$	-	-		-0.03	0.01	(∗∗)
res_cit	-	-		0.04	0.02	(.)
$att\_antionltech$	-	-		-0.03	0.01	(∗∗)
$cons.$	0.18	0.05	(∗∗)	0.29	0.08	(∗∗)
$var(RE_1)$	0.05	0.01		0.04	0.01	
$var(RE_2)$	0.02	0.00		0.02	0.01	
$cov(RE_1, RE_2)$	0.00	0.00		0.00	0.00	
$var(\varepsilon_1)$	0.32	0.02		0.34	0.05	
$var(\varepsilon_2)$	0.11	0.01		0.13	0.02	
$cor(RE_1, RE_2)$	0.12			0.17		
Goodness of fit (AICc; RMSEA)		6’738; 0.33			6’718; 0.27	

Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1

2’623 Complete observations on 336 people

Table 15: Results of the model "Out-of-home vs. online shopping activities" (M3)

Variable $shop\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	0.07	0.49		$shop\_trips$	-0.01	0.18	
$wave_1$	0.03	0.04		$wave_1$	-0.02	0.03	
$wave_2$	0.02	0.04		$wave_2$	-0.01	0.03	
$tuesday$	-0.07	0.04		$tuesday$	-0.04	0.03	
$wednesday$	-0.04	0.05		$wednesday$	-0.05	0.03	(.)
$thursday$	-0.07	0.05		$thursday$	-0.05	0.03	
$friday$	0.00	0.06		$friday$	-0.08	0.03	(∗∗)
$saturday$	0.20	0.06	(∗∗)	$saturday$	-0.08	0.05	(.)
$sunday$	-0.31	0.06	(∗∗)	$sunday$	-0.11	0.06	(.)
$week$	0.02	0.04		$week$	-0.03	0.03	(.)
age	0.00	0.00	(∗)	hh_size	-0.01	0.01	
$working\_h$	0.00	0.00		res_cit	-0.03	0.01	(∗∗)
$income$	0.00	0.00		$att\_envisensi$	0.04	0.02	(.)
$att\_envisensi$	0.01	0.02		$att\_antionltech$	-0.03	0.01	(∗∗)
hh_veh	-0.02	0.01		it_tool	0.02	0.01	
$cons.$	0.28	0.14	(.)	$cons.$	0.16	0.12	
$hh\_veh \leftarrow$	Estimate	Std. Err.		$it\_tool \leftarrow$	Estimate	Std. Err.	
hh_size	0.25	0.06	(∗∗)	$income$	0.04	0.02	(∗)
res_cit	-0.58	0.13	(∗∗)	res_rur	0.66	0.44	
$att\_carlove$	0.13	0.05	(∗)	age	-0.02	0.01	(∗)
res_rur	0.89	0.32	(∗∗)	$att\_antionltech$	-0.55	0.11	(∗∗)
$cons.$	0.81	0.16	(∗∗)	cut_1	-6.61	1.09	(∗∗)
				cut_2	-2.95	0.47	(∗∗)
$var(RE_1)$	0.04	0.01		cut_3	-0.79	0.44	(.)
$var(RE_2)$	0.02	0.00		cut_4	0.88	0.45	(.)
$cov(RE_1, RE_2)$	0.01	0.00					
$var(\varepsilon_1)$	0.32	0.02					
$var(\varepsilon_2)$	0.11	0.01					
$var(\varepsilon_{hh\_veh})$	1.19	0.12					
$cor(RE_1, RE_2)$	0.20						
Goodness of fit (AICc; RMSEA)					21’092; 0.40		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

Table 16: Results of the model "Out-of-home vs. online shopping activities" (M4)

Variable							
$log\_shop\_km\_trav \leftarrow$	Estimate	Std. Err.			Estimate	Std. Err.	
$shop\_trips$	0.76	0.07	(∗∗)	$var(\varepsilon_{km})$	1.44	0.12	
$shop\_onl\_act$	0.02	0.07		$var(\varepsilon_{dur})$	0.85	0.07	
$cons.$	-0.11	0.11	(∗∗)	$cov(\varepsilon_{km}, \varepsilon_{dur})$	0.85	0.09	(∗∗)
$log\_shop\_trav\_dur \leftarrow$	Estimate	Std. Err.					
$shop\_trips$	0.63	0.06	(∗∗)				
$cons.$	1.49	0.09	(∗∗)				
Goodness of fit (AICc; RMSEA)						24'596; 0.40	
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

In *M4*, the constants describing the newly introduced variables, are of a very small scale (see Table 16). The initial key variables are describing the logarithm of the travelled kilometres and minutes rather well. On the other hand, the online shopping activities have no influence on these two variables. The model fit decreased slightly in comparison to the previous models.

6.3.2 Activity vs. E-Activity Duration

Section B.3 gives an insight of models using shopping durations both online and offline as key variables. Figure 16 shows the used model structures. As seen in that figure, no *M4* has been estimated with these variables because of convergence issues.

An overview of the estimation results of *M2* is given in Table 30. The effects of the weekdays are positive only Saturdays, though not significantly. The time spent for shopping out-of-home is significantly shorter for males than females. The effect of Saturday and Sunday on out-of-home shopping duration are also significant. These effects are as expected positive on Saturday and negative on Sunday, since most of the shops are closed on Sunday. The RMSEA indicates a rather poor fit (0.76).

The estimation results of *M3* are summarised in Table 31. The effects stay more or less the same as in the previous model but the fit is slightly better. The introduced endogenous variable has no significant impact on the model. There seems to be no preference on which day of the week one shops online, because all the effects are roughly of the same scale, though mostly not significant.

6.4 Long Term Shopping

Long term shopping is described in section 4.3. The first part of this section consists of models concerning the number of activities and the second part their summed daily durations.

6.4.1 Activity vs. E-Activity

Figure 10 shows the estimated models accounting only for long term shopping trips in relation with online shopping activities. Because *M1* did not converge it is not presented. Table 17 sums up the result of the estimation of *M2*. The effect between shopping trips and online shopping activities is significant in both directions, negative from trips to online activities and opposite in the other direction. Again the weekend dummies indicate less shopping trips on Sunday and more trips on Saturday. Online shopping activities occur the fewest on a Sunday. The RMSEA indicates the best fit so far. Yet it is still not below 0.1, which would indicate a good model fit.

There are not much changes from *M2* to *M3* (summed up in Table 18). The effects between the key variables stay more or less the same and also the other effects seem to be stable. The newly introduced endogenous variables have only small and insignificant influence on the described variables. Some significant effects are from such a small magnitude that they could be neglected (i.e. income or household size). The model presents a fit worse than the previous models.

M4 displays also a strong relationship between the initial key variables and small constants (see Table 19). The fit did increase slightly by adding the additional variables, but still is worse than *M2*. In comparison with the results of the aggregated model in Table 16 the direct effects have increased substantially by only looking at long term shopping trips.

6.4.2 Activity vs. E-Activity Duration

Section B.4 includes all models using the shopping activity duration for long term goods as a key variable. Figure 17 illustrates the different models. Again, convergence issues prohibited the estimation of a *M4*.

In Table 32 the models *M1* and *M2* are summarised. Both show a rather poor model fit (1.11 and 0.74 respectively), despite that some interesting effects could be observed. The effects are similar to the model including all kinds of shopping trips but at a smaller scale. The socio-demographic variables have a pretty low influence on the out-of-home and online duration. The online shopping activity duration seems to be shorter on a Sunday.

Figure 10: Path diagram of the models *M2*, *M3* and *M4* for the key variable pair : Out-of-home vs. online shopping activities for long term goods

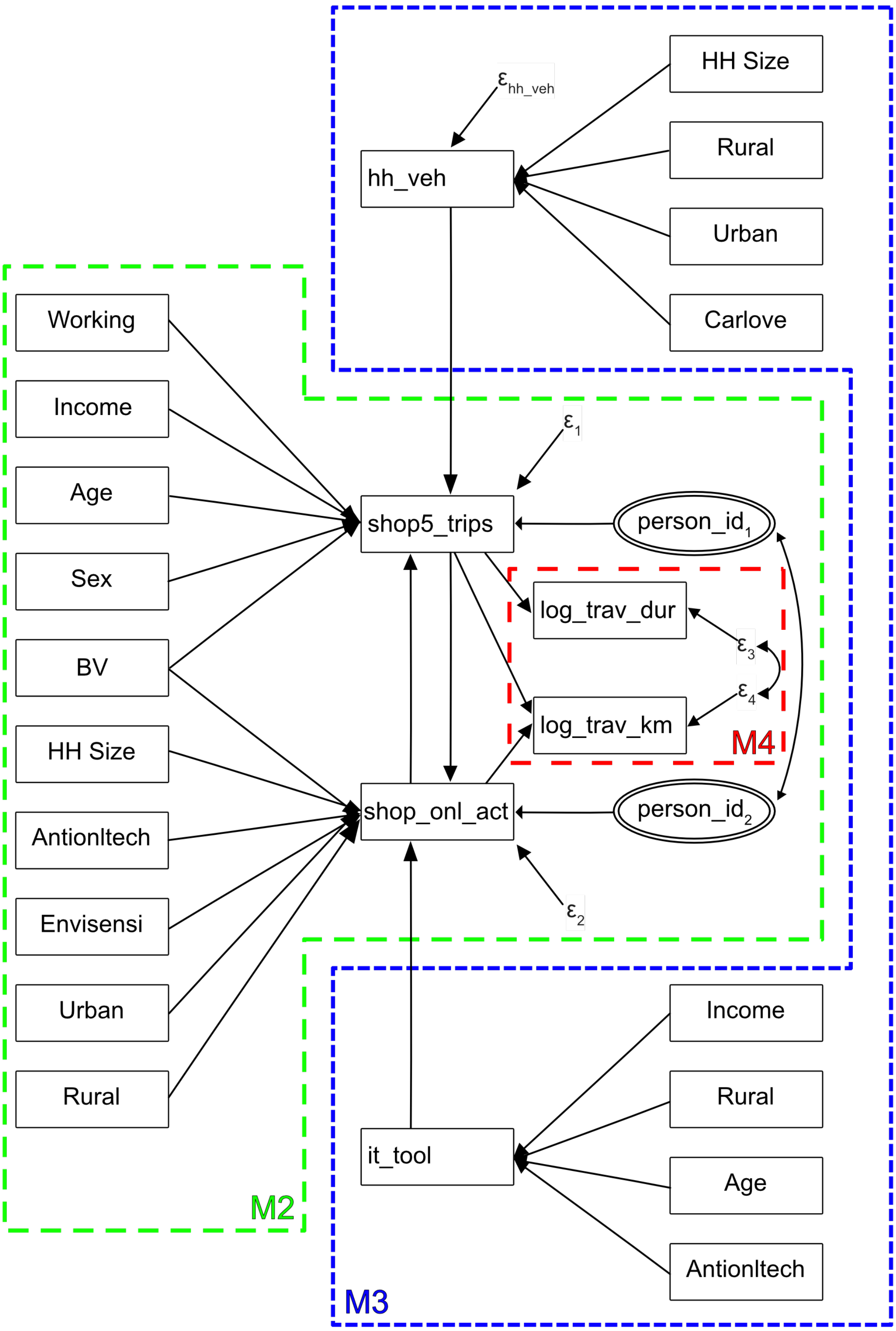


Table 17: Results of the model "Out-of-home vs. online shopping activities for long term goods" (M2)

Variable $shop5\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	0.38	0.21	(.)	$shop5\_trips$	-0.32	0.17	(.)
$wave_1$	0.03	0.02		$wave_1$	-0.02	0.03	
$wave_2$	0.01	0.03		$wave_2$	-0.01	0.03	
$tuesday$	-0.03	0.03		$tuesday$	-0.06	0.03	(∗)
$wednesday$	0.00	0.03		$wednesday$	-0.06	0.03	(∗)
$thursday$	-0.02	0.03		$thursday$	-0.06	0.03	(∗)
$friday$	0.04	0.03		$friday$	-0.08	0.03	(∗∗)
$saturday$	0.11	0.04	(∗∗)	$saturday$	-0.05	0.03	
$sunday$	-0.09	0.03	(∗∗)	$sunday$	-0.15	0.04	(∗∗)
$week$	0.01	0.02		$week$	-0.04	0.03	
sex	-0.03	0.02		hh_size	-0.02	0.01	(.)
age	0.00	0.00		res_cit	0.03	0.02	
$income$	0.00	0.00	(.)	res_rur	-0.03	0.05	
$working$	-0.04	0.03		$att\_envisensi$	-0.04	0.01	(∗∗)
				$att\_antionltech$	-0.04	0.01	(∗∗)
$cons.$	0.08	0.08		$cons.$	0.26	0.05	(∗∗)
$var(RE_1)$	0.01	0.00					
$var(RE_2)$	0.02	0.01					
$cov(RE_1, RE_2)$	0.00	0.00					
$var(\varepsilon_1)$	0.15	0.02					
$var(\varepsilon_2)$	0.13	0.02					
$cor(RE_1, RE_2)$	0.03						
Goodness of fit (AICc; RMSEA)					4’389; 0.22		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

Looking at Table 33 which represents the estimation results of *M3*, one is not able to identify substantial changes from *M2*. All the explanatory variables retained their effect approximately. But the added endogenous variable it_tool has no significant influence on the model, although the fit did increase slightly.

