PhD THESIS IN ENVIRONMENT AND TERRITORY

XXVIII Cycle

Interuniversity Department of Regional and Urban Studies and Planning

Evaluation of the potential modal shift induced by the use of a real time multimodal navigator: psycho-social study of travel behaviour and attitudes

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List of Acronyms and Abbrevations

ATIS	Advanced Traveller Information System
CTT	Classical Test Theory
EEA	European Environment Agency
GHG	GreenHouse Gas
IEA	International Energy Agency
IPCC	Intergovernemental Panel on Climate Change
IRT	Item Response Theory
ITF	International Transport Forum
NAT	Norm Activation Theory
SEM	Structural Equation Modelling
SSBC	Stage model of Self-regulated Behavioural Change
TIB	Theory of Interpersonal Behaviour
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TTM	TransTheoretical Model

Acknowledgment

The present thesis has become a reality thanks to the support and help of many people. I would like to thanks them all.

Foremost, I would like to address my gratitude to my family for the continous support and envouragement they provided to me since my birth.

I want to offer a special thank to Arnaud, Emilien, Guillaume and Kevin who, even though our lives happen 1 000 km apart, are always willing to spare some time to cure our friendship. This has been very important to me.

I am highly indebted to Khaled, who accompanied me from the beginning of my adventure in Italy, who thaught me the language, who offered me his special friendship and this quote I like to difuse around “L’Italia? E’ una grande scuola!”.

I would like to thank Andrea, Vito, Suzan, Pietro, Alessandro, Rocco, Matias, Gaia, Francesca, Sylvia, Chloé and, above all, Δήμητρα, for sharing my daily life and bearing me as a flatmate.

I address my sincerests appreciations to Francesca and Lorenzo who became, involuntarily, two referents and true friends here in Turin.

I am very gratefull towards Cristian, Valentina, José, Amandine, Valerio and Davide for their help, support and collaboration.

A very special thank goes to Gianni, who gave me more than I expected and more than he thinks.

And, of course, from all my heart, I thank Cristina for the trust she gave me, for her positivism, sincerity and all other qualities that would fill all these pages if enumerated.

Executive Sumary

Our modern world, and its relative stability, is facing two major threats. The first one is the depletion of fossil fuels resources that feed millions of trucks and boat worldwide, carrying goods from one side of the planet to another. The second one is climate change which, if not limited, will provoke drastically changes to our known environment. One way, that may be the most efficient, to mitigate both threats is to pull people out of their cars, and, to this end, The European White Paper (2011) on transport highlights the essential role of ITS. Today, many cities have deployed multimodal real-time information systems, but few have assessed the impacts of those systems on traveller behaviour (Ramalho Veiga Simao, 2014).

This global context guided the investigation made in the present thesis: in order to analyse potential modal shift induced by the introduction of multimodal navigators, we had to understand psychological factors of decision making. Chapter 1 proposed an extensive review of the current knowledge and state of the art of social psychology as applied in pro-environmental behaviours. We understood some concepts, highlighted some theoretical and methodological flaws that led us to use, though restrictively, some old-fashioned concept of attitude together with some – insufficiently recognised – powerful methodological tools that constitutes the IRT.

The objective of this thesis was twofold: 1) assessing the validity of a general attitude measures, in the sense of Campbell and understanding if the generally adopted measure of attitude is compelling within traditional frameworks derived from social psychology theories; 2) make use of psychological determinants influencing modal choice to highlight which segment of the population is more likely to perform a modal shift from cars to public transport or soft modes.

To this end, the research was divided in three methodological step: 1) fitting a Rasch model on the General Ecological Behaviour in order to obtain a valid measure of the attitude toward the environment; 2) psycho-social correlational model comparison using Structural Equation Modelling in order to extract the most determining factors behind decision making; 3) a psycho-social based segmentation of ATIS potential users, that would help in identifying the potentiality of ATIS in inducing a modal shift.

This research contributed, firstly, in gathering evidence that a wider use of IRT for psychological measurement may be a benefit for the scientific community. Secondly, some newly developed psychological constructs, based on specific values, have been shown to have a significant influence on travel behaviour. We hope that this contribution will allow some other use of specific values and innovative factors research. Finally, we suggest that up to 10% of our sample population may be induced toward a greener urban mobility.

As the Opticities research project – within which this thesis has been conducted – is still ongoing, further investigation will be made in the near future. The analysis of *in-itinere* and *ex-post* dataset will allow us to understand whether or not people have modified their mobility patterns using the multimodal navigator TUeTO.

Introduction

It is easily arguable that every pre-industrial civilization growth and development scheme can be reduced to their ability to produce and store food, to master water resources and to provide advance in transport systems, be it for good trading, information dissemination or war motivation. Indeed, early population concentration into cities presupposes connectivity and the network formed by these connections may be seen as the circuitry of civilization (Bosworth, 2000). The counterparts is that “the tyranny of distance” (Blainey, 1966) was then a major limit to the ability of a core political power to exercise its influence. Uruk, which is considered to be the first urban agglomeration of human history, despite its position in southern Mesopotamia - where virtually no resources were available except for land, water and animals - has grown thanks to the improvement made in ship design and wheel use that allowed the trade of goods with Anatolia. Thus, taking advantage of the downstream flow of the rivers, Sumerian could transport raw materials in less than two weeks whereas the upstream trip lasted at least 8 times longer and was thus restricted to higher valued transformed goods (Stein, 1999). Given this context, we can legitimately wonder if the emergence of writing in this exact place at this exact period participated in the growth of the Sumerian civilization, or if a written system had become a necessary tool to be invented in order to manage the logistics. Other illustrations of the importance of transport can simply be found thinking of the favourable position – along the Mediterranean coastlines – of the most important cities during the Phoenician empire, of the role played by the Silk Road for trades, cultural exchange and development of both sides of the world or the most famous Roman road network that allowed rapid movements of armies, diplomatic agents and administrative correspondence. It is clear that transport costs, which are a function of the technology, the distance, the weight and the bulk of the freight and the environmentally-constrained accessibility determines the content, the volume and the organization of exchange and thus the level of influence of a given civilization. Distance between two points is a fixed variable, so are environmentally determined condition of accessibility (rivers, mountains, seas etc.). In consequences, time and costs of transport depend mainly on the available technologies. Whereas for millennia human-related velocities remained comparable, “associating the metre to the second” (Ollivro, 2006), the 19th century and its industrial revolution has given birth to the steam machine, soon followed by the internal combustion engine that, for a great part, have shaped our actual physical, social and economic environment: continuous investment in infrastructure and decrease in transport costs have encouraged regional specializations following Ricardo's principle of comparative advantages[1].

In every moment, movements of goods and people between geographical places are supplying our societies with materials and knowledge that feed the globalized economic system. Inside European Union, for year 2013, goods transport activity was estimated at 3 481 billion ton-kilometres and passenger transport activity represented 6 465 billion passenger-kilometres (European commission, 2015a). In more catchable quantities, it represents a daily average per person of around 20 tonne-kilometres for goods and 35 kilometres for passenger. Although transport in Europe accounts for a relatively low share of households final consumption – 10% of total household expenditures[2] – its role as an economic factor of production is fundamental: independently from the price, any activity cannot go on without the transport factor. This is why, every year, investment in inland infrastructure still represent 1% of GDP for the OECD countries (ITF, 2012) where rates of return are mainly due to travel time savings. The semantic transition that occurs, from the "tyranny of distance" to the "value of time" says much about the transformation our relationship to the world has gone through: our capacity to shape it on demand thanks to cheap energy have structured our modern lifestyle.

Transport and fossil fuel consumption: a dangerous dependence

Transport is known to be the first sector for oil final consumption worldwide and it mainly depends on fossil fuels: more than 95% of total energy used by the transport sector come from gasoline or distillate fuels (IEA, 2015). Hubbert (1956) was the first to highlight that oil is a finite resource and, as such, its availability cannot grow indefinitely. By equating estimated reserves and consumption he was able to predict accurately the point of maximum resource extraction for the United States. Passed this point, without increasing import, the volume available on the market would decrease. Figure 1 shows the US oil

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[1] Ricardo, David. British economist (1772-1823) in *Principles of Political Economy and Taxation*

[2] Transport costs share in the total value of a good lies between 5 and 10 % (Rodrigue, 2013) and personal transport equipment and services represent, according to the European Commision (2015), 12.8% of total final consumption of households

production from 1900 to recent years. The peak was attained in 1970, as predicted by Hubbert in 1956. The following years were marked by the end of the Bretton Woods system and the first oil crisis in 1973. The recent rebound we observe in the late 2000's is due to unconventional oil production, made possible thanks to higher barrel price in the global market.

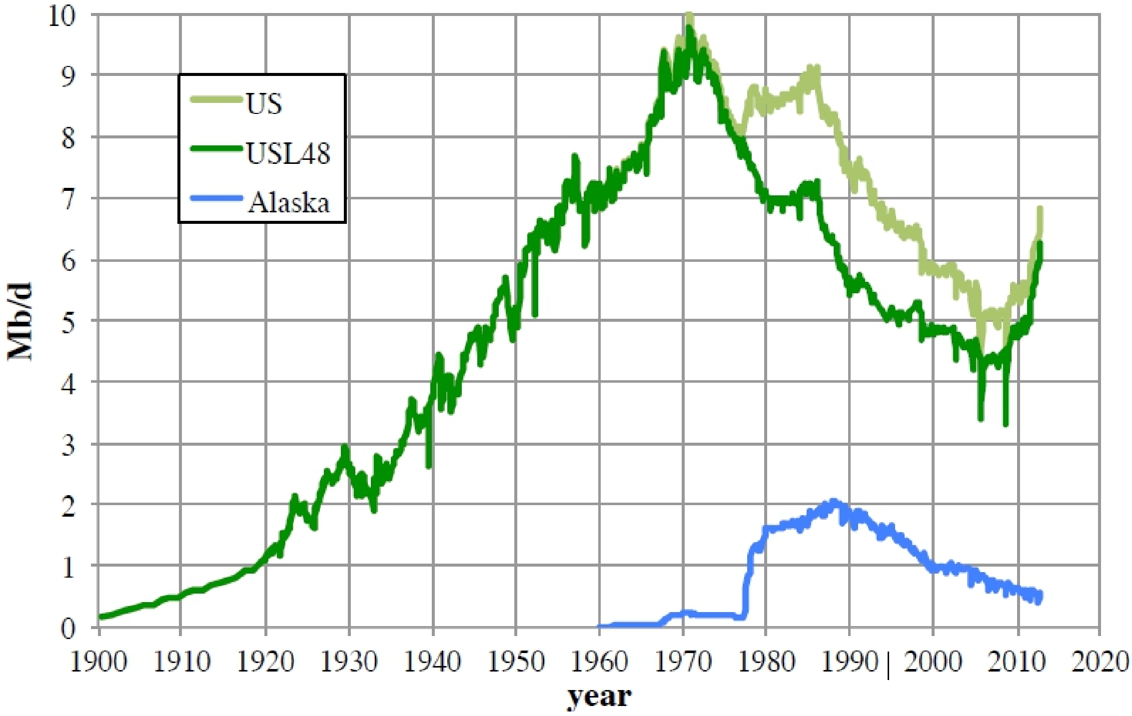

Figure 1: Contiguous US (USL48), Alaska and total oil production from 1900 to 2013. (source: Laherrére, 2014)

It is difficult to make a similar prevision for the worldwide peak oil as data on proven reserves are either confidential or subjected to political agenda. However, backdating[3] annual discoveries, some previsions can be made. Figure 2 shows annual backdated discoveries and conventional oil consumption (Owen et al., 2010). The discovered volume of conventional oil is given by the blue area under the world discoveries line[4]. Even though the investment in research and exploration has never really decreased, we observe that the largest fields, which form the most of the available resource, have already been discovered. The forecasted production line is constructed using an equal area approximation with the

[3] Backdating is used to attribute all subsequent reserve growth to the year of the original discovery.

[4] Technically, the discoveries reported here are 2P (proven + probable) reserves. Probable reserves are defined as reserves that have at least 50% probability to be recovered.

discoveries curve, with a hypothesis of Ultimately Recoverable Resources (URR) of 2 000 billion barrels (Owen et al., 2010).