6.5 Short Term Shopping

Short term shopping is described in section 4.3. Again in this section, at the beginning the number of activities are the observed key variables and secondly their related duration.

Table 18: Results of the model "Out-of-home vs. online shopping activities for long term goods" (M3)

Variable $shop5\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	0.32	0.19	(.)	$shop5\_trips$	-0.27	0.16	(.)
$wave_1$	0.03	0.02		$wave_1$	-0.02	0.03	
$wave_2$	0.00	0.03		$wave_2$	-0.01	0.03	
$tuesday$	-0.03	0.03		$tuesday$	-0.05	0.03	(.)
$wednesday$	0.00	0.03		$wednesday$	-0.06	0.03	(.)
$thursday$	-0.02	0.03		$thursday$	-0.06	0.03	(.)
$friday$	0.03	0.03		$friday$	-0.08	0.03	(∗∗)
$saturday$	0.11	0.04	(∗∗)	$saturday$	-0.06	0.03	(.)
$sunday$	-0.10	0.03	(∗∗)	$sunday$	-0.14	0.04	(∗∗)
$week$	0.00	0.02		$week$	-0.04	0.03	
sex	-0.02	0.02		hh_size	-0.02	0.01	(.)
age	0.00	0.00		res_cit	0.04	0.02	
$income$	0.00	0.00	(.)	res_rur	-0.03	0.05	
$working$	-0.04	0.03		$att\_envisensi$	-0.03	0.01	(∗∗)
hh_veh	-0.01	0.01		$att\_antionltech$	-0.03	0.01	(∗∗)
				it_tool	0.02	0.01	
$cons.$	0.10	0.07		$cons.$	0.21	0.06	(∗∗)
$hh\_veh \leftarrow$	Estimate	Std. Err.		$it\_tool \leftarrow$	Estimate	Std. Err.	
hh_size	0.25	0.06	(∗∗)	$income$	0.04	0.02	(∗)
res_cit	-0.58	0.13	(∗∗)	res_rur	0.66	0.44	
$att\_carlove$	0.13	0.05	(∗)	age	-0.02	0.01	(∗)
res_rur	0.89	0.32	(∗∗)	$att\_antionltech$	-0.55	0.11	(∗∗)
$cons.$	0.81	0.16	(∗∗)	cut_1	-6.61	1.09	(∗∗)
				cut_2	-2.95	0.47	(∗∗)
$var(RE_1)$	0.01	0.00		cut_3	-0.79	0.44	(.)
$var(RE_2)$	0.02	0.00		cut_4	0.88	0.45	(.)
$cov(RE_1, RE_2)$	0.00	0.00					
$var(\varepsilon_1)$	0.15	0.02					
$var(\varepsilon_2)$	0.12	0.02					
$var(\varepsilon_{hh\_veh})$	1.19	0.12					
$cor(RE_1, RE_2)$	0.07						
Goodness of fit (AICc; RMSEA)					18’909; 0.38		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

Table 19: Results of the model "Out-of-home vs. online shopping activities for long term goods" (M4)

Variable $log\_shop5\_km\_trav \leftarrow$	Estimate	Std. Err.			Estimate	Std. Err.	
$shop5\_trips$	0.50	0.17	(∗∗)	$var(\varepsilon_{km})$	1.40	0.18	
$shop\_onl\_act$	-0.12	0.09		$var(\varepsilon_{dur})$	0.77	0.11	
$cons.$	0.64	0.23	(∗∗)	$cov(\varepsilon_{km}, \varepsilon_{dur})$	0.81	0.13	(∗∗)
$log\_shop5\_trav\_dur \leftarrow$	Estimate	Std. Err.					
$shop5\_trips$	0.43	0.13	(∗∗)				
$cons.$	1.94	0.17	(∗∗)				
Goodness of fit (AICc; RMSEA)					20'025; 0.36		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

6.5.1 Activity vs. E-Activity

The tested models concerning only short term shopping activities are pictured in Figure 11. It has the same structure as the one used for long term shopping activities (see Figure 10). This makes it possible to compare the effects of the different types of trips. In Table 20 the estimation results of *M1* are summarised. Again the effects of the weekend days are significant and for the out-of-home activities also in the expected direction (positive on Saturday and negative on Sunday). The fit of the model is with a RMSEA of 0.29 not that bad.

The results of *M2* are exhibited in Table 21. The fit did improve slightly to a RMSEA of 0.24. The effect of weekend days did not change substantially and remained significant. People living in an urban residential location tend to shop more often online than people living in rural place. These effects are not significant and might therefore be wrong. Attitudes have a significant influence on the online shopping behaviour, but their effects are rather small.

Table 22 shows the results of the estimation of *M3*. In addition to the effects of *M2* there are the two endogenous explanatory variables it_tool and hh_veh. Although, both of them have a significant influence on the key variables the effects are rather small and negligible. All the other effects on the key variables remained more or less on the same level as before. The fit did worsen by including the two aforementioned variables. As in *M1* and *M2* the effects between the key variables are not significant. However, their effect is quite interesting as the number of trips decreases the number of online shopping activities and in the opposing direction the effect is the other way.

Figure 11: Path diagram of the models *M2*, *M3* and *M4* for the key variable pair : Out-of-home vs. online shopping activities for short term goods

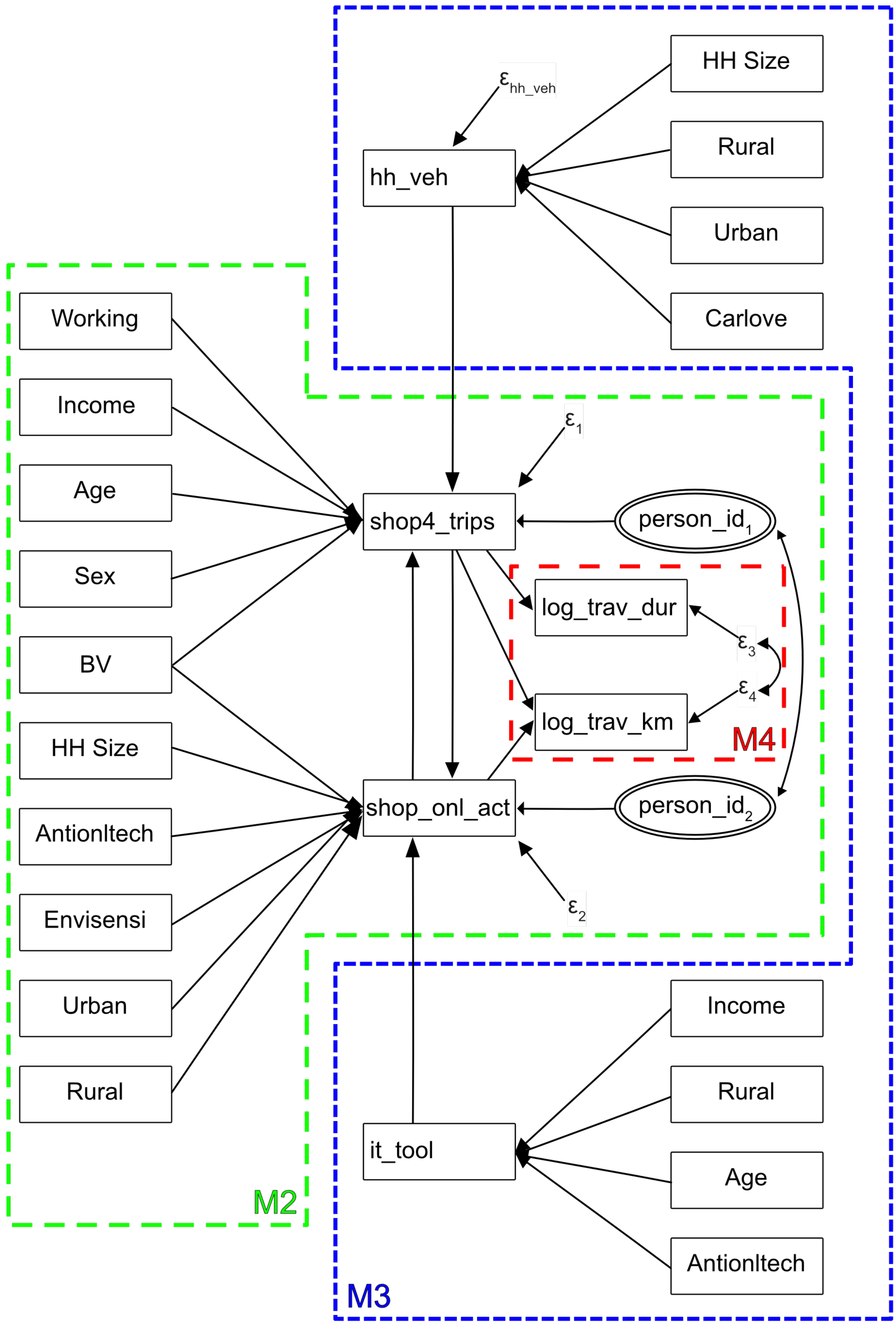


Table 20: Results of the model "Out-of-home vs. online shopping activities for short term goods" (M1)

Variable $shop5\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	0.00	0.08		$shop5\_trips$	0.02	0.04	
$wave_1$	0.00	0.04		$wave_1$	0.00	0.03	
$wave_2$	0.00	0.03		$wave_2$	0.01	0.03	
$tuesday$	-0.03	0.03		$tuesday$	-0.04	0.03	
$wednesday$	-0.03	0.03		$wednesday$	-0.05	0.03	(.)
$thursday$	-0.04	0.03		$thursday$	-0.05	0.03	
$friday$	-0.02	0.04		$friday$	-0.08	0.03	(∗∗)
$saturday$	0.12	0.04	(∗∗)	$saturday$	-0.08	0.03	(∗∗)
$sunday$	-0.18	0.03	(∗∗)	$sunday$	-0.10	0.03	(∗∗)
$week$	0.03	0.04		$week$	-0.03	0.03	
$cons.$	0.24	0.04	(∗∗)	$cons.$	0.17	0.03	(∗∗)
	Estimate	Std. Err.			Estimate	Std. Err.	
$var(RE_1)$	0.03	0.01		$var(\varepsilon_1)$	0.18	0.01	
$var(RE_2)$	0.02	0.00		$var(\varepsilon_2)$	0.11	0.01	
$cov(RE_1, RE_2)$	0.00	0.00		$cor(RE_1, RE_2)$	-0.02		
Goodness of fit (AICc; RMSEA)						5'305; 0.29	
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

Table 23 shows the additional effects gained through testing *M4*. The results lie in the same region as the results in Table 19, though the effect of the number of trips on the kilometres travelled is slightly smaller.

6.5.2 Activity vs. E-Activity Duration

Section B.5 includes the results of the models estimated including short term shopping durations as a key variable. In Figure 18 an overview is given of all the estimated models. *M4* has not been estimated due to convergence issues.

Table 34 summarises the estimation results of *M2*. Also in this model the socio-demographic variables are significant for the out-of-home shopping durations, but only at a small scale. Interestingly these durations have a significant impact on the online shopping durations (estimate of -0.31). In the other direction, the effect is slightly bigger and positive but not significant. As in all models including shopping durations, the variable indicating Saturday has a positive estimate

Table 21: Results of the model "Out-of-home vs. online shopping activities for short term goods" (M2)

Variable $shop5\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	-0.22	0.57		$shop5\_trips$	0.15	0.35	
$wave_1$	0.01	0.04		$wave_1$	-0.02	0.03	
$wave_2$	0.02	0.04		$wave_2$	0.00	0.03	
$tuesday$	-0.04	0.04		$tuesday$	-0.04	0.03	
$wednesday$	-0.04	0.04		$wednesday$	-0.05	0.03	
$thursday$	-0.05	0.04		$thursday$	-0.04	0.03	
$friday$	-0.04	0.06		$friday$	-0.08	0.03	(∗∗)
$saturday$	0.10	0.06	(.)	$saturday$	-0.10	0.05	(∗)
$sunday$	-0.20	0.07	(∗∗)	$sunday$	-0.08	0.07	
$week$	0.02	0.04		$week$	-0.04	0.03	
sex	-0.01	0.03		hh_size	-0.01	0.01	
age	0.00	0.00		res_cit	0.03	0.03	
$income$	0.00	0.00		res_rur	-0.03	0.06	
$working$	0.00	0.06		$att\_envisensi$	-0.04	0.01	(∗∗)
				$att\_antionltech$	-0.04	0.01	(∗∗)
$cons.$	0.17	0.18		$cons.$	0.17	0.11	
	Estimate	Std. Err.			Estimate	Std. Err.	
$var(RE_1)$	0.03	0.01		$var(\varepsilon_1)$	0.19	0.04	
$var(RE_2)$	0.02	0.00		$var(\varepsilon_2)$	0.12	0.02	
$cov(RE_1, RE_2)$	0.00	0.00		$cor(RE_1, RE_2)$	0.03		
Goodness of fit (AICc; RMSEA)						5’292; 0.24	
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

(13.52) and the one for Sunday a negative (-3.64) whereas both are significant. Although the effect of the household size on the duration of online shopping activities is rather small, interestingly it has a significant negative influence on the participant. Additionally, it is observable that environmentally sensitive people tend to shop online less long. The model fit is poor with a RMSEA of 0.76.

The estimation results of *M3* are shown in Table 35. Despite that the fit got a little better through including the endogenous explanatory variable it_tool, it has no significant effect. All the other variables retained more or less the estimated effect of *M2*. The fit, although better than *M2*, is also rather poor with a RMSEA of 0.70.

Table 22: Results of the model "Out-of-home vs. online shopping activities for short term goods" (M3)

Variable $shop4\_trips \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_act \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_act$	-0.60	0.58		$shop4\_trips$	0.39	0.35	
$wave_1$	-0.01	0.04		$wave_1$	-0.03	0.04	
$wave_2$	0.01	0.04		$wave_2$	-0.01	0.03	
$tuesday$	-0.06	0.04		$tuesday$	-0.03	0.03	
$wednesday$	-0.06	0.05		$wednesday$	-0.04	0.03	
$thursday$	-0.06	0.05		$thursday$	-0.03	0.03	
$friday$	-0.07	0.06		$friday$	-0.07	0.03	(∗)
$saturday$	0.07	0.06		$saturday$	-0.12	0.05	(∗)
$sunday$	-0.24	0.07	(∗∗)	$sunday$	-0.04	0.07	
$week$	0.01	0.04		$week$	-0.05	0.03	
sex	-0.01	0.03		hh_size	-0.01	0.01	
age	0.00	0.00		res_cit	0.03	0.03	
$income$	0.00	0.00		res_rur	-0.06	0.06	
$working$	-0.02	0.07		$att\_envisensi$	-0.04	0.01	(∗∗)
hh_veh	-0.02	0.01	(∗)	$att\_antionltech$	-0.03	0.01	(∗∗)
$cons.$	0.30	0.19		it_tool	0.03	0.02	(.)
				$cons.$	0.02	0.15	
$hh\_veh \leftarrow$	Estimate	Std. Err.		$it\_tool \leftarrow$	Estimate	Std. Err.	
hh_size	0.25	0.06	(∗∗)	$income$	0.04	0.02	(∗)
res_cit	-0.58	0.13	(∗∗)	res_rur	0.66	0.44	
$att\_carlove$	0.13	0.05	(∗)	age	-0.02	0.01	(∗)
res_rur	0.89	0.32	(∗∗)	$att\_antionltech$	-0.55	0.11	(∗∗)
$cons.$	0.81	0.16	(∗∗)	cut_1	-6.61	1.09	(∗∗)
				cut_2	-2.95	0.47	(∗∗)
$var(RE_1)$	0.04	0.02		cut_3	-0.79	0.44	(.)
$var(RE_2)$	0.02	0.01		cut_4	0.88	0.45	(.)
$cov(RE_1, RE_2)$	0.00	0.00					
$var(\varepsilon_1)$	0.22	0.08					
$var(\varepsilon_2)$	0.14	0.05					
$var(\varepsilon_{hh\_veh})$	1.19	0.12					
$cor(RE_1, RE_2)$	-0.02						
Goodness of fit (AICc; RMSEA)						19’659; 0.38	

Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1

2’623 Complete observations on 336 people

Table 23: Results of the model "Out-of-home vs. online shopping activities for short term goods" (M4)

Variable							
$log\_shop4\_km\_trav \leftarrow$	Estimate	Std. Err.			Estimate	Std. Err.	
$shop4\_trips$	0.86	0.11	$(**)$	$var(\varepsilon_{km})$	1.43	0.13	
$shop\_onl\_act$	0.02	0.09		$var(\varepsilon_{dur})$	0.90	0.05	
$cons.$	-0.45	0.15	$(**)$	$cov(\varepsilon_{km}, \varepsilon_{dur})$	0.86	0.09	$(**)$
$log\_shop4\_trav\_dur \leftarrow$	Estimate	Std. Err.					
$shop4\_trips$	0.67	0.10	$(**)$				
$cons.$	1.31	0.13	$(**)$				
Goodness of fit (AICc; RMSEA)					22’253; 0.38		
Significance codes: $(**)$ <0.01, $(*)$ <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

6.6 Networks of Interacting Variables

The models discussed in this section have an experimental character. The goal was to observe more complicated networks of interacting key variables. In section B.6 all the models are exhibited.

Figure 19 shows a network model where the number of trips for all purposes has been split up into shopping and leisure trips (excluding all the other purposes). The results of this model were compared with those found in the simpler models before. It is interesting to see that the number of online activities and the number of leisure trips seem to influence each other differently. Their effects are of the opposite sign and the same scale. Though, the effect of the trips on the online activities is not significant. With more observations, maybe the number of shopping trips and the number of leisure trips have a significant (indirect) interdependency. Interestingly, the effects of age and living in a rural residential area on the number of leisure trips became significant remaining on the same scale. On the other hand, the employment dummy lost its significance. The effects on the number of shopping trips did not change much. The effects on the number of online activities have not changed in comparison with the original model in Figure 7. The RMSEA of this adapted model is 0.42, which does not indicate a good fit.

The next network model estimated is pictured in Figure 20. In this model the approach was to observe what happens if the shopping activities of the model in Figure 9 are split into long and short term shopping activities. All the estimates of variables describing the number of online shopping activities became significant. Since the effects did not change substantially, they probably were already right in the base model (see section 6.3). The number of vehicles lost its significance but the age of the respondent now has no effect on the number of short term shopping trips. The significant relationship between the number of online shopping activities and long term shopping trips has become insignificant in this model. The RMSEA of this model is 0.34, which si slightly better than the previous model but not good either. The next step consisted in combining these two models, but it did not converge after 80 iterations (which took about 24 hours).

7 Interpretation

This part treats the interpretation of the estimation results. In section 7.1 the previously stated hypotheses are tested and then rejected or accepted. In the following section 7.2 other results of the estimated models are further discussed.

7.1 Testing of Hypotheses

The stated hypotheses in section 5.1 are tested and discussed in the following section.

H_1: It seems that shopping online leads to more shopping trips. Although not significant, this effect has been found for shopping trips for all purposes and for long term shopping trips with an even higher influence (see Tables 15 and 18). Nonetheless, the effect is the other way for short term shopping trips (see Table 22). This could be due to the fact that long term shopping might include some internet research for the product, which is later bought in a store. This internet research could have been marked as online shopping. Another explanation could be that people have shopped online more often on days they did not shop short term goods. This hypothesis is rejected for short term shopping trips and accepted for long term shopping and shopping for all purposes.

H_2: Comparing the *M3* models of long and short term shopping, it can be stated that the absolute value of the estimated influence of online shopping activities is higher for short term shopping trips (see Tables 18 and 22) and therefore the effect is stronger for short term shopping trips. Furthermore, the estimate for short term shopping trips is negative (i.e. the more shopping trips the less online shopping). Since only the long term shopping effect is significant a comparison is pointless. Nevertheless, a larger sample size could give significant results which state the same or contradict the results of this work. This hypothesis has therefore to be rejected partially.

H_3: In all models the socio-demographic variables have a relatively small influence, but if adjusted according to the respondent, they do matter and influence the variables quite a bit. An example for this is that the influence of the respondents age on the number of online activities is -0.03 (see Table 9). This effect seems rather small but if one puts the age of the participant in (which is always over 18), one gets a rather substantial change (<-0.54). This hypothesis is therefore rejected.

H_4: The residential location influences the behaviour directly and indirectly over endogenous explanatory variables. The indirect results tend to contradict the direct effects in all but one model (see Table 9). However, their influences are very small compared to the direct effects and can therefore be neglected. The model including both shopping types, gives the impression that accepting $H_{4.2}$ is true (see Table 15). But the results of the models with a separation of purposes contradicts this reasoning. In both models the resulting estimates are more in favour of accepting $H_{4.1}$ (see Tables 18 and 22). This seems also more intuitive, as urban people also tend to have less means of transportation and are therefore more likely to purchase something online. Nevertheless, the results have to be taken with precaution, as most of the observed effects are not significant or not on a high level of significance.

H_5: Interestingly, the number of online leisure activities has a negative influence on the number of leisure trips. In the opposite direction the effect is positive. But both effects are not significant and a change of sign is less than one standard error away (see Table 12). Nevertheless, the online leisure activity duration has a significant negative influence on the out-of-home activity duration. The effect in the other direction is negligible. Therefore, this hypothesis can be accepted only partially. Online activity durations tend to substitute the out-of-home activity duration but in the other way this effect is not observed. This seems surprising since both activities are exclusive to each other (e.g. while watching TV one cannot ride a bike in the woods and vice versa).