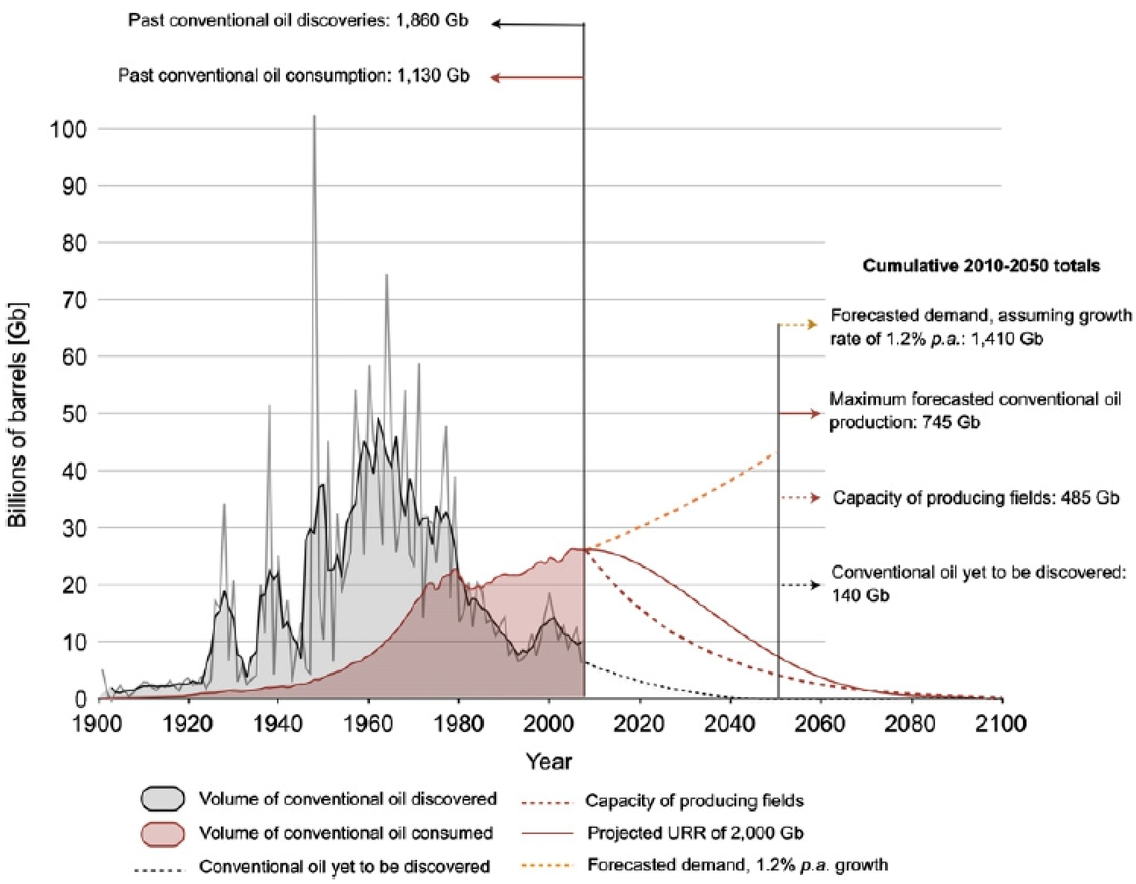

Figure 2: Backdated conventional oil discoveries, annual consumption and forecast. (source: Owen, Inderwildi and king, 2010)

Many researchers and independent institutions assert that conventional oil production is now in decline (Alekkett, 2007; Campbell and Laherrére, 1998; Laherrére, 2009; Robelius, 2007; Wells, 2007; Hallock et al., 2014; Jackson and Smith, 2014). The result is that oil will soon shift from a demand-led market to a supply constrained market. Even though unconventional oil production can support the gap for some years, we can expect that the more this peak will be high in its amplitude, the more asymmetric will be the production curve and the steeper will be the declining phase, and even more if we are to keep unburned 30% of total reserves until 2050 to limit global warming under 2°C (McGlade and Enkins, 2015). In fact, the general transport system now faces two major restrictions. The first one may be considered as the input restrictions, which are, as we have seen, due to the physical resource constraints that will force decline; the second one may be seen as output restrictions: the awareness of negative consequences of fossil fuels combustion shall encourage societies to voluntarily limit massive usage of road transport.

Transport and environment: a load of negative externalities

Indeed, the transport sector is the only main European economic sector for which GreenHouse Gas (GHG) emissions have increased since 1990, accounting for 30% of worldwide CO_2 emissions, which represent 15% of anthropogenic GHG emissions (Sims et al., 2014). Passenger cars contribution is evaluated to almost 45% and heavy duty vehicles add a further 20% of the transport sector emissions (EEA, 2015a). GHG are most probably causing a global warming that would, in the best case, change the ecological equilibrium we're used to (IPCC, 2014), or, if not kept below a certain limit, could destroy a high share of biodiversity that will not have time to migrate (Zhu, Woodall and Clarck, 2012; Corlett and Westcott, 2013). The consequence will trigger positive feedback loops into the climatic system by releasing CO_2 and methane now imprisoned below permafrost (Schuur et al, 2015) and make Mediterranean countries more similar to the actual Sahara and Siberia more similar to actual Austria (EEA, 2015b). But climate change is far from being the unique externality of the transport sector.

Every year, in Europe, 26 000 people are killed in road accidents and, for every death on Europe's roads there are an estimated 4 permanently disabling injuries –- such as brain or spinal cord damages – 8 serious injuries and 50 minor injuries (European Commission, 2016). Aside from human suffering, these injuries have a big impact on society as a whole, and the economic cost is also high. Apart from the direct effect of accidents on citizen's health, noise and air pollution are of greater and greater concern for urban areas with a high traffic volume.

Despite considerable improvements in past decades, air pollution is still responsible for more than 400 000 premature deaths in Europe each year. It also continues to damage vegetation and ecosystems. All transport modes have decreased their emissions, except for international aviation and shipping, for which emissions of each pollutant have increased since 1990. The main pollutants produced by engine include: Nitrogen Oxide (NO_x); Sulfur Oxide (SO_x); Carbon Monoxide (CO); a large variety of volatile organic components (NMVOCs) and Particulate Matter (PM). These compounds are responsible for ground-level ozone formation (O_3) – which is a powerful oxidizing agent – respiratory diseases, eutrophication of aquatic system and acid rains.

Environmental noise pollution has an adverse effect on quality of life and well-being: sleep disturbance, reduced performances, cardiovascular diseases, disturbance in hormones secretion and psychiatric disorders are amongst the proved effect of unwanted noise exposure (Stansfeld and Matheson, 2003). Over the past decades it has increasingly been recognized as an important public health issue. The European Environment Agency (EEA, 2014) reported that one out of four European citizens is potentially exposed to harmful levels of noise from road traffic. This is estimated to result in approximately 10 000 premature deaths per year, although gaps in the data reported leads to think that the true impact is likely to be much greater. Road traffic noise is still the most prevalent noise source, with at least 125 million people being potentially exposed to levels above the Environmental Noise Directive threshold of 55 dB L_{den}, followed by railways noise, which impact more than 10 million people. Finally, aircraft noise, which is very limited in space, impacts directly around 5 million people. However, its impact on population can be higher than other sources (Stansfeld et al., 2005; Clark et al., 2006).

Others environmental externalities include soil occupation, habitat fragmentation and loss of biodiversity. Within urban areas, the share devoted to car (road and parking slots) represents between 30 and 50% of land use and can be up to 65% in some US cities like Los Angeles (Manville and Shoup, 2005). In rural areas, the design and use of road, rail and waterborne transport infrastructure alters the quality and connectivity of habitats, this leads to: wildlife injuries and deaths from vehicle collisions (Ogden, 2012); isolation of populations due to habitat fragmentation (Bennett, Smith and Betts,2011); increased pollution levels in surrounding habitats where traffic affects both air quality and waste production, oil spills, noise pollution (van der Ree et al., 2011); behavioural changes that put the survival of individuals and populations at risk (changes in migratory behaviour or communication patterns) (van der Ree et al., 2011; Bennett et al., 2011); built infrastructure serving as a vector for the spread of non-native and invasive species (von der Lippe and Kowarik, 2008). At the current rate of infrastructure implementation, biodiversity loss and the degradation of ecosystem services are expected to continue with significant implications for the capacity of biodiversity to meet human needs in the future (European Commission, 2015b).

Finally, congestion of traffic flow is one of the major problems in dense metropolitan areas, causing loss of time, increase in vehicle operating costs and stress for millions of European Citizen. In European countries, the annual congestion costs were estimated to reach at least 150 billion euros (European Commision, 2011), representing 22% of total external costs of transport (Figure 3) which were estimated to reach 660 billion euros annually for EU-27. Road transport, even excluding congestion costs, is responsible for more 92% of all transport external costs (CE Delft, 2008).

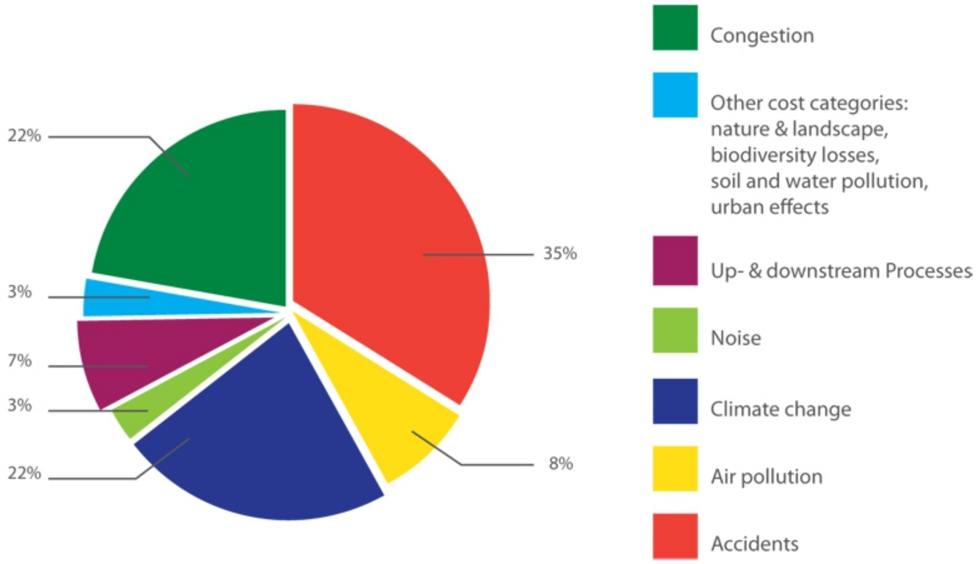

Figure 3: Total external costs of transport in 2008 by externality. (source: CE DELFT, 2008)

Thus, it is clear that road transport, due to its dependences on fossil fuels and to the externalities it implies – even though is vital to feed modern economy – cannot be sustained in the following years. That is why a great effort of research and development is now focussing on alternative fuels and propulsion system.

Alternative fuels and "new" energies.

Biofuels are the only large-scale substitute for liquid transport fuels and their production has been almost quadrupled between 2004 and 2014 (figure 4). North American countries represent the largest producers with more than 30 million tons oil equivalent and in 2014 the United States already dedicated 40% of their corn production to ethanol distillation, which made ethanol the first end product of corn (Wisner, 2016). The *450* *scenario* presented by the International Energy Agency (IEA 2009) expects biofuels to provide 9% of the total transport fuel demand in 2030, doubling its share from now. But IEA baseline scenario also foresees a continuous increase in oil supply at a rate of 1% per year, which is unlikely to happen due to resources depletion (Figure 2). Anyway, the demand for biofuels will continuously grow, but its production is not without risks for the stability of the food market (Babcock, 2012), Europe's agricultural trade deficit (Banse et al., 2011) and even for climate change if the regulation is deficient (Searchinger et al., 2008; Tilman et al., 2009).

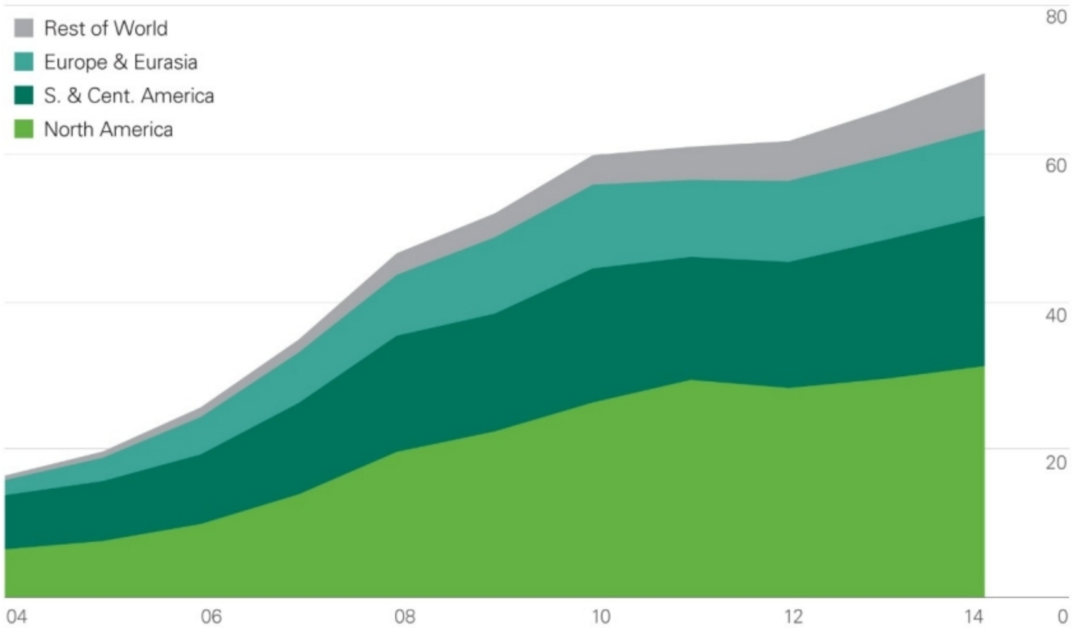

Figure 4: World biofuels production in million tons oil equivalent. (source :BP statistical review, 2015)

Other trending alternatives for vehicles propulsion derive mainly from electricity production, whether directly stocked in chemical batteries or through other storage technologies (hydrogen, compressed air etc.). Their overall efficiency on reducing CO_2 emissions greatly depends on the energy mix of electricity production. In a world where coal supply grew faster than any other major fuel in the last decade – producing more than 40% of world electricity (IEA, 2015) – inducing a new demand for electric output will certainly stress the climatic system a bit more faster, while selling illusive good practices to the consumers. Moreover, doing a life-cycle assessment of conventional and electric vehicles, Hawkins et al. (2013) conclude that the development of electric vehicles, although it may bring a significant reduction from 10 to 15% in terms of global warming potential, may also lead to different major negative impacts, such as: significant increase in human toxicity; freshwater eco-toxicity; freshwater eutrophication; and metal depletion. Overall, combining efforts that could be made in technology development and diffusion, even if global warming is the only problem we focus on, the potential for global green car mobility is very low (Moriarty and Honnery, 2008).