H_6: The hypothesised effect is only observable by looking at indirect effects. In models including activities the working status is only explaining the number of trips. By multiplying the effect on trips by the effect of trips on online activities one gets a positive effect. This could lead to the conclusion that working implies more online shopping activities. But this result has to be taken with precaution, since both effects are not significant. In models which include the activity durations it is easier to identify the effects, as the effect of the number of weekly working hours on the online shopping duration is estimated. It is negative and not significant. As no effect is significant it is impossible to accept or reject the hypothesis. Though, it seems that working has a positive influence on the number of online shopping activities and on the other hand, the more working hours a week the less time is used for it.

H_7: Environmentally sensitive people have a significant tendency to shop less online, especially to a shorter time than other people. As an indirect effect also fewer trips and shorter out-of-home durations can be observed. However, this effect is rather small and sometimes even insignificant. It can be stated that the hypothesis is accepted for online shopping and further research has to be done to evaluate in-store shopping.

H_8: This hypothesis is clearly accepted, since in almost all models such effects can be found. Especially the out-of-home activities are largely influenced by the according day of the week. Great differences can be observed in between plans during the week and the weekend. This seems rather intuitive. Though, the online activities are not as differentiated between weekends and days during the week. As online activities can easily be undertaken at home during the evening, this seems not surprising at all.

H_9: The gender of the respondent has nearly no effect on the number of shopping trips, neither for long term nor for short term trips (see Tables 15, 18 and 22). However, the shopping activity duration is significantly shorter for men than for women (see Table 31). This implies that men are faster in their out-of-home shopping process, which was not hypothesised. Therefore, this hypothesis has to be rejected but the findings point out that there are gender related differences.

H_{10}: Looking at all direct and indirect effects of the factor *ANTIONLTECH* on the number of trips regardless of the purpose, it can be stated that the relationship is always positive except for the models in Figures 9 and 10 (i.e. combined shopping activities and long term shopping activities). The effects are rather small and since this factor is never influencing the number of trips directly, the effects are even smaller. Therefore, this hypothesis is partly accepted.

7.2 Discussion of other Estimation Results

Not all findings are discussed within the previous section concerning tests of the hypotheses. Therefore, in this section other interesting findings, regularities or irregularities are reviewed.

It is interesting to observe different subgroups (of purposes) and if they have deviating effects as proposed by Ren and Kwan (2009). It can be stated that also this has been found at some points. For example observing the aggregated data, did not show that the number of different IT tools has neither an effect on online shopping activities nor on its duration. Also for leisure activity durations the sex of the participant looses its significance through grouping the activities. Being male has a positive influence on the number of trips and online activities. This effect is not that small with additional 20 % of an activity a day. This effect disappears if the models are aggregated into different purposes. An explanation for this could be that men are more often the main working force in the household. Since working trips are not included in the specialised models these trips are not accounted for. Hence, the gender of the participant has no influence in these models.

The endogenous explanatory variable it_tool has a significant influence on the online activities for all purposes and for the leisure models. But in shopping models no reaction to this variable can be observed with significance. One might say that the number of tools has no influence on the number of online shopping activities during one day. This would be not that surprising since usually online shopping is done on a desktop pc or a laptop (Holmes et al., 2013; Kawsar and Bernheim Brush, 2013). Therefore, only one device is needed to do online shopping. On the other hand, some leisure online activities can not be done without a smartphone (e.g. mobile gaming). Additionally, purposes like social networking are not included in the aggregated models as they were in the model with all purposes. There might be some information loss through aggregating the models.

The influence of the number of trips on the distance travelled and travel duration is positive as expected. This effect is found in all *M4* models. The number of online activities also has a significant effect on the distance travelled in the model including all purposes. As for the aggregated models, the effect of online shopping activities looses its significance to describe the travelled distance. The travelled distances are slightly higher for long term shopping trips than for short term shopping trips. This seems to be reasonable since one is possibly willing to travel further for furniture or a similar product.

The presented estimates in Table 1 of section 2 have been compared with the observed estimates of this work. Table 24 shows an overview of all compared relationships. Not all previously found effects are compared since not all of them have been estimated in this work. It seems that quite a few results are contradicting previous findings. This could be due to different definitions of activities or descriptive variables. Another possibility to explain these contradictions, is the poor fit of the models presented in this work and their perhaps doubtful estimates. Nevertheless, some effects do confirm findings by other researchers.

Table 24: This table contains a comparison of observed estimates and the aforementioned results by other authors (see Table 1). Only the estimates which are comparable are listed here.

Author	Explanatory Variable	Dependent Variable	Comparison
Axhausen et al. (2000)	Being male	PT trips	Same sign but for all trips
	Income (Thousand CHF)	PT trips	Indirect, same sign but for all trips
Bagley and Mokhtarian (2001)	Being female	log(vehicle miles)	Same sign but for kilometres
Farag et al. (2007)	Frequency of in-store shopping	Online buying	Other sign for number of activities
	Age (continuous)	Frequency of in-store shopping	No effect
	Income (three categories)	Frequency of in-store shopping	No effect
	# Vehicles (0, 1, >1)	Frequency of in-store shopping	Same sign
Ferrell (2004)	Home shopping activities	Shopping trips per household	Same sign but on personal level
Gould and Golob (1997)	Age (continuous)	Shopping trips per person	No effect
	# Vehicles	Shopping trips per person	Other sign
Simma (2000)	Car availability (women only)	Shopping trips per person	Other sign for both genders
Wang and Yuk (2007)	Being employed	# Trips	Same sign
	Age (continuous)	# Leisure activities	Other sign

8 Conclusion

In this work it has been a big issue to overcome convergence problems. These could be due to: False assumptions about the distribution of the variables, too few assumptions about the starting values, false assumption of independence between explanatory variables or others. The only possible distribution to use with *STATA 14.1* is a normal distribution for the dependent variables (if one uses clustered standard errors). Therefore, the variables should be better adapted to the given boundary conditions (i.e. transformation). Another solution would be to use a different software than *STATA 14.1*, which is able to compute non-recursive models with clustered standard errors where the variables have other than normal distributions. This other software should also be capable to compute other goodness of fit indices, since the used indices are calculated manually and might use false assumptions.

The estimation results of all models suggest that the day of the week has a major influence on peoples travel behaviour. Mostly the weekends have a significant impact on people's schedules. Additionally, there are observed significant effects on the online activities, generated by the weekdays. It can be observed that there is not only a difference between workdays and weekends, but also in between workdays. Nonetheless, the relations between the different days are not observed in more detail.

The main goal of this work was to find interdependencies between ICT usage and travel behaviour. To find such relationships several SEM models have been estimated. These models differ in the used aggregation group of the activities or their durations. These groups include leisure and shopping related activities. The aforementioned interdependencies are demonstrated in this work. At least for some models there is a significant relation between online and out-of-home activities. Usually they are of opposing signs, which implies a certain decrease of substance when computing the total effects. On the other hand, the effects are rather small and therefore this decrease is also small. The activity duration seems to be more exclusive, because in these models the effects are of a larger scale, at least for the model including all purposes. The aggregated models also have a rather small relation between the key variables. The models estimated match sometimes findings of other researchers but also contradict them. Nonetheless, this seems not surprising because there is an ongoing debate if ICT usage replaces or generates travel. This work leads to the conclusion that ICT usage replaces travel to some extent. But it depends on the purpose as for long term shopping trips and the combined shopping trips no such effect can be observed.

9 Outlook

This section summarises ideas for further research with the «Post-Car-World»-data. If one tries to find interdependencies between ICT usage and daily activities.

- In this work the working activities have not been looked at, although these activities represent a substantial part of the respondents' daily schedules. There are also possibilities that people tend to chain their trips after work and be more efficient by doing so.
- One could try to identify different groups in the sample as proposed by Muthén (1989) and Jedidi et al. (1997). These groups can be useful to account for group-level unobserved components.
- The models estimated in this work should be re-estimated using data of the third wave of the «Post-Car-World»-Project. This could lead to more significant results and a better fit.
- The still missing trips could be added manually according to the respondents travel diary. This could already increase the significance of the models.
- With a bigger sample, maybe bigger networks become possible to estimate. This could give additional insights in the mentioned interdependencies.
- Another possibility to improve the model would be implementing another random effect accounting for the household, since there are potentially correlating schedules of people living at the same place.
- The influence of weekdays on travel behaviour and on ICT usage is mostly significant. It is assumed that it goes beyond the differentiation between workday and weekend. Therefore, it would be interesting to test for relations between the days of the week.

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A Questionnaire

Figure 12: Travel diary page for two entries

Trip diary (Day of week): ☐ Mon ☐ Tue ☐ Wed ☐ Thu ☐ Fri ☐ Sat ☐ Sun

Trip No.	**1**	**2**
Start time	hh:mm	hh:mm
Verkehrsmittel	☐ Walk min. ☐ Bicycle min. ☐ Motorbike min. ☐ Car (as driver) min. ☐ Car (as passenger min. ☐ Tram / bus min. ☐ Train min. ☐ Other min. Wating time: min.	☐ Walk min. ☐ Bicycle min. ☐ Motorbike min. ☐ Car (as driver) min. ☐ Car (as passenger min. ☐ Tram / bus min. ☐ Train min. ☐ Other min. Wating time: min.
Arrival time	hh:mm	hh:mm
Total distance	km (estimated)	km (estimated)
Destination (Address or locality)	Str. No. ZIP City **Locality**	Str. No. ZIP City **Locality**
Trip purpose: Please choose **only 1 activity**!	☐ Return home ☐ Drop off / Pick up someone ☐ Work / Education ☐ Shopping (daily needs) ☐ Shopping (long term needs) ☐ Services ☐ Business-related ☐ Leisure, specify: ☐ Other, specify:	☐ Return home ☐ Drop off / Pick up someone ☐ Work / Education ☐ Shopping (daily needs) ☐ Shopping (long term needs) ☐ Services ☐ Business-related ☐ Leisure, specify: ☐ Other, specify:
Number of involvevd persons / dogs	Weg (**Please do not include yourself**) Aktivität Household memebers Other acquainted persons dogs	Weg (**Please do not include yourself**) Aktivität Household memebers Other acquainted persons dogs
Planning horizon	☐ Routine activity / Return home trip ☐ One or several days in advance ☐ During the same day ☐ Spontaneous / immediately	☐ Routine activity / Return home trip ☐ One or several days in advance ☐ During the same day ☐ Spontaneous / immediately
Expenses / Travel cost	☐ PT passes CHF ☐ Parking fees CHF ☐ Taxi fees CHF ☐ Rental costs (e.g. for car, bike etc.) CHF ☐ No travel expenses for this trip	☐ PT passes CHF ☐ Parking fees CHF ☐ Taxi fees CHF ☐ Rental costs (e.g. for car, bike etc.) CHF ☐ No travel expenses for this trip

Source: Schmid and Axhausen (2015)

Figure 13: Online diary page for one day

Online- and telecommunication diary:	**Monday**

	Duration	Expenses
(Online-)Shopping: Purchase / bookings of (please also indicate *phone* orders) ...		
☐ Tickets for events, flights, train trips, hotel bookings (e.g. starticket.ch, ebookers.com, SBB.ch, etc.)	min.	CHF
☐ Clothes or sports equipment (e.g. zalando.ch, sportxx.ch, etc.)	min.	CHF
☐ Electronics and accessoires (e.g. digitec.ch, hshop.ch, melectronics.ch, distrelec.ch, exlibris.ch, etc.)	min.	CHF
☐ Furniture and accessoires (e.g. möbel-online.home24.ch, micasa.ch, etc.)	min.	CHF
☐ Books and magazines (e.g. amazon.de, etc.)	min.	CHF
☐ Groceries (e.g. leshop.ch, nespresso.ch, coopathome.ch, muesli.ch, etc.)	min.	CHF
☐ Other:	min.	CHF
(Online-)Entertainment: Download / stream / watch / play ...		
☐ Music	min.	CHF
☐ TV / movies / TV shows / youtube	min.	CHF
☐ Computer games	min.	CHF
☐ Other :	min.	CHF
☐ E-Banking / Bank transactions	min.	
☐ Social networks (e.g. facebook.com, twitter.com, etc.)	min.	
☐ Non-work communication (e.g. phone calls, SMS, Email, WhatsApp, online-chatting; with friends, acquaintances, etc.)	min.	
☐ Inquiries and education (e.g. google, online-news, vacation planning, restaurants, hotels, online-tutorials, blogs, price comparison, etc.)	min.	
☐ Online dating (e.g. parship.ch, c-date.ch, etc.)	min.	
☐ Other:	min.	CHF
	min.	CHF
☐ No online- and/or telecommunication activities on this day		

Source: Schmid and Axhausen (2015)

B Further Models

B.1 All Purposes

Figure 14: Out-of-home vs. online activity duration for all purposes

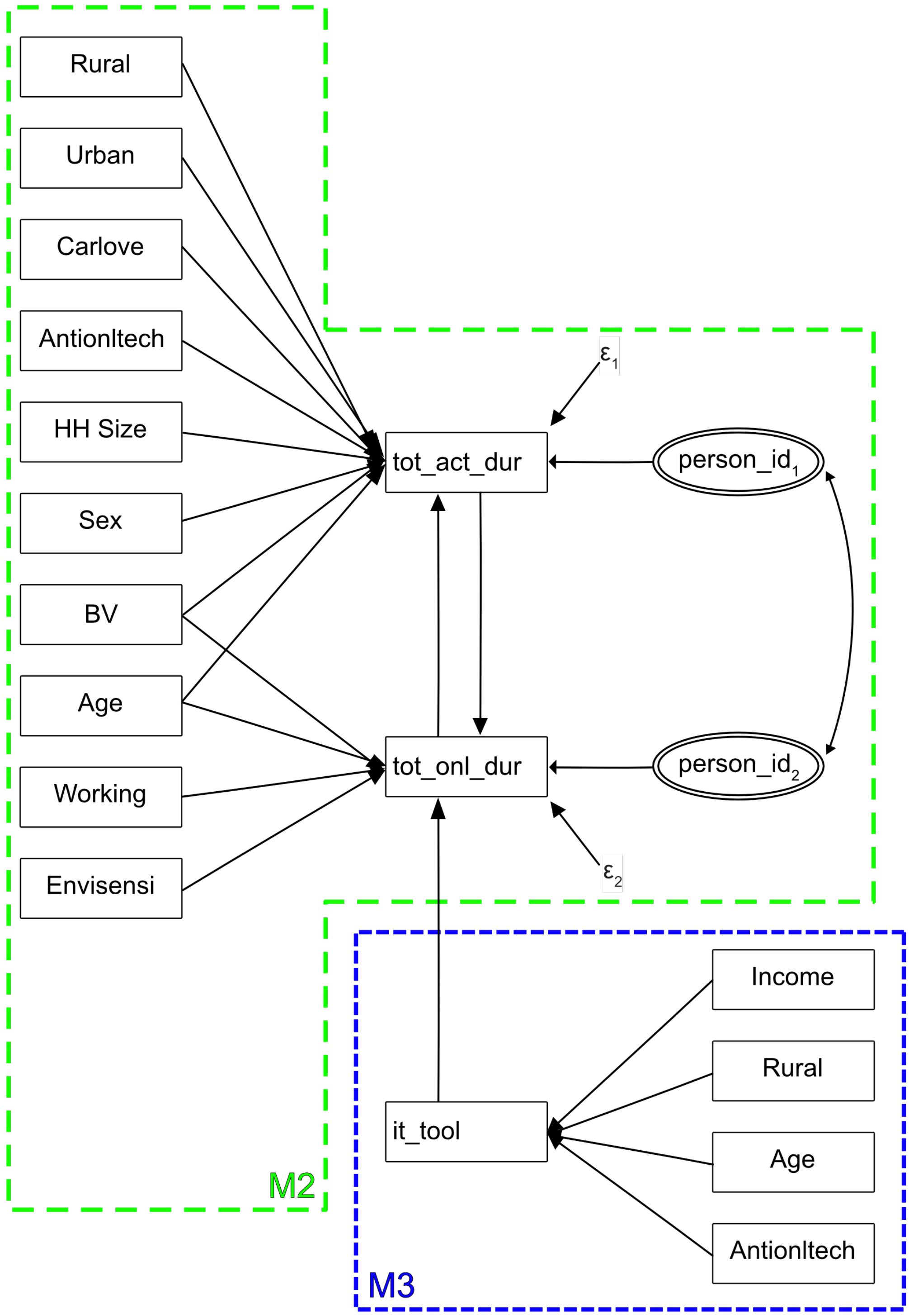

Table 25: Results of the model "Out-of-home vs. online activity duration for all purposes" (M1)

Variable $tot\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $tot\_onl\_dur \leftarrow$	Estimate	Std. Err.	
tot_onl_dur	-0.74	0.11	$(**)$	tot_act_dur	0.01	0.01	
$wave_1$	7.00	28.92		$wave_1$	-6.56	13.60	
$wave_2$	67.73	26.64	$(*)$	$wave_2$	-4.16	11.88	
$tuesday$	11.26	13.78		$tuesday$	-8.27	4.35	(.)
$wednesday$	-5.82	14.87		$wednesday$	-8.40	4.66	(.)
$thursday$	11.54	15.74		$thursday$	-14.80	4.60	$(**)$
$friday$	-13.72	15.30		$friday$	-16.95	5.01	$(**)$
$saturday$	-136.34	17.53	$(**)$	$saturday$	-24.18	5.37	$(**)$
$sunday$	-282.92	16.51	$(**)$	$sunday$	-8.98	6.29	
$week$	-9.26	13.01		$week$	-5.84	5.31	
$cons.$	508.27	26.96	$(**)$	$cons.$	104.43	11.12	$(**)$
	Estimate	Std. Err.			Estimate	Std. Err.	
$var(RE_1)$	19'684.43	1'722.06		$var(\varepsilon_1)$	44'857.82	2'089.81	
$var(RE_2)$	6'324.82	1'190.17		$var(\varepsilon_2)$	4'284.39	421.13	
$cov(RE_1, RE_2)$	3'407.20	968.83	$(**)$	$cor(RE_1, RE_2)$	0.31		
Goodness of fit (AICc; RMSEA)						66'232; 0.99	

Significance codes: $(**)$ <0.01, $(*)$ <0.05, (.) <0.1

2'623 Complete observations on 336 people

Table 26: Results of the model "Out-of-home vs. online activity duration for all purposes" (M2)

Variable $tot\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $tot\_onl\_dur \leftarrow$	Estimate	Std. Err.
tot_onl_dur	-6.60	3.23	(∗)	tot_act_dur	0.86	0.71
$wave_1$	-90.89	84.79		$wave_1$	-3.77	24.91
$wave_2$	-33.31	84.61		$wave_2$	-39.50	35.58
$tuesday$	-36.19	41.56		$tuesday$	-22.88	18.61
$wednesday$	-54.87	43.76		$wednesday$	-8.98	14.49
$thursday$	-73.50	57.22		$thursday$	-33.92	21.84
$friday$	-113.40	63.95	(.)	$friday$	-15.97	15.50
$saturday$	-286.59	94.31	(∗∗)	$saturday$	75.45	85.18
$sunday$	-355.35	55.94	(∗∗)	$sunday$	223.28	194.90
$week$	-43.95	38.67		$week$	-1.14	15.05
age	-15.53	6.38	(∗)	age	0.12	2.01
sex	180.37	78.09	(∗)	$working$	-188.88	119.58
res_cit	34.02	61.09		$att\_envisensi$	19.43	16.78
res_rur	-252.64	141.93	(.)			
$att\_antionltech$	-31.04	42.88				
$att\_carlove$	10.36	46.85				
$cons.$	1877.47	641.61	(∗∗)	$cons.$	-105.70	303.84
	Estimate	Std. Err.			Estimate	Std. Err.
$var(RE_1)$	233’254.30	235’522.90		$var(\varepsilon_1)$	196’082.80	163’373.00
$var(RE_2)$	18’413.80	19’851.20		$var(\varepsilon_2)$	42’927.88	60’587.70
$cov(RE_1, RE_2)$	34’088.68	25’599.26		$cor(RE_1, RE_2)$	0.52	
Goodness of fit (AICc; RMSEA)						66’142; 0.84
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1						
2’623 Complete observations on 336 people						

Table 27: Results of the model "Out-of-home vs. online activity duration for all purposes" (M3)

Variable $tot\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $tot\_onl\_dur \leftarrow$	Estimate	Std. Err.	
tot_onl_dur	-7.32	4.90		tot_act_dur	1.02	1.22	(.)
$wave_1$	-102.40	104.40		$wave_1$	-2.32	29.28	
$wave_2$	-43.77	103.96		$wave_2$	-45.35	52.58	(.)
$tuesday$	-41.93	53.82		$tuesday$	-25.72	26.74	
$wednesday$	-60.83	56.30		$wednesday$	-9.10	16.89	
$thursday$	-83.84	80.05		$thursday$	-37.66	32.49	
$friday$	-125.46	91.36		$friday$	-15.83	18.05	
$saturday$	-304.80	163.23	(*)	$saturday$	94.71	144.57	(.)
$sunday$	-364.09	75.54	(**)	$sunday$	268.31	334.68	(*)
$week$	-48.15	47.08		$week$	-0.16	18.15	
age	-16.82	9.22	(.)	age	0.51	3.22	(.)
sex	195.51	105.55	(.)	$working$	-211.57	195.50	(.)
res_cit	38.37	71.58		$att\_envisensi$	22.10	24.84	
res_rur	-283.71	200.16		it_tool	-7.45	21.07	(**)
$att\_antionltech$	-35.10	56.60					
$att\_carlove$	14.84	62.39					
$cons.$	2'017.30	963.59	(*)	$cons.$	-157.91	473.61	(**)
	Estimate	**Std. Err.**		**Variable $it\_tool \leftarrow$**	**Estimate**	**Std. Err.**	
$var(RE_1)$	285'725	393'145		$income$	0.04	0.02	(*)
$var(RE_2)$	23'262	39'110		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	39'889	42'016		age	-0.02	0.01	(*)
$var(\varepsilon_1)$	234'180	277'287		$att\_antionltech$	-0.55	0.11	(**)
$var(\varepsilon_2)$	58'149	122'501		cut_1	-6.61	1.09	(**)
$cor(RE_1, RE_2)$	0.34			cut_2	-2.95	0.47	(**)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)						72'604; 0.78	