The necessary modal shift

Cars greatly dominate passenger transport, accounting for 80% of total passenger kilometres in Europe (European commission, 2015a). The fact that half of car trips are less than 5km and 30% are less than 3 km makes it clear that there is a large potential for modal diversion, especially in urban areas where public transport and soft-mode infrastructure are implemented. As we showed, future modal diversion from cars is not only a desirable situation for the overall benefit it can set off in our daily lives: it *will* happen, regardless of the judgement that can be given. In fact, modal diversion will be either imposed by external constraints or self-committed as a rational choice. The more social communities and cities in particular, will be able to anticipate and pro-actively activate the transition, the softer this transition will be, leading to greater resilience of the whole system at play.

To tackle the above problems, but also to improve accessibility, quality of life and environmental conditions, a change in transport policy paradigm occurred nearly 25 years ago. It was accepted that we cannot rely only on better traffic control, infrastructure improvements or economic incentives to enhance mobility efficiency due to the scarce public acceptance of economic policies and the limited effects on modal diversion of investments in public transport infrastructures (Stopher, 2004). As a consequence, interests veered towards “soft measures” that are, for example, promoting modal shift through marketing and public awareness programs, mobility management tools, etc. Early voices have claimed that social psychologists must be involved in policy design process (Steg and Tertoolen, 1999). Through the understanding of motives for car-use, of social values and of norms concerning mobility, as well as of cognitive processes of modal choice, tailored campaigns should help in reducing car-use through information dissemination, education or methods for breaking the habits.

To this end, Advanced Traveller Information System (ATIS) may play a major role: by providing real-time information, as well as an economic and environmental impacts comparison between modes allowing travellers to plan their route and estimate their travel time (Nagaraj, 2011), as well as to take better decisions to improve the convenience, safety and efficiency of their travels (Shekhar and Liu, 1994). The first ATIS applications appeared in the early 1960's as *in-route* information with the use of Variable Message Signs (VMS), which are traffic control devices used for traffic warning, regulation, routing and management, and are intended to affect the behaviour of drivers by providing real-time traffic-related information. In the 1970's, radio broadcasts of traffic conditions were developed, firstly in the United States and in Germany (Ramalho Veiga Simao, 2014), soon followed by the first videotex online services – mainly used in France in the 1980's – before the arrival of the GPS technology that allowed a rapid development of more advanced in-car navigation system in the late 1990's. Nowadays, the combination of positioning system with Information Technology allows the rapid spread of online applications for route planning, navigation, traffic predictions, bike sharing availability, etc. However, multiple and disperse websites cause people to miss useful information or to be unaware of the extensive transport options available in the region. Therefore, the actual tendency is to create a system that provides integrated information for automobile, public transport, cycling and walking, leading to the deployment of multimodal ATIS.

In which measure these multimodal ATIS will induce a modal shift? What is the typical end-user profile and what do they expect from such a service? To answers these questions, we need to understand personal motives behind modal choice in order to acknowledge which kind of user could concede to bail out from cars.

After this introductory chapter, an extensive literature review of theories and methods from the field of psycho-sociology applied to environmental behaviours in general, and transport research in particular, will be drawn. Therefore, chapter I will presents how environmental psychologists and social behaviourists define the cognitive process of decision making. The chapter is divided in 3 parts: (1.1) a review of psycho-social variables that were found, in the literature, to have an effect on behaviour; (1.2) a selected presentation of behavioural theories that articulates variables in pre-supposed causal cognitive process; and finally (1.3) some comments, remarks and clarifications about what we think conceptual and/or methodological flaws are.

Chapter II is devoted to describe in detail the objective of this research, the methodology adopted in our study, explaining how the data were gathered, which models were used and what statistical treatments were carried out.

Chapter III reports the results of the study and is divided in five sub-sections. The first provides a description of the sample of participants (3.1); the second and third one focuse on assessing a general measure of attitudes towards the environment (3.2 and 3.3); the fourth one is dedicated to various psycho-social model testing in order to individuate the main determinant of travel behaviour (3.4); lastly, on the basis of the two previous findings, we portray potential multimodal ATIS users and evaluate the possibilities of induced modal shifts (3.5).

Chapter IV presents a discussion, giving a critical analysis of the research and, finally, a conclusion will summarize the results of our studies discussing the future researches that can be made as follow up of this study.

I. The psycho-social perspective in Transport Research: a critical review of Theories and Methods

This chapter aims at giving an extensive vision of the state of the art of behavioural theories coming from social and environmental psychologists as applied to transport research. The limits of such theories, the good practices but also the misuses of the main methodologies and models found in the literature will be discussed. Starting from the empirical exploration of determinant variables and moving on to the development of behavioural theories, this review aims at providing a – necessarily not exhaustive but – relevant clue to critically evaluate current research. Social scientists and environmental psychologists began to study travel behaviour since the 70's but, from the 90's, a large amount of research has been carried out to better understand modal choice from a socio-psychological point of view and to use this knowledge to try and 'pull people out of their cars'.

To those scholars unfamiliar with the topic, the chapter offers a key to understand and critically review present and future publications, as well as relevant bibliographic references for further development. As for the others, the chapter aims at presenting some topics to discuss about and widening research opportunities.

The next section briefly presents psycho-social variables that have been studied in transport. Section 1.2 presents the most significant behavioural theories that have been found in relevant literature in the lasts 20 years. Finally, the last part of the chapter is devoted to discuss methodological tools – good practices and misuses – and to critically assess current literature, providing recommendations for further research

1.1. Review of main psycho-social variables

"Psycho-social variables" are intended as the combination of psychological factors (mental states, individual-level processes) and social factors (concerning social processes and human society structures) meant to point out that the individual is socially driven and that social processes may be mediated by psychological states. Reference will be made, when possible, to studies that have assessed the effects of those factors on travel behaviour.

Otherwise, research on consumer behaviour will be cited and expected outcomes on travel behaviour will be forecast.

Arguably, psycho-social factors entered into transport studies through the door opened by the environmental psychology, which aims at understanding the determinants of pro-environmental behaviour. In environmental psychology, an important distinction between behaviours having an *impact-oriented* approach and those having an *intention-oriented* approach may be established. The first ones include *pertinent behaviours* – aimed at reducing environmental externalities even though people are not aware of those – whereas the intention-oriented behaviours include *significant behaviours* performed with the intention of acting pro-environmentally even though the positive consequences are negligible or inexistent (as the case of a frequent flyer – having a high ecological footprint – yelling at someone for not turning the light off when leaving the bathroom). These two different approaches allow researchers to understand the motivation behind *significant behaviours* and the drawbacks associated to *pertinent behaviours*.

In 1987, Hines et al. conducted a meta-analysis to define psycho-social determinants of pro-environmental behaviour and classified them in three categories: (I) cognitive factors, (II) affective factors, (III) situational factors. Then, the authors focused on the individual level and on the personal representation of the cognitive process behind the transport modal choice, considering three spheres of behaviours: 1) the public sphere: ecological citizenship; 2) the private sphere: ecological consumerism; and 3) the company sphere: ecological professionalism. These three spheres originate from: a) values and belief; b) status and social class and capacities; c) technologies, industrial norms, laws and social norms.

Thereon, it is possible classify the psycho-social variables into eight main groups: 1) knowledge and beliefs; 2) values; 3) worldviews (weltanschauung); 4) norms; 5) personality traits and lifestyles; 6) emotions and personal stories; 7) attitudes and intentions; 8) habits and past behaviours. Although the last group cannot be considered as psycho-social determinants they, nonetheless, play an important role in our understanding of the issue under discussion.

In Table 1, the eight groups of variables are presented, specifying their typologies, descriptions and the scientific reference.

Although ***knowledge*** shows, empirically, a low correlation with sustainable behaviour (Hines et al., 1987), its effect relies more probably on the convergence and combination of its different forms, that can enhance or inhibit each other. The convergence of all of these forms is, for some authors, a necessary – though not sufficient – condition for ecological behaviour (Kaiser & Fuhrer, 2003).

The role of ***values*** as regards the travel behaviour has been studied using three different paradigms (Table 1). It has been found that the social value orientation of cooperation is positively correlated with self-transcendent values, such as equality, social justice and solidarity (Garling, 1999). Concerning their influence on travel behaviour, self-transcendence, social cooperation and eco-centrism values seem to correlate with decision to favour public transport over car (Vugt et al., 1995) and with a greater wish to reduce car-use (Nordlund and Garvill, 2003)

Worldviews **(*Weltanschauung*)** can be analysed according to three different approaches (Table 1). Although post-materialism has never been studied in a transport context, it is not clear if its values can explain pro-environmental behaviour (Aoyagi-Usui et al., 2003) or policy support (Stern et al., 1999).

The risk perception, known as cultural theories or "myths of nature", studied by Steg and Sievers (2000), shows that people adopting an ephemeral point of view were more aware of car-use problems and more favourable towards supporting car reduction policies. The myth of nature has been referred to the general environmental concern measured by the New Environmental Paradigm scale (NEP) (Poortinga et al, 2002), which assesses on one dimension the propensity of people to adopt or support pro-environmental behaviours.

The influence of religious orientation on pro-environmental behaviour is considered positive by Kearns (1997), but the opposite has also been argued (White, 1967). Indeed, empirical research shows some contradictory results (Hand and Van Liere, 1984; Hayes and Marangudakis, 2001), due to the complex interactions between religious beliefs, political orientation and environmental concern, as explained by Sherkat and Ellison (2007). These authors argue that Protestants are more willing to accept a personal pro-environmental behaviour but, being influenced by conservative stances on the seriousness of risks, they give little support to environmental activism.

Table 1: Review of main psycho-social variables

Variables	Typology / Paradigm	Description	References
Knowledge and believes	Declarative knowledge	It describes the case (the system)	Kaiser and Fuhrer (2003)
	Procedural knowledge	It allows to know how to act	
	Effectiveness knowledge	It is the knowledge of relative effectiveness of different behaviours aiming at the same outcome	
	Social knowledge	It is the representation of normative beliefs or, in other words, what one believes his/her referents think about a given behaviour	
Values	Social value orientation	Individualism versus cooperation, as the case of prisoner's dilemma	Messick and McClintock (1968)
	General value orientation	It is appraised on a bi-dimensional scale representing four higher order values: self-transcendence versus self-enhancement and openness to change versus conservatism	Schwartz (1992)
	Environmental value	There are different, but similar definitions. We will retain here the eco-centrism (the ecosystem has an intrinsic value versus anthropocentrism dimension (the environment is valued as it supports human life)	Thompson and Barton (1994)
Worldviews	Post-Materialism	It explains environmental concerns because people pay attention to greater general welfare in a society where basic needs are guaranteed	Inghelgart (1995) Maslow (1943)
	Myth of nature	It refers to the risk perception, where people are supposed to adopt one of the four different views about the vulnerability of nature: 1) benign and resilient; 2) tolerant and moderately vulnerable; 3) ephemeral and fragile; 4) capricious and unpredictable whatever action is taken	Douglas and Wildavsky (1982) Steg and Sievers (2000)
	Religious orientation	It refers to the influence that religion has on people choices and behaviour, showing a potential effect on the willingness to make sacrifice	Discussion in Sherkat and Ellison (2007)
Norms	Social prescriptive norms	They reflect the beliefs of "what we should do"	Cialdini et al. (1990)
	Social descriptive norms	They are based on the direct observation of "what people do", being mostly context-dependent	Cialdini et al. (1990)
	Personal norms/moral	They are internalized social norms. They are activated when the subject is aware of the consequences of his/her own actions, deliberately taken	Schwartz (1977)
	Normative believes	They refer to the perceived behavioural expectations of the referent individuals or groups (parents, relatives, friends, etc.)	Ajzen (1985) Ajzen (1991)
	Subjective norms	They are determined by the combination of normative beliefs with the person's motivation to comply with the different referents	
Lifestyles and personality traits	Allport's trait theory	No agreements emerge on the definition (see Engler, 2013)	Allport and Allport (1921)
	16 Personality Factors		Catell and Mead (2008)
	Goldberg's Big Five personality traits		Goldberg (1990)
Emotions/Personal Stories	Emotional response	It expresses the affective dimension of the objects (e.g. car) related to a choice (e.g. modal choice) that influences such choices	Carrus et al. (2008) Farag and Lyons (2008) Bamberg et al. (2011)

	Past experience	It expresses the life experiences or habits in the past (also in the early stage of life) that influence people choices	Chawla (1999)
	Utilitarian response	It is used for obtaining a certain benefit, sometimes overcoming the emotional response	Bonnes et al. (2006)
Attitudes and Intention	Attitudes	They generally refer to one-dimensional evaluations, more or less favourable, towards a mentally represented object, concrete or abstract	Allport (1935)
	Intention or "behavioural intention"	It is a mental state that directly precedes behaviour, a form of motivational driver that leads to the behaviour itself	Ajzen (1991)
	Perceived behavioural control	It refers to people's perceptions of their ability to perform a given behaviour	Ajzen (1991)
Habits and past behaviour	Habits	It is a recalled action-script	First used in Triandis (1977) Aarts and Dijksterhuis (2000) Discussion in Verplanken (2006)
	Past Behaviour	It is the previous behavioural pattern, when repeated several times	

However, the variables related to values and worldviews may have low effect on behaviour and, sometimes, they can be in contradiction with the observed behaviour. The reason is that the values go beyond the context and their role in explaining behaviour is largely mediated by many other variables, such as situational limits (Dietz et al, 1998) or the cultural background (Aoyagi-Usui et al, 2003).