Significance codes: (**) <0.01, (*) <0.05, (.) <0.1

2'623 Complete observations on 336 people

B.2 Leisure

Figure 15: Out-of-home vs. online leisure activity duration

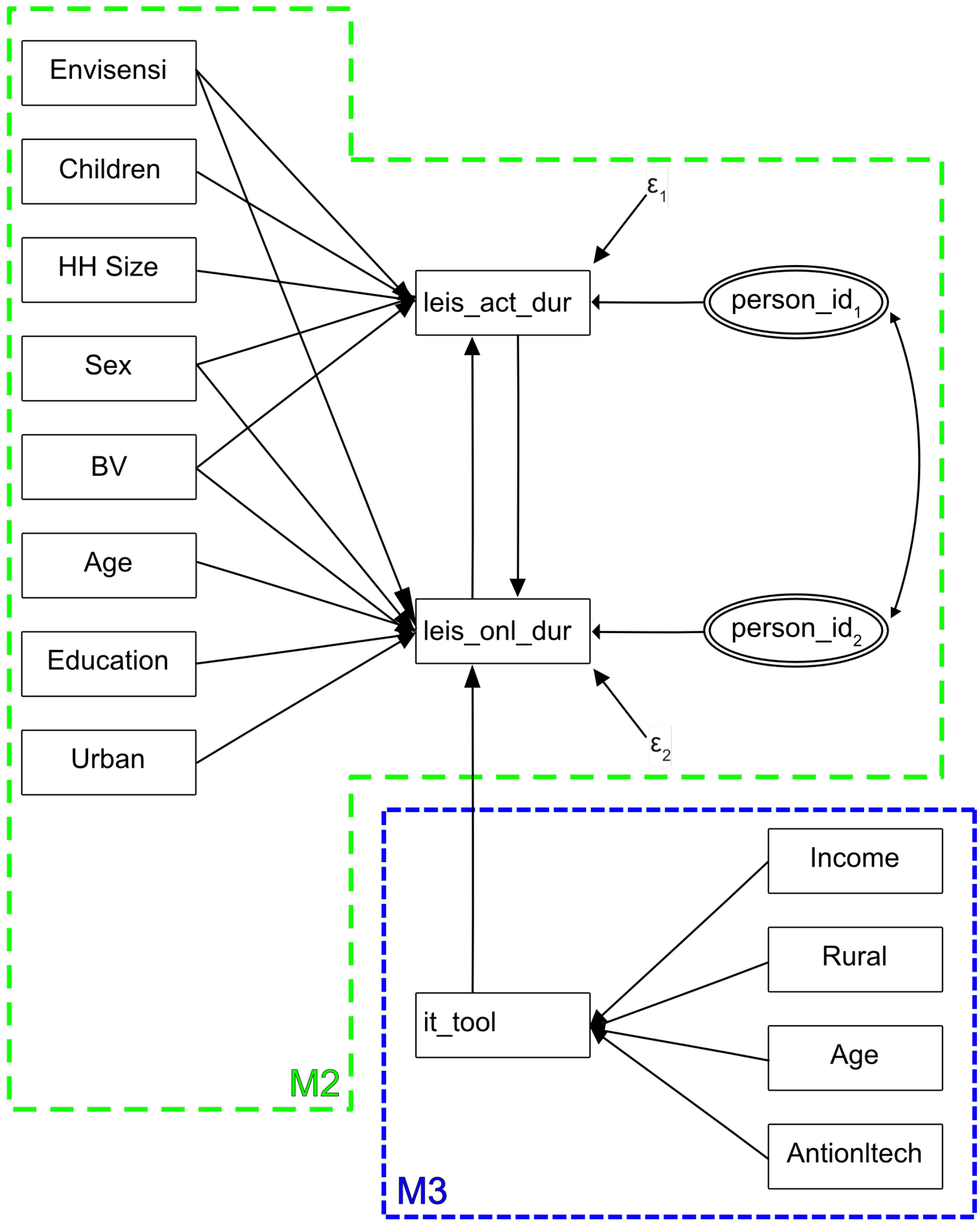

Table 28: Results of the model "Out-of-home vs. online leisure activity duration" (M1 and M2)

Variable $leis\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $leis\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$leis\_onl\_dur$	-0.38	0.25		$leis\_act\_dur$	0.02	0.04	
$wave_1$	-5.65	13.05		$wave_1$	-4.71	10.81	
$wave_2$	-3.42	12.14		$wave_2$	-8.19	9.42	
$tuesday$	13.26	7.52	(.)	$tuesday$	-1.09	2.92	
$wednesday$	12.09	7.10	(.)	$wednesday$	-3.58	2.80	
$thursday$	9.71	7.23		$thursday$	-6.00	3.11	(.)
$friday$	30.53	7.54	(∗∗)	$friday$	-4.53	3.56	
$saturday$	88.67	11.04	(∗∗)	$saturday$	-7.02	5.42	
$sunday$	64.22	10.28	(∗∗)	$sunday$	5.85	5.06	
$week$	-2.81	8.37		$week$	-2.66	4.33	
age	-0.76	0.51		age	-0.91	0.29	(∗∗)
hh_size	7.59	3.88	(∗)	sex	22.50	7.06	(∗∗)
$hh\_children$	-14.51	4.97	(∗∗)	$educ$	-26.29	8.67	(∗∗)
$att\_envisensi$	-6.40	3.33	(.)	res_cit	6.23	7.20	
				$att\_envisensi$	2.83	2.94	
$cons.$	98.67	41.68	(∗)	$cons.$	94.07	17.53	(∗∗)
$var(RE_1)$	2'584.02	683.69					
$var(RE_2)$	3'343.85	949.39					
$cov(RE_1, RE_2)$	1'007.53	723.44					
$var(\varepsilon_1)$	14'651.53	970.47					
$var(\varepsilon_2)$	2'286.68	315.91					
$cor(RE_1, RE_2)$	0.34						
Goodness of fit (AICc; RMSEA)					61'478; 0.81		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

Table 29: Results of the model "Out-of-home vs. online leisure activity duration" (M3)

Variable $leis\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $leis\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$leis\_onl\_dur$	-0.39	0.23	(.)	$leis\_act\_dur$	0.02	0.04	
$wave_1$	-5.59	12.86		$wave_1$	-6.25	10.56	
$wave_2$	-3.40	11.98		$wave_2$	-9.62	9.09	
$tuesday$	13.26	7.52	(.)	$tuesday$	-1.11	2.91	
$wednesday$	12.06	7.11	(.)	$wednesday$	-3.59	2.80	
$thursday$	9.65	7.21		$thursday$	-6.01	3.10	(.)
$friday$	30.48	7.51	(∗∗)	$friday$	-4.56	3.49	
$saturday$	88.59	11.05	(∗∗)	$saturday$	-7.11	5.18	
$sunday$	64.27	10.28	(∗∗)	$sunday$	5.79	4.96	
$week$	-2.78	8.34		$week$	-2.71	4.33	
sex	-0.76	0.49		age	-0.83	0.29	(∗∗)
hh_size	7.88	3.93	(∗)	sex	19.94	6.95	(∗∗)
$hh\_children$	-14.76	5.12	(∗∗)	$educ$	-28.24	8.67	(∗∗)
$att\_envisensi$	-6.39	3.31	(.)	res_cit	7.01	7.14	
				$att\_envisensi$	3.32	2.95	
				it_tool	9.57	2.88	(∗∗)
$cons.$	98.52	38.61	(∗)	$cons.$	67.15	17.35	(∗∗)
	Estimate	**Std. Err.**		**Variable $it\_tool \leftarrow$**	**Estimate**	**Std. Err.**	
$var(RE_1)$	2’603.68	714.57		$income$	0.04	0.02	(∗)
$var(RE_2)$	3’267.50	940.58		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	1’039.82	646.21		age	-0.02	0.01	(∗)
$var(\varepsilon_1)$	14’656.98	975.70		$att\_antionltech$	-0.55	0.11	(∗∗)
$var(\varepsilon_2)$	2’289.26	312.71		cut_1	-6.61	1.09	(∗∗)
$cor(RE_1, RE_2)$	0.36			cut_2	-2.95	0.47	(∗∗)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)					67’933; 0.76		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

B.3 All Shopping Purposes

Figure 16: Out-of-home vs. online shopping activity duration

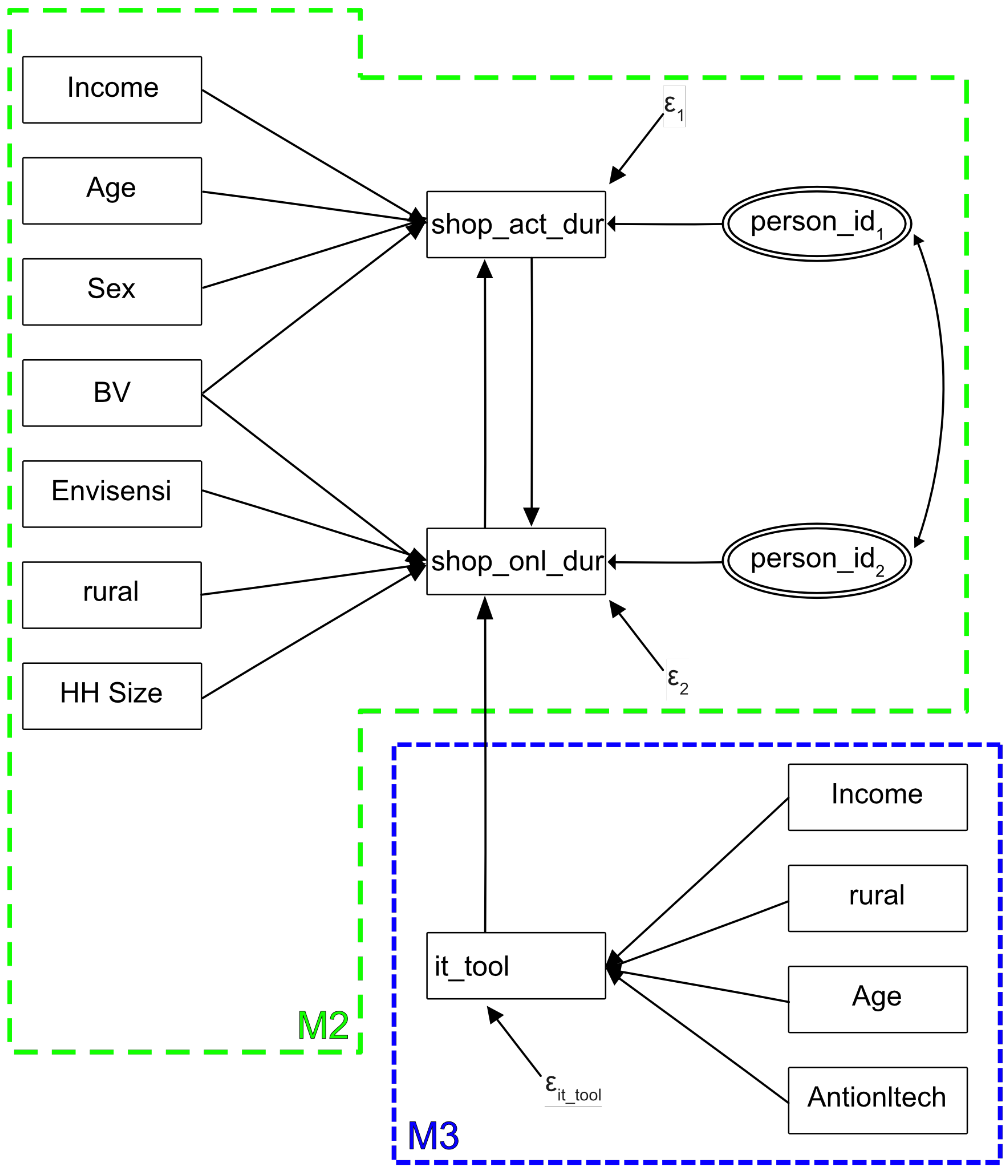

Table 30: Results of the model "Out-of-home vs. online shopping activity duration" (M2)

Variable $shop\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_dur$	0.35	0.28		$shop\_act\_dur$	-0.11	0.08	
$wave_1$	2.35	2.41		$wave_1$	0.20	1.46	
$wave_2$	1.54	2.34		$wave_2$	-0.84	1.19	
$tuesday$	0.13	2.14		$tuesday$	-2.16	1.78	
$wednesday$	2.59	2.58		$wednesday$	-0.21	2.72	
$thursday$	0.73	2.18		$thursday$	-2.81	1.59	(.)
$friday$	4.34	2.56	(.)	$friday$	-2.25	1.81	
$saturday$	23.69	4.07	(**)	$saturday$	0.35	2.56	
$sunday$	-8.94	1.90	(**)	$sunday$	-4.08	1.93	(*)
$week$	-0.31	2.16		$week$	0.75	2.03	
sex	-5.62	1.63	(**)	hh_size	-0.64	0.33	(.)
age	0.16	0.08	(*)	res_rur	-2.28	1.47	
$income$	-0.34	0.11	(**)	$att\_envisensi$	-1.40	0.39	(**)
$cons.$	6.05	4.83		$cons.$	8.68	2.69	(**)
$var(RE_1)$	29.22	16.47					
$var(RE_2)$	14.11	6.99					
$cov(RE_1, RE_2)$	17.91	9.42	(.)				
$var(\varepsilon_1)$	1'525.64	203.75					
$var(\varepsilon_2)$	494.06	177.74					
$cor(RE_1, RE_2)$	0.88						
Goodness of fit (AICc; RMSEA)					50'364; 0.76		
Significance codes: (**) <0.01, (*) <0.05, (.) <0.1							
2'623 Complete observations on 336 people							