The ***norms*** can be social or personal (Table 1). Social norms can be acquired and internalised, becoming personal norms, through a process of self-categorisation inside the dynamics of social identity construction (Schwartz, 1977). When a person feels being part of a group, (s)he tends to act in line with the group prescriptive norms. Other norms may remain external to oneself, but still have an influence on behaviour. Social prescriptive norms may be followed even though they are not part of the self-identity, as one may wish to avoid the social consequences of punishment and sanctions of a socially proscribed behaviour. The adherence to internalised social norms (personal norms) follows the same scheme, but the sanctions are self-attributed in the form of sense of guilt and self-attribution of moral responsibility, or shame and embarrassment for not following own personal moral (Staub, 1978). On the contrary, a self-satisfaction emerges when behaviour is in line with own personal norms, in form of pride. Finally, when there is a motivation to comply with different referents, normative beliefs become subjective norms, that is what one thinks their referents think (s)he should do (Ajzen, 1985).

Nordlund and Garvill (2003) linked personal norms with personal values and found evidence that individuals showing self-transcendence and eco-centrism felt more morally forced to cooperate in a social dilemma context of modal choice. Bamberg et al (2007) studied the strength of socio-normative influence and argued that more the social norms are anchored, stronger is the association between social norms, personal norms and behaviour.

Lifestyles and personality traits are thought to influence travel behaviour and activity patterns (Pronello and Camusso, 2011). Hilderbrand (2003) used socio-demographic variables to cluster elderly people in six lifestyle groups and used these clusters to run a micro-simulation of an activity based model. A series of studies tried to investigate the role of personality traits: Mokhtarian et al. (2001) defined four typologies (adventure seekers, organizers, loners and calm people) thanks to a 17-item questionnaire and Cao and Moktarian (2005a; 2005b) used a 18-item questionnaire that individuated again four lifestyles. Findings showed that adventure-seekers travel the most and are more flexible, and that they tend to consider a greater set of strategies to reach a personal travel adaptation (Clay and Mokhtarian, 2004; Cao and Mokhtarian, 2005a; 2005b). However, this classification does not seem related to any psychological accepted definition of personality traits such as Allport's trait theory (Allport and Allport, 1921), the 16 Personality Factors questionnaire by Cattell and Mead (1969) and Goldberg's Big Five personality traits (Goldberg, 1990). The lack of both common definition of lifestyle (Engler, 2013) and common methods for measuring it is a problem for carrying out comparative studies.

Modal choice is strongly linked with personal and collective sensibility, ***emotions and personal stories***. The affective dimension tying some people to their car is not only a psychological factor but is generated by collective cultural and symbolic patterns (Sheller, 2003; Steg, 2005); such aspect has been understood early by manufacturers that developed emotion-targeted advertisements. When talking about modal choice, we cannot deny the fear of airplane, bad memories associated with a bike accident, the thrill felt when driving at high speed, etc. In transport research, emotion as an explanatory variable of modal choice is measured in terms of anticipated emotions, that is, the thoughts about future feelings for attaining a specific goal (see Carrus et al, 2008; Farag and Lyons, 2008; Bamberg et al., 2011).

The more people were used to live in close relation with nature in early age, the more they participate in active environmental citizenship (Chawla, 1999); thus, significant life experience can lead to environmental sensitivity and support to environmental policy. Pronello et al. (2015) showed that the direct observation of air pollution effects on children's chronic respiratory disease could explain, by itself, the choice of a sustainable travel mode.

Gobster (1996) argued that people prefer landscapes showing the most damaged ecosystem, due to the biased vision of nature, perceived as a means to attain a certain useful result (Bonnes et al., 2006). However, such a preference is challenged when considering that the motor vehicle, as a technology, evolved from utilitarian use to "object of desire" and many people would admit how well they feel while, immersed in nature, driving a car on rural roads in the middle of pasture fields.

Attitudes are a key-concept in social psychology. Despite many different definitions in psychological literature (Fishbein and Ajzen, 1972) often confused with other concepts in social sciences, such as opinions or values (Bergman, 1998), attitudes are hidden psychological states of an individual about something not directly observable but partly measured through some indicators – opinions, judgements, feelings. In the early years of social psychology, attitude was considered the direct predecessor of behaviour, although evidences showed inconsistencies in the attitude-behaviour relationship (Wicker, 1969); thus, ***behavioural intention*** was introduced as a mediator variable between attitude and behaviour (Fishbein and Ajzen, 1975). The stronger the intention to act, the likelier the adoption of a certain behaviour. However, in order to take into account exogenous factors hampering the adopting of a behaviour – weakening the correlation between intention and behaviour – some subjective variables related to the perceived difficulty or judgements about one's own ability to behave in a determined way may be considered (Webb and Sheeran, 2006). Such variables can be expressed by the ***perceived behavioural contro***l that is determined by the total set of accessible control beliefs (Ajzen, 1991).

Habits in transport research are usually intended as travel patterns repeated over time, whose strength is often measured through the frequency of past behaviours (Ouelette and Wood, 1998; Aarts et al, 1998). In traditional transport economic models, habitual patterns are often implicitly accepted without questioning their validity (Hanson and Huff, 1981). From a cognitive perspective, when a behaviour becomes habitual, it is no longer seen as a deliberative choice, but it is recalled through an action-script from past experience to minimise the cognitive effort and can be measured as the response-time of a given person confronted to a given situation. It has been indeed demonstrated that the more automatic is the activation of a behaviour, the less people are looking for information to make a deliberate choice (Verplanken et al., 1997; Aarts et al., 1997).

1.2. Review of behavioural theories

As described in the previous section, a wide range of psycho-social variables may contribute to explain individual behaviour; however, contradictory results, overlapping concepts and ambiguous definitions are often encountered. This is expected for all and holds true when trying to understand and predict human decision-making processes: in fact, entanglement, reciprocal moderations or enhancement, nonlinear relationships between factors and behaviours have to be taken into account.

As regards the transport field, in the early 90's, a shift was observed from the empirical correlation between variables and behaviour towards the construction of theories, psycho-social constructs and causal processes generating the behaviour (Bamberg and Schmidt, 2003).

The role of theories is to find rational explanations to a given phenomenon; in psychology the theory is needed to build measures of subjective mental states in response to questions or observation of body movement, drawings, etc. Furthermore, when constructing a theory based on subjective psychological constructs, tellings are necessary to give sense to data because one can subjectively relate his/her own experience with what those tellings express. Thus, to support a theory, not only data are needed: definitions have to be precise, concepts should be intelligible and cause and effects should be coherent with one's own pace of thinking. The development of a theory is not independent from the construction of psycho-social variables, as some of them are constructed *ad hoc* in order to support the narratives. A large number of theoretical frameworks have been developed over the years in order to capture the factors leading to decision making or behavioural choice.

Table 2: Review of Behavioural theories

Approach	Theory	Description	References
Individual-focused theories of decision making	Theory of Planned Behaviour (TPB)	It states that behaviour depends on both motivation (intention) and ability (behavioural control) and proposes six constructs that collectively represent a person's actual control over the behaviour: three types of beliefs (behavioral, normative, and control), attitudes, subjective norms, perceived behavioural control	Ajzen (1991)
	Theory of Interpersonal Behaviour (TIB)	It shows that behaviour in any situation is a function of the intention (influenced by social and affective factors as well as by rational deliberations), habitual responses, situational constraints and conditions. Behaviour is influenced by moral beliefs, but the impact of these is moderated both by emotional drives and cognitive limitations	Triandis (1977)
	Norm Activation Theory (NAT)	It describes the relationship between activators, personal norms, and behaviour. Norm activation refers to a process in which people construct self-expectations regarding pro-social behaviour. These behavioural self-expectations are termed 'personal norms' and are experienced as feelings of moral obligation. Central in the process of norm activation are four situational factors ('situational activators') and two personality trait activators	Schwartz (1970; 1975; 1977) Schwartz and Howard (1984)
	Value-Belief-Norm theory (VBN)	It states that individual choice about pro-environmental actions can be driven by personal norms that are activated when an individual believes that violating them would have adverse effects on what (s)he values and that by taking action, (s)he would bear significant responsibility for those consequences. Personal values (e.g., altruistic values, egoistic values) are antecedents of environmental beliefs	Stern (2000)
Individual-focused of behavioural change	TransTheoretical Model (TTM)	It is an integrative, biopsychosocial model to conceptualize the process of intentional behavioural change, seeking to include and integrate key constructs from other theories into a comprehensive theory of change that can be applied to a variety of behaviours, populations, and settings (e.g. treatment, prevention and policy-making settings, etc.). One of the key constructs of the TTM is the Stages of Change: precontemplation, contemplation, preparation, action, maintenance	Prochaska and DiClemente (1983) Prochaska, DiClemente and Norcross (1992)
	Stage model of Self-regulated Behavioural Change (SSBC)	It assumes that the temporal path of behavioural change can be broken down into four independent, qualitatively different stages. In each of these four stages, a person is confronted with solving a specific task in order to successfully change her/his behaviour	Bamberg et al. (2011)
	Protection-Motivation Theory (PMT)	It proposes that the intention to protect oneself depends on four factors: 1) the perceived severity of a threatened event (e.g., a heart attack); 2) the perceived probability of the occurrence, or vulnerability; 3) the efficacy of the recommended preventive behaviour (the perceived response efficacy); 4) the perceived self-efficacy (e.g. the level of confidence in one's ability to undertake the recommended preventive behaviour)	Rogers (1983)
Community-focused theories and Social interactions theories	Social Cognitive Theory (SCT)	It states that learning occurs in a social context with a dynamic and reciprocal interaction of the person, environment and behaviour, emphasysing the social influence and its external and internal social reinforcement	Bandura (1999)
	Social Comparison Theory	It deals with how a person forms beliefs and opinions about one's own capabilities. Human beings have the drive to assess their opinions and to know more about their abilities; when they are incapable of evaluating their opinions and abilities, they tend to compare themselves with others	Festinger (1954)

There are three different approaches in theory construction, namely (1) ***individual-focused theory of decision making***, (2) ***individual-focused theory of behavioural change***, (3) ***community-focused theory*** (Table 2).

1.2.1 Individual-focused theory of decision making

Individual-focused theories of decision making represent the largest part of psycho-social studies applied to transport research; among the most significant are the *Theory of Planned Behaviour (TPB)* (Ajzen, 1991), the *Theory of Interpersonal Behaviour (TIB)* (Triandis, 1977), the *Norm Activation Theory (NAT)* (Schwartz, 1977), the *Value-Belief-Norm theory (VBN)* (Stern et al., 1999; Stern, 2000) (Table 2).

The Theory of Planned Behaviour (TPB) was put forward as an extension of the Theory of Reasoned Action (TRA)(Fishbein & Ajzen, 1975). This latter was developed to understand the relationship among attitudes, behavioural intention and actual behaviour. It is assumed that behaviour is directly determined by intention which is, in turn, explained by attitudes, on one hand, and subjective norms, on the other hand. The TPB was later developed to add another component, namely the perceived behavioural control (PBC), in order to cover behaviours that are hardly under volitional control (Ajzen, 1991).

The TPB is certainly the best known behavioural theory in transport research, environmental psychology and health related studies. It is in turns acclaimed for its great success and remarkable predictive power in empirical studies (Armitage and Conner, 2001) or profoundly criticised and utterly disregarded (Sniehotta et al., 2014). Through years of widespread applications in many fields, it has been modified and many variations exist in literature; researchers have added more variables to try to better predict future behaviour: anticipated emotions (Perugini and Bagozzi, 2001), perceived mobility needs (Haustein and Hunecke, 2007), personal norms (Bamberg et al. 2007). Furthermore, Conner and Armitage (1998) proposed to add six variables to the initial model: belief salience; locus of control, that constructs the perceived behavioural control together with self-efficacy; moral norms; self-identity, that reflects the extent to which an actor sees him/herself as fulfilling the criteria for any societal role; affective beliefs, anticipated emotions or regret; past behaviour/habit.