Table 31: Results of the model "Out-of-home vs. online shopping activity duration" (M3)

Variable shop_act_dur ←	Estimate	Std. Err.		Variable shop_onl_dur ←	Estimate	Std. Err.	
shop_onl_dur	0.37	0.29		shop_act_dur	-0.12	0.09	
$wave_1$	2.34	2.41		$wave_1$	0.12	1.51	
$wave_2$	1.54	2.35		$wave_2$	-0.92	1.19	
tuesday	0.17	2.15		tuesday	-2.17	1.79	
wednesday	2.60	2.59		wednesday	-0.20	2.73	
thursday	0.78	2.18		thursday	-2.81	1.59	(.)
friday	4.39	2.57	(.)	friday	-2.23	1.82	
saturday	23.73	4.10	(**)	saturday	0.50	2.62	
sunday	-8.88	1.93	(**)	sunday	-4.14	1.97	(*)
week	-0.32	2.17		week	0.74	2.03	
sex	-5.61	1.63	(**)	hh_size	-0.66	0.35	(.)
age	0.16	0.08	(*)	res_rur	-2.36	1.48	
income	-0.34	0.11	(**)	att_envisensi	-1.39	0.40	(**)
				it_tool	0.35	0.53	
cons.	5.98	4.83		cons.	7.93	2.85	(**)
	Estimate	**Std. Err.**		**Variable it_tool ←**	**Estimate**	**Std. Err.**	
$var(RE_1)$	28.56	16.63		income	0.04	0.02	(*)
$var(RE_2)$	14.28	7.12		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	17.64	9.55	(.)	age	-0.02	0.01	(*)
$var(\varepsilon_1)$	1'532.39	212.17		att_antionltech	-0.55	0.11	(**)
$var(\varepsilon_2)$	496.22	178.92		cut_1	-6.61	1.09	(**)
$cor(RE_1, RE_2)$	0.87			cut_2	-2.95	0.47	(**)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)					56'825; 0.72		

Significance codes: (**) <0.01, (*) <0.05, (.) <0.1

2'623 Complete observations on 336 people

B.4 Long Term Shopping

Figure 17: Out-of-home vs. online shopping activity duration for long term goods

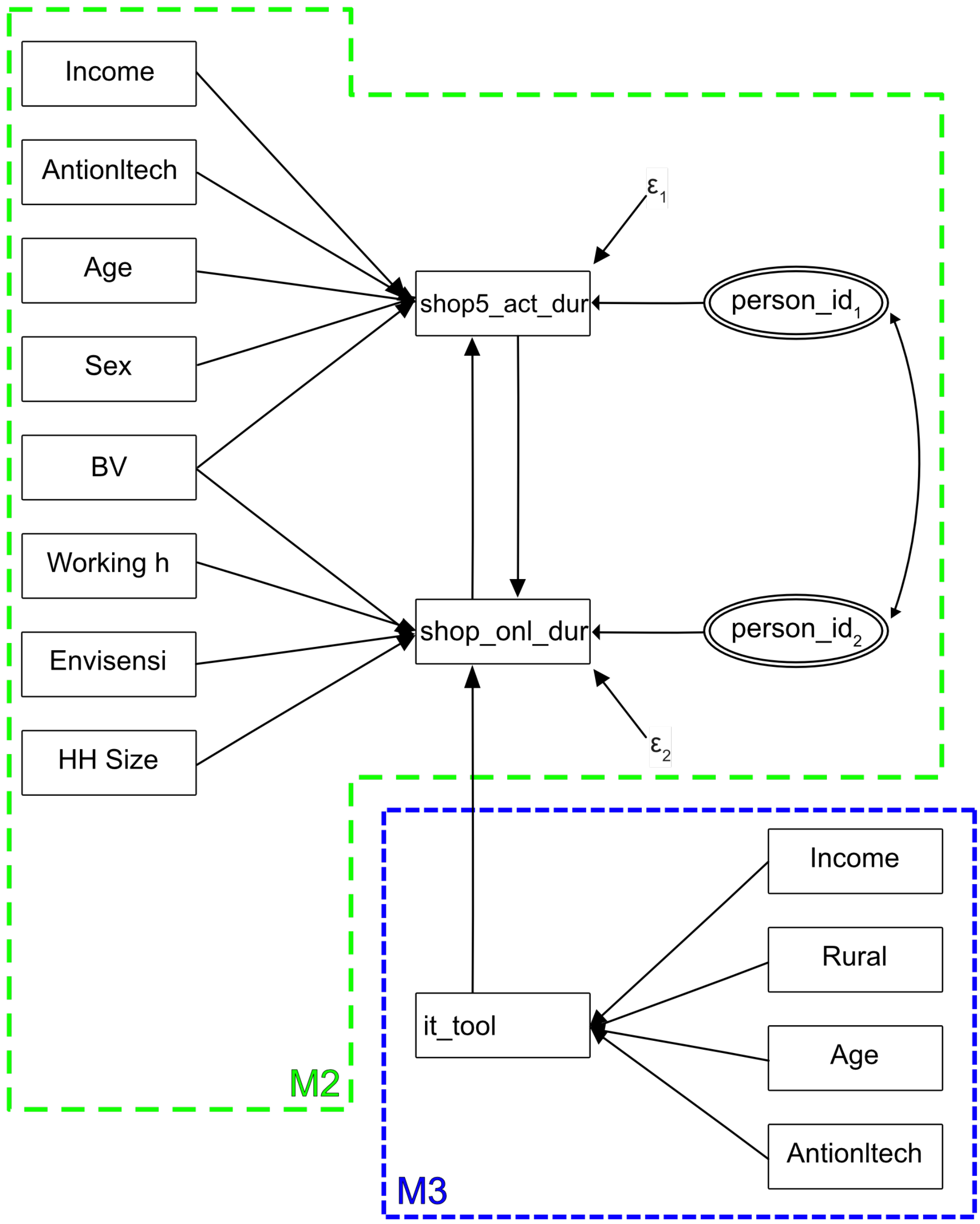

Table 32: Results of the model "Out-of-home vs. online shopping activity duration for long term goods" (M1 and M2)

Variable	M1|		M2		
shop5_act_dur ←	Estimate	Std. Err.	Estimate	Std. Err.	
shop_onl_dur	-0.06	5.99	0.36	0.34	
$wave_1$	2.88	3.20	2.83	1.69	(.)
$wave_2$	0.59	3.44	1.58	1.52	
tuesday	-0.47	12.53	0.43	1.87	
wednesday	1.87	3.50	2.10	2.12	
thursday	0.54	16.21	1.75	2.08	
friday	2.26	15.31	3.41	2.20	
saturday	10.34	13.13	11.32	2.79	(∗∗)
sunday	-5.06	17.76	-3.73	1.77	(∗)
week	0.72	4.89	0.40	2.02	
sex	-	-	-3.40	1.25	(∗∗)
age	-	-	0.06	0.05	
att_antionltech	-	-	-1.24	0.52	(∗)
income	-	-	-0.18	0.09	(∗)
cons.	4.14	29.55	1.34	3.46	
shop_onl_dur ←	Estimate	Std. Err.	Estimate	Std. Err.	
shop5_act_dur	0.04	3.80	-0.23	0.24	
$wave_1$	0.32	11.05	1.17	1.72	
$wave_2$	-0.55	2.63	-0.12	1.19	
tuesday	-2.05	2.26	-2.15	1.79	
wednesday	-0.56	7.78	-0.03	2.93	
thursday	-2.79	3.06	-2.60	1.59	
friday	-2.70	9.41	-2.06	1.83	
saturday	-2.59	39.91	0.23	2.77	
sunday	-2.76	18.65	-4.09	2.21	(.)
week	0.74	3.27	0.94	2.19	
working_h	-	-	-0.05	0.05	
hh_size	-	-	-0.59	0.35	(.)
att_envisensi	-	-	-1.35	0.43	(∗∗)
cons.	4.95	14.84	9.00	3.77	(∗)
$var(RE_1)$	16.67	118.22	3.85	7.39	
$var(RE_2)$	12.23	68.52	14.92	8.25	
$cov(RE_1, RE_2)$	9.43	15.00	7.03	8.41	
$var(\varepsilon_1)$	736.80	380.78	796.34	153.27	
$var(\varepsilon_2)$	475.45	268.81	515.47	229.62	
$cor(RE_1, RE_2)$	0.66		0.93		
Goodness of fit (AICc; RMSEA)	48'505; 1.11		48'521; 0.74		

Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1

2'623 Complete observations on 336 people

Table 33: Results of the model "Out-of-home vs. online shopping activity duration for long term goods" (M3)

Variable $shop5\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_dur$	0.47	0.34		$shop5\_act\_dur$	-0.30	0.25	
$wave_1$	2.79	1.70	(.)	$wave_1$	1.29	1.75	
$wave_2$	1.63	1.54		$wave_2$	-0.09	1.25	
$tuesday$	0.64	1.95		$tuesday$	-2.18	1.80	
$wednesday$	2.15	2.21		$wednesday$	0.10	2.97	
$thursday$	2.03	2.14		$thursday$	-2.55	1.63	
$friday$	3.67	2.24	(.)	$friday$	-1.89	1.90	
$saturday$	11.54	2.90	(**)	$saturday$	0.93	2.93	
$sunday$	-3.43	1.89	(.)	$sunday$	-4.41	2.28	(.)
$week$	0.33	2.09		$week$	0.97	2.22	
sex	-3.46	1.29	(**)	$working\_h$	-0.06	0.06	
age	0.06	0.05		hh_size	-0.65	0.39	
$att\_antionltech$	-1.23	0.53	(*)	$att\_envisensi$	-1.34	0.43	(**)
$income$	-0.18	0.09	(*)	it_tool	0.73	0.72	
$cons.$	0.87	3.47		$cons.$	7.92	3.36	(**)
	Estimate	Std. Err.		Variable $it\_tool \leftarrow$	Estimate	Std. Err.	
$var(RE_1)$	2.80	7.50		$income$	0.04	0.02	(*)
$var(RE_2)$	16.00	8.47		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	5.90	9.10		age	-0.02	0.01	(*)
$var(\varepsilon_1)$	835.74	185.18		$att\_antionltech$	-0.55	0.11	(**)
$var(\varepsilon_2)$	541.60	250.22		cut_1	-6.61	1.09	(**)
$cor(RE_1, RE_2)$	0.88			cut_2	-2.95	0.47	(**)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)						54’981; 0.70	
Significance codes: (**) <0.01, (*) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

B.5 Short Term Shopping

Figure 18: Out-of-home vs. online shopping activity duration for short term goods