It may be noticed that trying to reinforce a theory supposedly explaining reasoned (or planned) behaviour by adding “habits” – a non-deliberative variable – is an auto-destructive idea. It is clear from figure 5 that such additions would lead to a model closer to the Theory of Interpersonal Behaviour (TIB) than to the TPB. It can be wondered if this blinded approach to Ajzen’s theory is driven by ignorance, fashion and trends or bibliometric considerations.

As argued above ***the theory of interpersonal behaviour*** (TIB) by Triandis (1977) shows great similarity with Ajzen’s TPB; in fact, both theories aim at explaining intention to engage in a certain behaviour and the performing of such a behaviour. In TIB, however, intention is not only driven by personal cognition (subjective norms [SN] and attitude [ATT]), but also by emotions (affective constructs), social norms and self-identity (social constructs) factors. Moreover habits play a direct role in explaining behaviour, as Triandis argues that automatic performance of a behaviour decreases the level of conscious control over such behaviour. Finally, whereas in the TIB the presence of objective external restriction in performing a behaviour has a direct effect, the TPB assumes a subjective representation of those factors influencing intention.

The Norm-Activation Theory (NAT) (Schwartz, 1977) was first developed as a model for explaining altruistic behaviour. The reasoning is that pro-social behaviour depends on the activation of personal moral norms, which are kicked-on once individuals expect a negative outcome to a given situation (problem awareness [PA] and adverse consequences [AC]) and when they believe their action may have a role in reducing this threat (ascription of responsibility [AR]). It seems that there is confusion among researchers about how operatively analysing the NAT: the causal relationship between the model variables has been interpreted differently as at least three models have appeared in the literature: (1) the relationship between Personal Norms (PN) and Behaviour is moderated by Problem Awareness (PA) and Ascription of Responsibility (AR) (e.g., Schultz and Zelezny, 1998; Vining and Ebreo, 1992); (2) Problem Awareness (PA) influences Ascription of Responsibility (AR), which in turn influences Personal Norms (PN) and PN influence behaviour (e.g., Gärling et al., 2003; Nordlund and Garvill, 2003; Steg, Dreijerink and Abrahamse, 2005; Stern et al., 1999); and (3) both Problem Awareness (PA) and Ascription of Responsibility (AR) influence PN, while PN, in turn, influence behaviour (e.g., Bamberg and Schmidt, 2003; Harland et al., 2007).

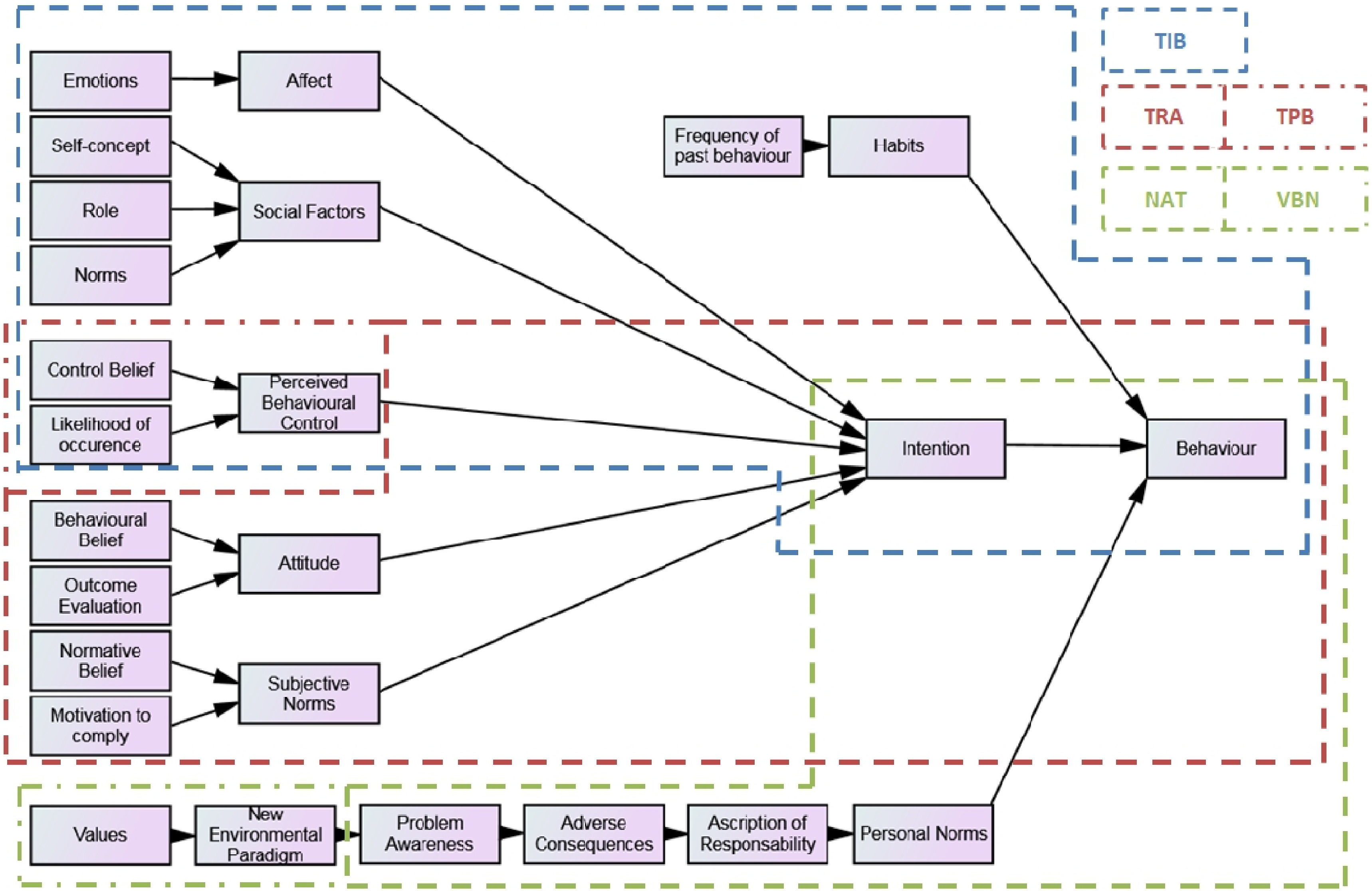

Figure 5: Relationships among individual-focused theories

The first interpretation refers to a moderator model, while the other two interpretations assume a causal or mediation model. In a series of studies, de Groot and Steg (2009; Steg and de Groot 2010) compared all three models and found most consistent support for the second one, which is the one represented in figure 5. Moreover, they were able to follow an experimental design that supports causal relationships among the model variables.

More recently, Stern proposed to link Schwartz's Theory with values and worldviews (Stern, 2000) and constructed the ***Value-Belief-Norm Theory*** to explain environmentally significant behaviour through a causal chain from stable general values and beliefs to specific behavioural norms. The idea is that a particular behaviour will follow a subjective norm activation only if it does not contradict with one's own personal values.

Bamberg and Moser (2007) updated the meta-analysis two decades after Hines et al. (1987), gathering their data from theory-driven studies and concluded that pro-environmental behaviour is driven by both pro-social motives and self-interest and confirmed that behavioural intention mediates the attitude-behaviour relationship.

1.2.2 Individual-focused of behavioural change

The approach, focused on behavioural change, includes three main theories: the *TransTheoretical Model* (TTM), *the Stage model of Self-regulated Behavioural Change* (SSBC) and the *Protection-Motivation Theory* (PMT) (Table 2).

Firstly developed in the field of health-related behavioural changes, such as stop from smoking, exercise, low-fat diet or condom uses, the ***TransTheoretical Model*** (TTM) is a model of intentional change, focusing on the individual and his/her emotions, cognitions and behaviours. The main innovation brought about by the TTM is the temporal dimension of change: where behavioural change was previously analysed as an event, the TTM recognises it as a process involving five stages – Pre-contemplation, Contemplation, Preparation, Action and Maintenance – and different processes, or activities, in which people implicate themselves to overcome difficulties encountered through the stages. These activities involve, for example, emotions, cognition, behaviour, social support or information gathering. The theory states that the effectiveness of a process/activity depends on individual's position towards change; it is considered as a theory of ideal change, due to strong criticism towards the arbitrary threshold of stages (West, 2005), the nonlinear patterns of progression through stages (Weistein et al., 1998; Sutton, 2001) and the lack of effectiveness of interventions using TTM framework (Bridle et al., 2005). For a detailed discussion about pros and cons of the model, refer to Armitage (2009). The TTM, as a model of voluntary behavioural change, has been rightfully applied to consumer behaviour (He et al., 2010); Bamberg (2007) adapted the TTM to develop the ***Stage model of Self-regulated Behavioural Change*** (SSBC), sometimes referred to as MaxSem model (Carreno et al., 2010; 2011) for interventions on personal travel plans focusing on car-use. Interestingly enough, Bamberg (op.cit) retained four stages, by combining preparation and action, that are identified from constructs taken from both Ajzen's TPB and Shwartz's NAT. This approach is in line with Armitage and Arden (2002), although these latter argued in favour of TPB over TTM in furnishing tools for behavioural change. Bamberg et al. (2011) support their voluntary behavioural change approach, which is obviously limited in range for a systemic change; however, they point out, and we join their claim, that stronger and wider empirical evidence is required to prove the efficiency of this model promoting sustainable transport.

The ***Protection-Motivation Theory*** (PMT) (Rogers, 1983) sets out a framework to develop and evaluate persuasive communication as well as a social cognition model to predict health behaviour. The origins of the theory lay on the study of the persuasive impact of fear on attitude and behaviour (Rogers, 1975) that were first conducted through the ***Health Belief Model***, from which PMT derives. The theory postulates that behavioural intention – here named protection motivation – to perform the recommended behaviour is assessed through a process of both threat and coping appraisal. Threat is supposedly determined by the assessment of both the severity of the threat and the likelihood of being directly affected. On the other hand, the coping appraisal is driven by the evaluation of the efficacy of the recommended behaviour on limiting the threat and individuals' ability to perform the recommended behaviour. Kim et al (2013) used the PMT together with Fishbein and Ajzen's TRA to predict pro-environmental behaviour with quite a good success.

1.2.3 Community-focused theories and Social interactions theories

The Social Cognitive Theory (SCT) (Bandura, 1999) rejects the assumption that a behaviour is led by a stimuli-response phenomenon, making people to act in a mechanical way, like for example, computing information to choose the best alternatives in accordance to self-stated rules of decision making. According to Bandura, people are seen as agents interacting among themselves, having expectations about the future, being influenced by environmental considerations and prompted to self-reinforcement and adaptive behaviour. People learn by doing, by observing others and they can modify the reality; thus, the human mind is “generative, creative, proactive, and reflective, not just reactive” (Bandura, 1999). According to SCT, the most important influential factor of behaviour is self-efficacy, or the confidence about their own capability to reach a goal. This goal is defined thanks to outcome expectations (at different levels) and socio-structural factors (the environment that can facilitate or impede a given achievement). It is then assumed that the goal, expected outcome and self-efficacy itself can predict behaviour. No studies have been found applying SCT neither in transport sector nor in pro-environmental behaviour, while many researches encourage the use of SCT framework as a theory-based intervention to promote healthy behaviour.

Festinger’s ***Social Comparison Theory*** (1954) states that when someone has no clue about how to judge or to act, (s)he will compare him/herself with most similar individuals and tend to adapt and reduce the gap between own’s and other’s behaviour. This is a direct implication of descriptive social norms, viewed as a dynamic process towards an asymptotic goal instead of a static injunction of what should be made.

When attitudes and behaviour are inconsistent, what is called *cognitive dissonance* (Festinger, 1962), individuals are more likely to change their attitudes instead of behaviour, in many ways (see Juvan and Dolnicar, 2014). A few years ago, Tertoolen et al. (1998) showed that the effect of making the gap between attitudes and behaviour obvious could cause undesirable consequences defined as social dilemmas and reactance from people to change their habits.

1.3. Findings and remarks

It is almost impossible – if not foolish – to think that scientists will one day be able to untangle the mind: a) taking into account all possible factors leading one person to act in a certain way; b) taking into account, at the individual level, both endogenous variables – from real-time information gathering to lifelong memories and unconscious decision-making processes – and exogenous variables – from particular weather conditions to normative demands.

However, several methodological tools and models have been developed to try and forecast human behaviour; data collection appears as an important asset both to better understand the phenomena and to develop such methods and models. To understand what are the good practices but also the misuses of methods and models, a critical analysis of the literature follows, focussing on two main aspects: 1) the role of data (collection and analysis); 2) the rethinking of received wisdom.

1.3.1 The data collection and analysis

Data collection

Self-reported questionnaires are the main source of data for most studies. Although this collection method has been judged valid – or at least better than nothing – by some authors (Werriner et al., 1984), we know that data from questionnaires are often biased because of social desirability, difficulty of memory recall, lack of knowledge or insufficient willingness to answer correctly (Corall-Verdugo, 1997). We will not discuss about sample size and random errors, largely treated in the literature and broadly known. However, the assessment of systematic errors is still too scarce, due to survey design, under-reporting – especially of walk and bike trips – (Clarke et al., 1981), response rate (Brög and Meyburg, 1980), or diminished motivation in a travel/activity diary along time (Meurs et al., 1989; Golob and Meurs, 1986). Although the assessment of systematic errors has been researched and some estimation and correction methods have been put forward (Brög and Erl, 1999), those errors are too often neglected by researchers, and even more by planners and politicians. Transport field is driven by figures and statistical significance and the validity of inferences slumps when systematic errors are ten times larger than random sampling ones (Brög and Erl, 1999; Brög et al., 2009). The validity of self-reported behaviour has been widely studied by environmental psychologists (Kormos and Gifford, 2014) and, in the field of transport, addressed by studies about extreme driving behaviour, road violations (Lajunen & Summala, 2003) and risk prevention (Nelson, 2014). Nevertheless, there is arguably no study assessing the reliability of self-reported surveys dealing with modal choice, travel patterns and routine behaviour. Certainly, we can agree that data from questionnaires we are familiar with, may be reliable enough, but this issue is problematic from an epistemological point of view.