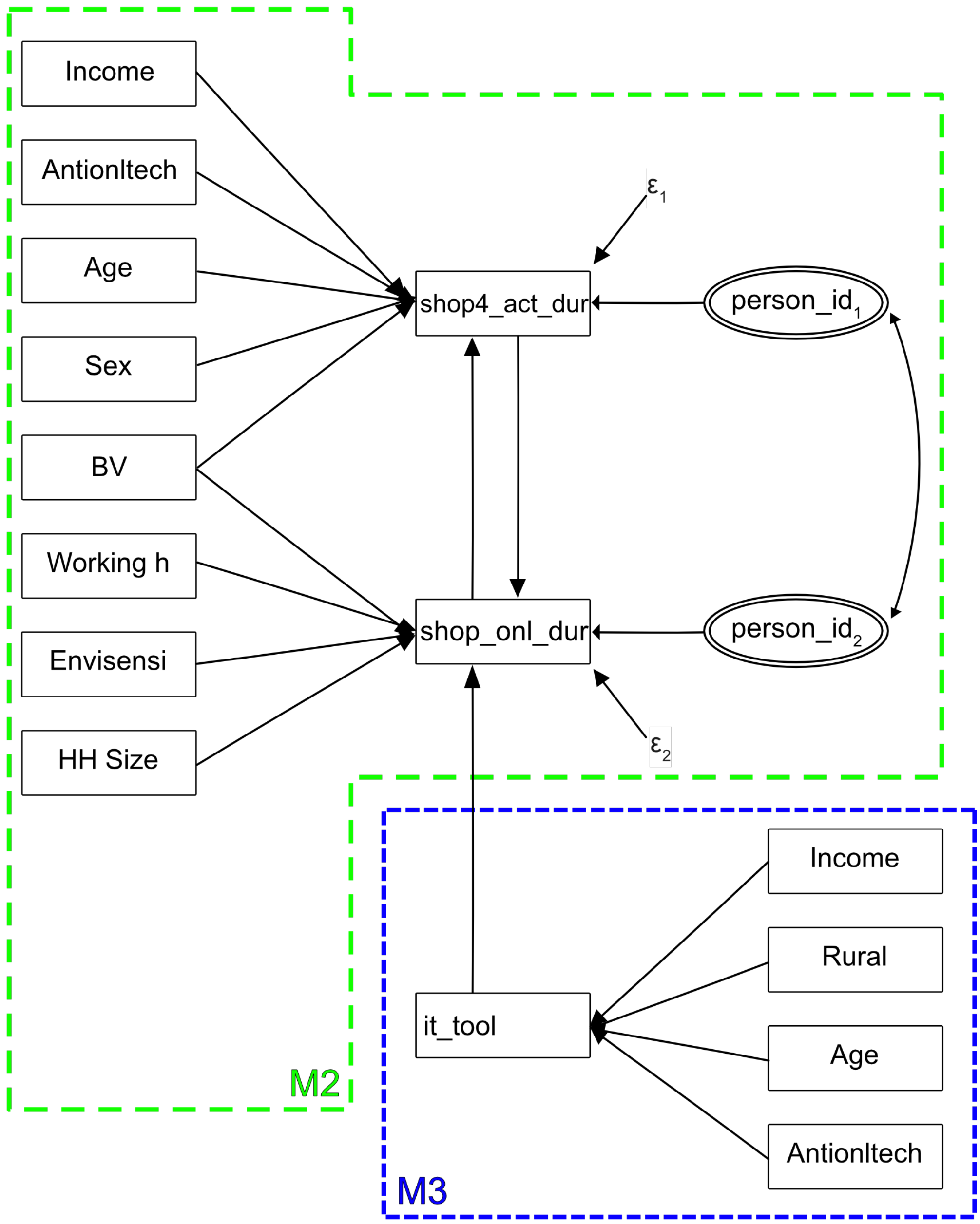

Table 34: Results of the model "Out-of-home vs. online shopping activity duration for short term goods" (M2)

Variable $shop4\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_dur$	0.51	0.31		$shop4\_act\_dur$	-0.31	0.18	(.)
$wave_1$	-0.60	1.89		$wave_1$	0.28	1.49	
$wave_2$	0.31	1.96		$wave_2$	-0.30	1.20	
$tuesday$	0.78	1.74		$tuesday$	-2.18	1.86	
$wednesday$	0.73	2.06		$wednesday$	-0.33	2.75	
$thursday$	0.43	1.70		$thursday$	-3.08	1.68	(.)
$friday$	2.30	2.06		$friday$	-2.33	1.81	
$saturday$	13.52	3.36	(∗∗)	$saturday$	1.73	2.73	
$sunday$	-3.64	1.75	(∗)	$sunday$	-4.57	2.03	(∗)
$week$	-1.10	1.78		$week$	0.57	2.00	(∗∗)
sex	-2.68	1.35	(∗)	$working\_h$	-0.07	0.05	
age	0.10	0.06	(.)	hh_size	-0.59	0.36	
$income$	-0.18	0.09	(∗)	$att\_envisensi$	-1.36	0.41	(∗∗)
$att\_antionltech$	1.39	0.66	(∗)				
$cons.$	2.03	3.80		$cons.$	10.96	3.65	(∗∗)
$var(RE_1)$	22.12	13.06					
$var(RE_2)$	15.97	9.55					
$cov(RE_1, RE_2)$	9.03	7.29					
$var(\varepsilon_1)$	899.54	221.56					
$var(\varepsilon_2)$	552.43	202.22					
$cor(RE_1, RE_2)$	0.48						
Goodness of fit (AICc; RMSEA)					48’707; 0.74		
Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1							
2’623 Complete observations on 336 people							

Table 35: Results of the model "Out-of-home vs. online shopping activity duration for short term goods" (M3)

Variable $shop4\_act\_dur \leftarrow$	Estimate	Std. Err.		Variable $shop\_onl\_dur \leftarrow$	Estimate	Std. Err.	
$shop\_onl\_dur$	0.53	0.33		$shop4\_act\_dur$	-0.32	0.19	(.)
$wave_1$	-0.61	1.89		$wave_1$	0.20	1.53	
$wave_2$	0.31	1.98		$wave_2$	-0.35	1.21	
$tuesday$	0.82	1.75		$tuesday$	-2.18	1.86	
$wednesday$	0.74	2.08		$wednesday$	-0.32	2.76	
$thursday$	0.48	1.73		$thursday$	-3.09	1.68	(.)
$friday$	2.35	2.08		$friday$	-2.32	1.82	
$saturday$	13.55	3.38	(∗∗)	$saturday$	1.86	2.87	(∗)
$sunday$	-3.59	1.77	(∗)	$sunday$	-4.61	2.05	(∗)
$week$	-1.12	1.80		$week$	0.55	1.99	
sex	-2.69	1.36	(∗)	$working\_h$	-0.07	0.05	
age	0.10	0.06	(.)	hh_size	-0.62	0.38	
$att\_antionltech$	-0.18	0.09	(∗)	$att\_envisensi$	-1.33	0.42	(∗∗)
$income$	1.38	0.66	(∗)	it_tool	0.53	0.56	
$cons.$	1.96	3.86		$cons.$	9.96	3.66	(∗∗)
	Estimate	Std. Err.		Variable $it\_tool \leftarrow$	Estimate	Std. Err.	
$var(RE_1)$	22.02	13.27		$income$	0.04	0.02	(∗)
$var(RE_2)$	16.02	9.82		res_rur	0.66	0.44	
$cov(RE_1, RE_2)$	8.79	7.29		age	-0.02	0.01	(∗)
$var(\varepsilon_1)$	907.73	241.46		$att\_antionltech$	-0.55	0.11	(∗∗)
$var(\varepsilon_2)$	557.34	209.80		cut_1	-6.61	1.09	(∗∗)
$cor(RE_1, RE_2)$	0.47			cut_2	-2.95	0.47	(∗∗)
				cut_3	-0.79	0.44	(.)
				cut_4	0.88	0.45	(.)
Goodness of fit (AICc; RMSEA)						55’168; 0.70	

Significance codes: (∗∗) <0.01, (∗) <0.05, (.) <0.1

2’623 Complete observations on 336 people

B.6 Networks of Interacting Variables

Figure 19: Network model of all online, leisure and shopping activities. Only effects with a p-value below 0.1 are shown.

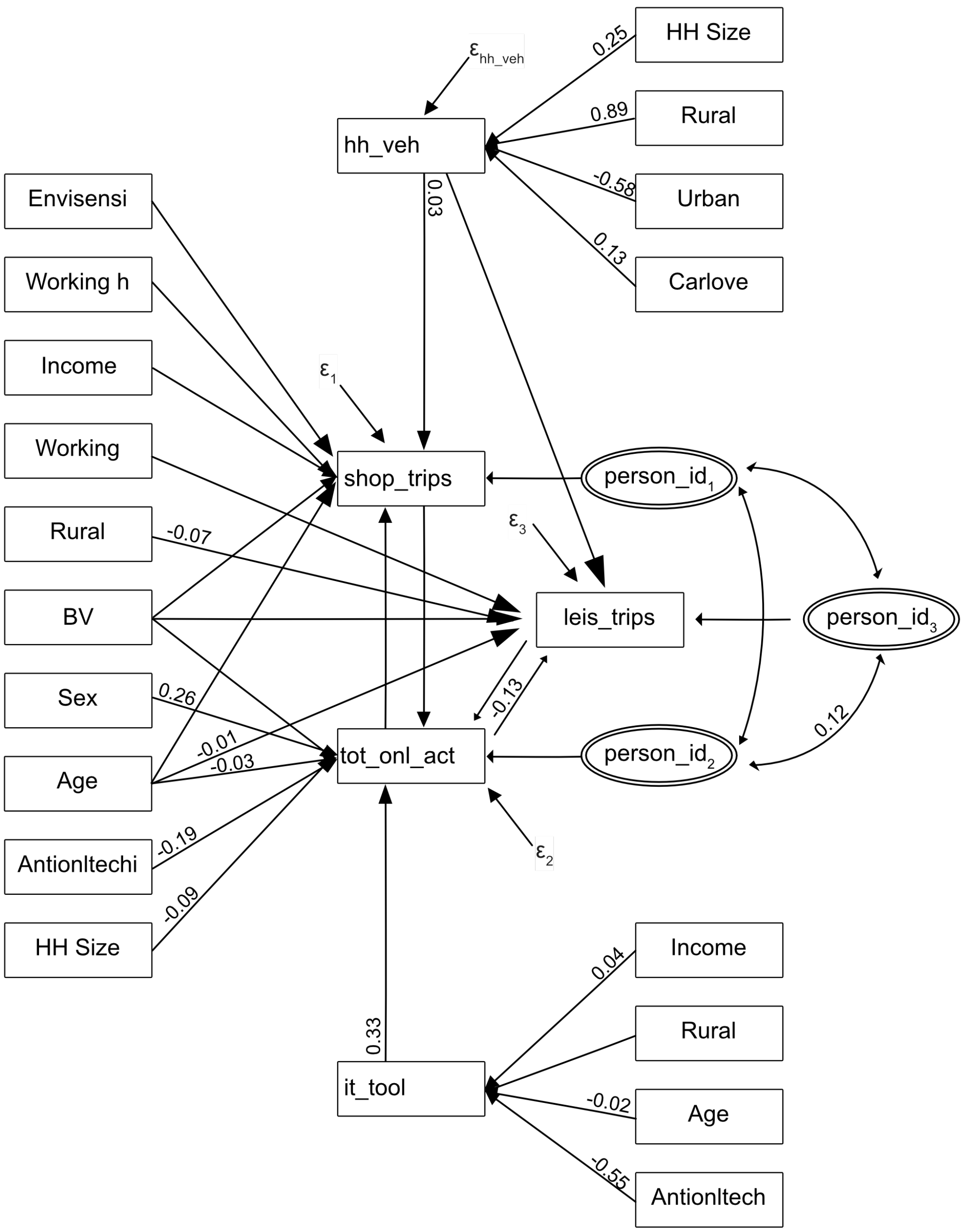

Figure 20: Network model of online shopping, short and long term shopping activities. Only effects with a p-value below 0.1 are shown.