Another important point is to cope with the inability of quantitative questionnaire to underpin complex behaviours: on one hand, the willingness to capture a wide range of emotions, feelings and cognitive processes and, on the other hand, the need of keeping the questionnaires simple and short. Indeed, if we include in our model more independent variables that have proved to have an influence in decision making or behavioural intentions, the collection process becomes more time consuming and less reliable.

Qualitative analysis from interviews or focus groups can greatly help researchers in understanding complex relationships between ideologies, feelings, subjective (mis-)perception, motivations and attitudes (see for eg. Kenyon and Lyons, 2003; Pronello and Rapazzo, 2014); to this extent, the use of mixed method (Jonhson and Onwuegbuzie, 2004) is clearly lacking, not only in transport research, but in social science in general.

Data analysis.

The complexity of interaction between supposed independent variables is largely underestimated. The causal chain that leads to decision making, or behavioural intention, is hypothesised by the formulation of the theory and, the majority of studies being observational, our certainty about the direction of causality is inexistent. The use of Structural Equation Modelling (SEM) as a method to derive causality from observational data is misleading. The aim of the SEM is to support a narrative to explain the causality; thus, the methodological weakness is due to the researcher's assumptions so far, not sufficiently discussed. Feedback loops or non-linear relationships are mostly unexplored. Can we really claim that a positive attitude towards cycling will lead someone to ride and is not a consequence of it? The question is not new: Bandura (1971) regretted that most psychodynamic processes are inferred by the behavioural response they ought to explain.

In psychology, the measurement of psycho-social constructs, such as attitudes, norms, affect, etc. is mainly performed under the paradigm of Classical Test Theory. Practically, as it is assumed that internal states of mind are unobservable, the variables of interests are determined through the use of questionnaire items: a latent factor that will capture the covariance of different items is constructed. However, the validity of measures of unobservable variables depends on the strength of their concept and on the ability of items – carrying their own measurement error – to reflect a specific psychological construct without accidentally measuring an outside variable. Applying complex correlational models (as the SEM) to the data necessary leads to the *multiplicative invalidity problem* (Trafimow, 2006), where relationships among unobserved variables may be illusions created by the multiplication of invalidities of measures.

In several studies, inferences are generally of poor quality and, most of the time, only reflect the researcher thought through the way questions are asked. Some issues closely related to correct data interpretation are given here as explicit: we lack univocal definitions of psychological constructs; we often lack conformity between measures and behaviour (Ajzen's compatibility principle, discussed further in the section 1.3.2); many known modulating factors, both internal (ambiguity of ecological attitudes) and external (peer pressure, context such as costs, built environment and normative system) are not acknowledged by the theories; when measuring past behaviour to predict future behaviour, are we sure we are not measuring the same thing ? This aspect raises also the problem of forward-looking, because the literature clearly shows a lack of longitudinal (before/after) studies; are we aware of mathematical implications of our model and statistical analysis ? Too often questions of mutual causality and the validity of linear response are overlooked.

Chorus et al. (2006), in their meta-analysis, clearly showed that the expected effects of travel information are below expectations although they may be effective in some specific cases. Hunecke et al., 2007 used a hierarchical regression analysis to assess the effects of psychological variables when socio-demographic and infrastructures are controlled for. They show that, in terms of ecological impact, the psychological factors have an explanation power of 14% (reaching 60 % of total variance); this clearly shows that our understanding of the effect of psychological factors on travel behaviour is very low.

1.3.2 Rethinking familiar concepts.

Behavioural researches point out the existing gap between the measured attitude, the measured behavioural intention and the observed behaviour. This inconsistency between what people say and what people do is interchangeably referred as the *attitude-behaviour gap* (e.g. Godin, Conner and Sheeran, 2005; Moraes, Carrigan and Szmigin, 2012) or the *intention-behaviour gap* (e.g., Sheeran, 2002; Sniehotta, Scholz and Shwarzer, 2005), demonstrating the volatility of the concepts of attitude or intention. Mostly attributed to information deficit, which refers to the level of knowledge about behavioural consequences or, in a more tangible way, to the existence and the characteristics of possible alternatives, such gap poses a real problem for any policy maker. The idea is that education about environmental responsibility and real-time information about available behavioural choices would naturally lead people of goodwill to environment-friendly behaviours. When the information deficit is not directly called forth, the role of habits, as a shortcut to decision making, explains why information, although available, is not processed by individuals (Aarts et al., 1997; Verplanken et al., 1997).

Moreover, there is clear confusion about whether to measure psychological construct at a specific or general level. Taking the example of NAT applications, some researchers measured the various model variables on a general level (e.g., Gärling et al.,2003; Stern et al, 1999), while others measured them on a specific level (e.g., De Ruyter and Wetzels, 2000; Nordlund and Garvill, 2003; Steg, Dreijerink and Abrahame, 2005). Ajzen (1989) clearly explained that, within the TPB framework, measures of attitudes, intention and behaviour should respect the same level of specificity, thus ensuring strong attitude-behaviour correlations. He points out that "*verbal measures of global attitudes are poorly correlated with nonverbal measures of specific behaviour*" and continues by stating that "*attitudes toward a specific behaviour tend to correlate quite well with performance of the behaviour in question*" (Ajzen, 1989). This is what Ajzen and Fishbein (1977) formulated as the compatibility principle, where the level of the specificity or generality of two indicators must be equivalent in terms of action, target, context and time elements. In practice, this means that the TPB is powerful at predicting that someone will make use of his/her bike to go to the market on next Sunday if the weather is fine if their intention to go by bike to the market on next Sunday if the weather is fine has been asked to them, together with some other model variables on the same level of specificity. We're getting close to get insights of the mind!

Adding complexity in the behavioural theories will not, arguably, solve the gap between attitude and behaviour, while a deeper understanding of travel behaviour requires a redefinition of the concepts (attitude and habits) and a comprehension of how such concepts and psychological constructs are understood. In a comprehensive article recalling an historic debate, Kaiser et al. (2010) stated that what is considered "the attitude-behaviour gaps are empirical chimeras". They give a paradigmatic answer to the issues cited above using Campbell's definition of "behavioural disposition" (Campbell, 1963). Within this concept, attitude and behaviour are ideally perfectly connected through a "behavioural disposition", making unnecessary the "blurred" causal relationship. Attitude towards a given object is, in that case, only person-dependent and reflects itself through a set of behaviours transitively ordered according to the level of difficulty (cost) to perform them: in practice, attitudes are measured by means of what people do, not what they say. With such a Campbellian attitude measures, as explained by Kaiser and Byrka (2015), "*there is no room for hypocrisy*": people put their general attitudes into specific attitude-relevant practices and differences in people's general attitudes can be derived from their attitude-relevant behaviour. Indeed, we can consider that a bike commuter shows a higher behavioural disposition to bike than someone who states loving, feeling good and feeling pressured by peers to use the bike. This implies that answers to a given set of behaviours, defined by the researcher, are direct projections of latent attitude on real behaviours.

Concerning habits, Schwanen et al. (2012) initiated a philosophical discussion about our understanding of how they develop and are perceived. We are sceptical that past-behaviour (or habit strength) properly explains future behavioural intention: as observed by Schwanen et al. (2012) "*both dependent and independent variable may well be measuring one and the same thing – a general tendency to perform the behaviour in question*". Although little is said about an operational paradigmatic change, this paper has the benefit of questioning the effectiveness of actual perception of the concept of habits in transport behavioural research. However, without any surprise, past behaviour has been successfully used as a predictor of both behavioural intention and behaviour itself, at least when context is stable (Ouelette and Wood, 1998; Bamberg et al, 2003) and may represent the main drawback behind behavioural change (Aarts and Dijksterhuis, 2000; Garling and Axhausen, 2003).

II. Objectives and methodology

Modern cities show an increasing interest in Advanced Traveller Information Systems (ATIS), with a growing attention to real time multimodal information. Through those systems, decision makers hope to achieve a shift from the car to environment-friendly modes of travel. Unfortunately, not many comprehensive assessments have been undertaken to verify the contribution of ATIS to such modal shift.

The present research wants to contribute to bridge the gap of knowledge on the effects of ATIS and takes place within the European project OPTICITIES "Optimise Citizen Mobility and Freight Management in Urban Environments (www.opticites.org)", a Collaborative project gathering 25 partners from across Europe (6 cities, service providers, car industry, research laboratories and major European networks). The OPTICITIES project, within a vision of optimised urban mobility, develops ad hoc tools (for passengers, freight and public administrations) focussing on user needs, urban mobility public policy and business models of service providers. The tool analysed in this thesis is the real time multimodal urban navigator designed for three European cities (Torino, Gothenburg and Madrid) but focussing on Torino, whose Navigator is code-named TUeTO. This is a smart-phone application designed according to the users' requirements (operational, ergonomics, performances) and offering the possibility to plan trips using real time information about car, public transport, bike, foot, including bike and car sharing and a car pooling module. Special attention is paid to the potential of the application to spur the modal diversion through a real time and reliable information favouring the multimodality.

To this end, a better understanding of people behaviour deems necessary, this being the key to define transport policies meant to prompt an effective modal shift from cars to alternative modes. Indeed, very little is known about the ways in which travel behaviour interacts with people personality, attitudes, life-style, context and how this information can be used to support the reshaping of the cities through a more sustainable mobility.

To reach the objectives of Opticities project, a mixed method was adopted in the three test cities along three phases of the research: 1) the ex-ante phase aimed at investigating the users' mobility patterns and attitudes as well as their requirements to properly develop the app TUeTO. This phase provided a web-questionnaire and 24 focus groups; 2) the in-itinere phase focused on the test of the app developed so far to monitor problems and bugs as well as the reaction of participants to their use when travelling. To this end, periodical (each month) web-questionnaires were administered to the participants; 3) the ex-post phase aimed at evaluating the potential travel behaviour changes as well as changes of perception, expectation, preferences spurred by the use of the app. Such changes will be evaluated through a web-questionnaire and 21 focus groups, symmetrical to the ex-ante survey. The survey will start in June 2016.

In exchange for their engagement in the project, the participants were offered a Smartphone they could use to test TUeTO and then keep for their personal use.

Within the above framework, this research has been carried out, partly using the data collected in the project and partly conceiving a new survey to complement such data with additional information useful to test the theories described in Chapter 1. To this end, the objective of this thesis is twofold: 1) assessing the validity of a general attitude measures, in the sense of Campbell (cf. §1.3.2) and understanding if the generally adopted measure of attitude is compelling within traditional frameworks derived from social psychology theories; 2) make use of psychological determinants influencing modal choice to highlight which participants are more likely to perform a modal shift from cars to public transport or soft modes.

More precisely, the first objective aims at understanding if a general attitude towards the environment is legitimately assessed using Item Response Theory and, notably, the Rasch model. The second objective aims at understanding which factors drives decision makings, comparing different correlational models of theories described in chapter 1. The final goal is the definition of different market segments of potential ATIS users, resting upon various psychological constructs that play a role in defining personal mobility patterns.

The methodology is working in synergy with that adopted in the Opticities project (briefly mentioned above) that is the main source of data and comprises five steps:

- sample selection;
- design and administration of surveys;
- Rasch model estimation for attitude measure;

- selection of psychological constructs and correlational model comparison using Structural Equation Modelling (SEM);
- psychological-based market segmentation of ATIS users.

For a detail of methodology of Opticities project, see the Deliverable D7.11 (www.opticites.com). In the next sections the different methodological steps of this thesis will be described in detail.

2.1 Sample selection

The participants of the OPTICITIES project are those used in this research. They were selected following a stratified sampling plan of convenience. Concerning transport users, 150 "common transport users" were selected according to the following criteria:

- gender;
- age: classes related to people having different technological skills;
- profession/educational level/income;
- presence of children under 14 in the household;
- transport mode used: motorized, public transport (PT) users, soft modes, intermodal (motorized + PT);
- residential location: city centre, suburbs, extra-urban locations considering also the geographical position (north, east, south, and west). It is important to get the origins and destinations to better choose the people profile also in terms of their residential location.

Due to the potential withdrawal of a few participants (that effectively occurred), more than 150 were contacted. Thus, in the first phase (ex-ante) of the project, 159 people participated to the two-year experiment to define the users' requirements to develop the real-time multi-modal navigator, TUeTO. After the ex-ante survey, a few participants abandoned the project and 142 continued testing the app (in-itinere phase ending in May 2016) and, finally, evaluating its effects on their travel behaviour (ex-post phase starting in June 2016).

2.2 Design and administration of surveys

The methodology defined for the thesis research refers to the ex-ante phase, being the test process still on-going at the time being. To this end, jointly with the ex-ante survey designed within the OPTICITIES project, providing a web-questionnaire and some focus groups, a second web-survey to analyse the general attitude towards the environment has been conceived.

2.2.1 Design of the ex-ante survey to investigate mobility patterns and users' requirements towards ATIS

The ex-ante survey, which was the main source of data for this research, was divided into seven sections:

1. the first section aimed at getting information about the most frequent trip: origin and destination; mode used; weekly frequency; duration and distance; habitual detour details; Park & Ride usage, reasons expressed for choosing their mode of transport and availability of alternative transport modes;
2. the second section focussed on general travel habits: weekly usage frequency and scope for all modes of transport; satisfaction with daily travelling condition and personal objectives about car use (increase/decrease);
3. the third part investigated the attitudes towards mobility and presented a wide range of statements about the use of time when travelling and the evaluation of various travel preferences and mode preferences;
4. the fourth section aimed at analysing the relationship between transport and the environment. Respondents were asked if they agree or disagree to a set of statements about relationship between own mobility and the environment, about the general environmental condition in Torino and about their perception of what could help them to use alternative modes of transport;
5. the fifth section of the questionnaire aimed at understanding the familiarity of the respondents with technological tools: ownership and usage of electronic devices; information seeking habits; knowledge about diverse operating systems and various statements they were asked to agree or disagree with about the role of technology in their daily life and on modern society in general;

6. the sixth section investigated expectation, intention, anticipated feelings and willingness to pay about the multi-modal navigator (TUeTO) they ought to test in the coming months;
7. finally, the last section of the questionnaire was devoted to socio-economic and personal information: gender; age; education; activity; household income; household composition; car ownership; public transport and sharing service subscription.

After having answered to the web-questionnaire, people were asked to participate to the focus groups, formed by 6-8 persons, whose layout (similarly to questionnaires) investigated: personality traits; attitude towards technology; perception about real time information; expectations about TUeTO application; willingness to pay and barriers for using the app. The results of the focus groups are not object of this thesis.

2.2.2 Design of the survey to investigate the General Ecological Behaviour

The second survey aimed at investigating the general attitudes of participants towards the environment to analyse their ecological behaviour. To this end the General Ecological Behaviour (GEB) web-questionnaire was designed. The GEB questionnaire derives from Kaiser and Wilson (2000), adapted to the Italian context and translated, and consists of 40 dichotomous (yes/no) items (table 3), grouped in seven different categories. Seven items represent pro-social behaviours (CS1-CS7) while the other 33 items represent pro-environmental behaviours, distributed in 6 ecological domains: garbage handling (R1-R6), water and power saving (AE1-AE7), consumerism (CE1-CE6), garbage inhibition (RR1-RR5), environmental activism and volunteering (V1-V4) and transport (T1-T5).

The idea of combining pro-social behaviour with pro-environmental relevant behaviour into a questionnaire designed to measure on one scale the general attitude toward the environment comes from findings that pro-environmental values are highly correlated with social-value orientation (§1.1).

Table 3: Structure of the GEB questionnaire

N°	Item description	Item Code
	Pro-social behaviour	
1.	Sometimes I give money to panhandlers.	CS1
2.	From time to time I give money to charity.	CS2
3.	If an elderly or disabled person enters a crowded PT vehicle, I offer him/her my seat.	CS3
4.	If I were an employer, I would not hesitate hiring a person previously convicted of crime.	CS4
5.	If a friend or a relative had to stay in the hospital for a week or two for minor surgery I would visit him or her.	CS5
6.	Sometimes I ride public transport without paying a fare.	CS6 (-)
7.	I would feel uncomfortable if people from another ethnicity were my neighbours.	CS7 (-)
	Ecological garbage handling	
8.	I put dead batteries in the garbage.	R1 (-)
9.	I make use of rechargeable batteries.	R2
10.	I bring unused medicine back to the pharmacy.	R3
11.	I sort paper wastes for recycling.	R4
12.	I sort glass wastes for recycling.	R5
13.	I sort plastic wastes for recycling.	R6
	Water and power saving	
14.	Before taking a shower, I let the water run so it get to the temperature I want.	AE1 (-)
15.	I prefer to shower rather than to take a bath.	AE2
16.	In winter, I keep the heat on so that I do not have to wear a sweater.	AE3 (-)
17.	I turn off the heat at night.	AE4
18.	I wait until I have a full load before doing my laundry.	AE5
19.	In winter, I leave the windows wide open for long periods of time to let in fresh air.	AE6 (-)
20.	I wash dirty clothes without pre-washing.	AE7
	Ecologically aware consumerism	
21.	I use fabric softener with my laundry.	CE1 (-)
22.	If there are insects at home, I kill them with a chemical insecticide.	CE2 (-)
23.	I use a chemical air freshener in my bathroom.	CE3 (-)
24.	I use specific cleaners for different rooms rather than an all-purpose cleaner.	CE4 (-)
25.	I use phosphate-free laundry detergent.	CE5
26.	I always look to buy vegetables from biological agriculture.	CE6
	Garbage inhibition	
27.	I re-use plastic bag from the groceries.	RR1
28.	I sometimes buy beverage in cans.	RR2 (-)
29.	If I am offered a plastic bag in a store, I will always take it.	RR3 (-)
30.	For shopping, I prefer paper bag to plastic ones.	RR4
31.	Usually, I buy water with returnable bottles.	RR5

	Environmental activism	
32.	I often talk with friends about problems related to the environment.	V1
33.	I am a member of an environmental organization.	V2
34.	In the past, I have pointed out to someone his or her un-ecological behaviour.	V3
35.	I sometimes contribute financially to environmental organizations.	V4
	Transport	
36.	Usually, I do not drive my automobile in the city.	T1
37.	I usually drive on freeways at speeds lower than 100km/h.	T2
38.	When possible, I do not use a car for distance lower than 30km.	T3
39.	If possible, I do not insist on my right of way and make the traffic stop before entering crossroads.	T4
40.	I walk, ride or take public transport to go to work/university	T5

(-) items positively formulated as environmentally damaging, recoded

The answers were recoded, ("Yes" in place of "No" and "No" in place of "Yes") when the items were positively formulated as environmentally damaging. 273 (5.2%) out of 5240 item-responses (40 items x 131 respondents), were missing values. In order to perform some non-parametric tests when missing values are not allowed, it has been decided to intervene on missing data. The most problematic items were:

- 25-CE5 ("I use phosphate-free laundry detergent"), with 35 missing values (26.7%), which were filled with "No", assuming that who does not know if (s)he uses a phosphate-free laundry detergent may not buy it voluntarily;
- 4-CS4 ("If I were an employer, I would not hesitate hiring a person previously convicted of crime."), with 31 missing values (23.6%), which were filled with "No" for all of them, assuming that the doubt or unwillingness to answer is revealing of the hesitation itself;
- 31-RR5 ("Usually, I buy water with returnable bottles."), with 30 missing values (22.9%), which were filled with "Yes" for all of them, assuming that these people do not buy bottled water at all;
- 17-AE4 ("I turn off the heat at night."), with 15 missing values(11.5%), which were filled with "No" for all them, assuming these respondents live in apartments connected to central heating system with lack of individual control possibility;
- 36-T1 ("Usually, I do not drive my automobile in the city."), 37-T2 ("I usually drive on freeways at speeds under 100 km/h") and 38-T3 ("When possible, I do not use a car

for distance lower than 30km."), each of them with 11 missing values (8.3%). These missing values were removed after consideration for respondent's driving licence, car ownership and usage frequency from the Opticities questionnaire, and filled with "Yes", assuming that these respondents do not drive in general.

After these changes in the database, missing values rate fell to 2.4% of the item-responses. These last ones were generally filled with "No", assuming that not answering to certain items reveals either that the behaviour is, in general, not engaged or engaged by chance without the willingness to behave in that way.

2.2.3 Administration of the surveys

The ex-ante web-questionnaire was administered through the LimeSurvey[5] platform before the focus groups and before the test of the app. The administration was made between October and November 2014. Due to the length of the questionnaire whose mean compilation time was 45 minutes, participants had the possibility to save their answers at any time and to retrieve them later on. As mentioned before, participants received as incentive a Smartphone they also used to test TUeTO during the in-itinere phase.

The GEB questionnaire was administered when the app was ready to be tested, during a meeting with the users, early February 2016. The participants received by e-mail the link to fill in the questionnaire uploaded on the LimeSurvey platform, but they were asked if someone preferred to answer directly on paper format during the meeting. Responses were immediately collected early February 2016 (along a week). 131 out of the 159 people from the original sample, agreed to respond (81.8%).

2.3 Rasch model estimation for attitude measure

The estimation of the general attitude towards the environment is based on the data collected by the GEB questionnaire that will be analysed thanks to the use of the Rasch Model for scale measurement (Rasch, 1980). The Rasch Model is a special case of Item Response Theory (also known as Latent Trait Theory) , which is the alternative paradigm to Classical Test Theory (CTT). The general CTT model is based on a simple equation (1) (Zickar and Broadfoot, 2009):

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[5] https://www.limesurvey.org/

$$X_{ni} = T_n + E_{ni} \quad (1)$$

where X_{ni}, the observed test score for person n on testing item i, is a function of T_n, the true score, plus E_{ni}, an error score. The true score is defined as the expected value of the observed score for an individual on a particular test. Thus, there are no such test-independent true score which defines an individual: e.g. (s)he does not have only one true score for all intelligence tests but has different true scores for each intelligence test. CTT is also concerned with test reliability, which provides a measure of precision for the tests. Reliability is thus understood as a characteristic of the test and depends on the variance of the trait it measures; the characteristics of the items are expressed as correlations with total test scores or factor loadings on the latent variable(s) of interests. The main limitations of CTT include, but are not limited to, the fact that statistics and parameters are sample and test dependent (Fereira et al., 2011) and that CTT assumes that measurement precision is uniform across the range of the test (Magno, 2009).

Thus, whereas in CTT, all items are considered equivalent and treated in aggregation, IRT treats items differently: according to their relative difficulty and focus on the interaction between the item difficulty and the ability (or the location on a latent trait) of the individual, denoted as θ_n. Thus, IRT is a theory of how people respond to items and it is built around the idea that the probability of a respondent's answer on an item can be described as a function of the respondent's location on the latent trait and of one or more parameters characterizing the item. The item-response function is defined as Item Characteristic Curve (ICC). There are many advantages of using this approach compared to CTT, as there is less inconsistency when applying items to different samples (Revelle, 2011), it produces less measurement errors than the CTT (Magno, 2009) and people and items are calibrated on a common scale, which facilitates the interpretation of the measured variables (Embreston, 1996): it is possible to compare individuals in terms of probability of response, which is much more informative than saying that someone is one standard deviation above the mean score.

The Rasch model (Rasch, 1968) is the simplest case of IRT and it assumes only one parameter per item – the difficulty β_i – thus sometimes referred in literature as the *one-parameter logistic IRT*. Additional parameters used in *two* or *three parameters* IRT include discrimination (slope of the ICC) and pseudo-guessing parameters (that forces a lower asymptotic limit, so that the probability never reaches zero). Rasch worked as a mathematician and wanted to propose a statistical method for educational science that would reflect at best student's ability on a given subject using tests that would allow for comparisons among students independently from both the sample of respondents and the selection of the items included in the test (Magno, 2009).

Formally, considering a dichotomous random variable where $x = 1$ denotes a correct answer and $x = 0$ an incorrect one, the probability of person n answering correctly on item i is given by equation (2):

$$P(x_{ni} = 1) = \frac{e^{x_{ni}(\theta_n - \beta_i)}}{1 + e^{(\theta_n - \beta_i)}}. \tag{2}$$

where θ_n is the ability of person n and β_i is the difficulty of item i.

Figure 6 presents hypothetical Rasch Item Characteristic Curves for three items of various difficulties. The green curve represents an easy item: for a given ability, the probability of answering correctly is greater than for the medium orange item, or the red hard item.

According to Fisher, the assumptions from which the Rasch model is derived are the following:

- (1) one-dimensionality: all items are functionally dependent on only one underlying continuum;
- (2) monotonic functions: all item characteristic functions are strictly monotonic in the latent trait. The item characteristic function describes the probability of a predefined response as a function of the latent trait;
- (3) local stochastic independence: every person has a certain probability of giving a predefined response to each item and this probability is independent of the answers given to the other items;
- (4) sufficiency of a simple sum statistic: the number of predefined responses is a sufficient statistic for the latent parameter;

- (5) dichotomy of the items: for each item there are only two different responses.

Figure 6: Hypothetical ICCs as conceived within the Rasch model

The Rasch model, although is now used in a wide variety of scientific fields (Andrich, 2004), developped a specific vocabulary for the definitions of its concepts derived from educational science. Thus, we shall point out that in our applications of this method on the GEB questionnaire, there are no correct or incorrect answers, but engagement or not in given behaviours. Similarly, difficulty is intended as the difficulty to engage a given behaviour and ability is intended as the particular location of an individual on the general attitude we wish to measure. This measure will respond to the criterions of a Campbellian attitude as it is derived only by measuring specific attitude-relevant practices.

2.3.1 Parameter Estimation

Statistical methods for estimates of the Rasch model parameters may be seen as combinatorial calculus, across all items and all respondents, of the logistic equation (2). Various estimation methods exist: WINSTEPS[6] and the eRm package[7] for R were selected for computation. WINSTEPS uses two consecutive estimation methods: the Normal Approximation Estimation Algorithm (PROX; Linacre, 1994), recognised for its efficiency, followed by a Joint Unconditional Maximum Likelihood Estimation (JMLE or UCON; Wright

[6] http://www.winsteps.com
[7] https://cran.r-project.org/web/packages/eRm/index.html

and Douglas, 1977). As for eRm, its core Rasch Model estimation method is implemented with a Conditional Maximum Likelihood function (CML; Mair and Hatzinger, 2007). A detailed mathematical description of these estimations methods are reported in Appendix A.1.

2.3.2 Rasch model fits

The scope is to determine if items within the General Ecological Behaviour questionnaire are valid to assess a Rasch measure of a one-dimensional latent trait. To this end, we follow the general guidelines proposed by Linacre (2005). After estimating both items and persons parameters, we observe and analyse the point-biserial correlation and the fit statistics.

Point-biserial correlation: a positive answer to more-difficult items should correlate positively with person measures. The point-biserial correlation is an adaptation of Pearson's correlation when one of the variables is dichotomous (Jaspen, 1946) and is given by equation (3):

$$r_{pbi} = \frac{\sum_{n=1}^{N}(X_{ni} - \bar{X}_i)(\theta_n - \bar{\theta})}{\sqrt{\sum_{n=1}^{N}(X_{ni} - \bar{X}_i)^2 \sum_{n=1}^{N}(\theta_n - \bar{\theta})^2}}, \tag{3}$$

where $X_{ni}$is the observation of person n on item i, $\bar{X}_i$ is the mean of the X_{ni} on item i, θ_n is the trait measure for person n and $\bar{\theta}$ is the mean of θ_n. As X_{ni}=$E_{ni} \pm W_{ni}$, the expected observation and its variance, we can compute the expected point-biserial correlation (Olsson et al., 1982) with equation 4:

$$E(r_{pbi}) \approx \frac{\sum_{n=1}^{N}(E_{ni} - \bar{X}_i)(\theta_n - \bar{\theta})}{\sqrt{\sum_{n=1}^{N}((E_{ni} - \bar{X}_i)^2 + W_{ni}) \sum_{n=1}^{N}(\theta_n - \bar{\theta})^2}}. \tag{4}$$

Fit statistics : two kind of mean squared fit statistics are calculated, namely OUTFIT (standing for *Outlier-sensitive fit statistics*) mean square and INFIT (*Inlier-pattern-sensitive fit statistics*) mean square. They allow to describe the fit of the items to the model. Both OUTFIT and INFIT are based on the classical χ^2 fit statistics, as reported by Wright and

Panchapakesan (1969), which makes possible a transformation into Z-statistics. Equations (5) report the formulas for both OUTFIT ($\mathrm{U_i}$) and INFIT (V_i) for each item:

$$U_i = \frac{\sum_{i=1}^{N} Z_{ni}^{2}}{N}, V_i = \frac{\sum_{i=1}^{N} Z_{ni}^{2} W_{ni}^{2}}{\sum_{i=1}^{N} W_{ni}^{2}}, \quad (5)$$

where Z_{ni} is the standardised residual between the model and the observation and W_{ni}^{2} is the variance of X_{ni}. OUTFIT is sometimes reported as *non-weighted mean square error*, and it is sensitive to unexpected response far away from the item parameter (a person with a low measure on the latent trait engaging a difficult behaviour or a person with a high measure not engaging an easy behaviour) whereas INFIT is considered as the *information-weighted mean square error* and it is sensitive to unexpected responses close to the item parameter (Smith et al., 2008). INFIT and OUTFIT mean square statistics have an expected value of 1.0 and a range that goes from 0.0 to positive infinity (Bond and Fox, 2001). Values greater than 1.0 indicate more variation in the observed data than predicted by the model and is referred as *underfit*, where response patterns are unpredictable. In contrast, values lower than 1.0 show variation in the observed data lower than predicted by the model and it is referred as *overfit*, where response pattern are too much predictable, close to what will be expected with a Guttman pattern[8]. Although the range of acceptable values for INFIT and OUTFIT statistics are still open to debate (Smith et al., 1998; Karabatsos, 2000; Smith and Suh, 2003), it is common to refer to those proposed by Wright and Linacre (1994), accepting mean square values ranging from 0.5 to 1.5 (Table 4).

Table 4: INFIT and OUTFIT statistics interpretation

Interpretation of parameter-level mean-square fit statistics:	
>2.0	Distorts or degrades the measurement system.
1.5 - 2.0	Unproductive for construction of measurement, but not degrading.
0.5 - 1.5	Productive for measurement.
<0.5	Less productive for measurement, but not degrading. May produce misleadingly good reliabilities and separations.

[8] A Gutman Scale (Guttman, 1949) is a deterministic version of the Rasch one. If the items are ranked by difficulty, it states that: 1) if a given answer is correct, then all easier answers are also correct and 2) if a given answer is incorrect, then all more difficult answers are also incorrect. Thus, knowing the last correct answer, it gives all information needed to know the response to others answers and the person's ability of the respondents on the trait measured by the scale.

The corresponding standardised Z-score – showing the probability of the mean square following unit-normal deviate when the data fit the Rasch model – is expressed thanks to the Wilson-Hilferty cube root transformation (Wislon and Hilferty, 1931) (Equation (6)):

$$z(U_i) = \left(U_i^{1/3} - 1\right)\left(\frac{3}{\sigma_i}\right) + \left(\frac{\sigma_i}{3}\right), z'(V_i) = \left(V_i^{1/3} - 1\right)\left(\frac{3}{\sigma'_i}\right) + \left(\frac{\sigma'_i}{3}\right), \quad (6)$$

where σ_i and σ'_i stand respectively for the standard deviation of $U_i$and V_i and are not explicitly given here (refer to Wang and Chen, 2005). Z-score is interpreted as a classical t-statistic, where a value of 1.96 corresponds to a two-sided significance of 5%.

Observed and expected correlations as well as INFIT and OUTFIT statistics will allow us to focus our validation process on specific items but may not be used to blindly accept or reject one item or another. As explained by Linacre (2006), dealing with real world observations, misfits are very well expected and validation of the Rasch Model may be precautionary lead with the aim to give sense to data.

2.3.3 Rasch model testing

Different categories of tests, parametric and non-parametric were conducted to ensure, on one hand, the correctness of the assumptions of the Rasch Model (cf $2.3) – e.g. assessing the one-dimensionality of the measure and the absence of differential item functioning (sub-group homogeneity) – and, on the other hand, the reliability of the measure.

Testing one-dimensionality: one-dimensionality is one of the foundations of the Rasch model and, consequently, the strongest assumption to be checked. In the ideal case of a perfect Rasch scale, the Rasch dimension – i.e. the latent measure the Rasch model is estimating – is the only dimension in the data and all other unexplained variance should only be random noise. Two different tests have been conducted:

- according to Linacre (2005), one-dimensionality may be assessed by performing a Principal Component Analysis on the matrix of inter-item correlations of the standardized residuals produced by the model. The PCA evaluation produces components that are, in this case, called “contrasts”, in order to underline the fact that these components are derived from the residuals and not from the raw data matrix;

- Martin-Löf (1970) proposed the following test of one-dimensionality: for D disjoints sets of items, the hypothesis that the items measure the same one-dimensional latent construct can be tested using the following likelihood ratio test, based on equation (7) (Martin-Löf, 1970, cited by Christensen et al., 2002):

$$LR = 2\left(\sum_{r_1=0}^{k_1} \cdots \sum_{r_D=0}^{k_D} n_{r_1 \cdots r_D} \ln\left(\frac{n_{r_1 \cdots r_D}}{N}\right) - \sum_{r=0}^{k} n_r \ln\left(\frac{n_r}{N}\right) - \ln \Lambda\left(\hat{\beta}|R\right) + \sum_{d=1}^{D} \ln \Lambda\left(\hat{\beta}_d|R_d\right)\right) \quad (7)$$

$R_{1\cdots d}$ being the raw score from subset $D_{1\ldots D}$ composed of $k_{1\ldots D}$ items and $n_{r1\ldots D}$ the number of person with raw score $R_{1\cdots d}$.

Testing sub-group homogeneity and differential item functioning: a good Rasch model should produce similar item difficulty parameters independently from the population sample. To this purpose, Andersen (1973) proposed a Likelihood-Ratio test that consists in arbitrarily splitting the sample into two (or more) disjoint groups *G*. We expect that the parameters estimates β_{Gi} to be the same. In this regard, Rash himself proposed a graphical model check (Rasch, 1980), that can be obtained plotting β_{1i} against β_{2i}, where the items should not deviate too much from the diagonal. The test is, consequently, able to detect *differential item functioning*, which happens when individuals with the same level of an underlying latent trait differ in their response to an item depending on other characteristics. Andersen's LR tests is similar to Martin-Löf's but based on person sub-group splitting instead of item-subgroup splitting. We tested the model by means of different splitting procedure: firstly, we divided the sample in function of their raw score on the questionnaire (i.e. sum of positive answers). One group consisted of respondents having a score of less or equal the median score (n = 62), and the other group consisted of respondents having a score of more than the median score (n = 69). Secondly, we divided the sample based on their gender, one group consisting of male (n = 76), and the other one consisting of female (n = 55).

Non-parametric quasi-exact tests: Ponocny (2001), proposed a family of non-parametric tests using a Monte Carlo algorithm for goodness of fit. Based on the assumptions of sufficient statistics, all matrices with identical margins shall have the same parameters estimates. Let A_0 be the observed matrix of size $(n\ items\ \times p\ persons)$. We can, theoretically, generate all possible matrices with margins as in A_0, denoted $A_s\ \in\ \Omega_{\mathrm{np}}$, with $(s = 1, \cdots, S)$. In practice, the generation of all possible matching matrices is computationally very demanding, this is why Ponocny (2001) proposed to simulate a sample of possible matrices with a Monte-Carlo algorithm, which has been improved as a Markov Chain Monte-Carlo (MCMC) algorithm by Verhelst (2008). Because these tests are based on a reduced sample of all possible matrices, they are called *quasi-exact tests*, and are more reliable than parametric ones for small sample (Ponocny, 2001). A given test-statistic T is computed both for the observed matrix $A_0(T_0)$ and all generated matrices $A_s(T_s)$. By counting how often T_s shows similar or more extreme value than T_0, we can define the *re-sampling p-value* under the null hypothesis "The data conforms to the model" as the relative frequency given by equation (8):

$$\mathrm{p} = \frac{1}{\mathrm{S}} \sum_{\mathrm{s}=1}^{\mathrm{S}} \mathrm{t_s}\,, \text{where } \mathrm{t_s} = \begin{cases} 1 & , \quad \text{if } \mathrm{T_s} \geq \mathrm{T_0} \\ 0 & , \quad \text{elsewhere.} \end{cases} \tag{8}$$

The different tests we conducted on our data matrix are the following:

T_{10}, global test for sub-group invariance. This test is the non-parametric equivalent of Andersen's LR test described above. The idea is that, within the Rasch model, the quotient $\frac{n_{ij}}{n_{ji}}$ should be approximated by $e^{(\beta_j - \beta_i)}$, where $n_{ij}$is the number of persons who have a positive answer to item i but not on item j. This holds true for any sub-sample G of respondents. Therefore we may use the equation (9) into equation (8).

$$T_{10} = \sum_{ij} \left| n_{ij}^{(g_1)} n_{ji}^{(g_2)} - n_{ij}^{(g_2)} n_{ji}^{(g_1)} \right|, over\ all\ pairs\ (i,j), \tag{9}$$

We conducted this test with the same splitting criterion used for Andersen's LR test, i.e., based on median raw score and gender.

T_{11}, test for local stochastic independence. Good Rasch items should correlate to each other only through the latent dimension they measure, which is a consequence of the one-dimensionality assumption. In other word, an answer to a given item should not be determined by an answer to another item; statistically speaking, correlations of residuals should be zero. Therefore, a test for the violation of local stochastic independence may be expressed as in equation 10:

$$T_{11} = \sum_{ij} \left| r_{ij} - \widetilde{r_{ij}} \right|, over\ all\ pairs\ (i,j), \tag{10}$$

where r_{ij} are the observed inter-item correlation and $\widetilde{r_{ij}}$ its expected value, estimated as a mean r_{ij} for the simulated matrices. The model test is computed by using equation (8) on T_{11} (equation (10)) and defined as the relative frequency of $\mathrm{T_s}$ which have the same or a larger value than in T_0.

T_{md}, test for multidimensionality. Developed by Koller and Hatzinger (2013) on the principles formulated by Ponocny (2001) and based on Martin-Löf's test described above, this test is formulated as in equation (11):

$$T_{md} = Cor\left(r_n^{(d_1)}, r_n^{(d_2)}\right), \tag{11}$$

where $r_n^{(d_i)}$ is the raw score of person n on subscale d_i. If the Rasch model holds, the two sub-scaled raw scores should be positively associated. The model test is given in equation (8) and is defined as the relative frequency of $\mathrm{T_s}$ which have the same or a smaller correlation value than in T_0.

Reliability. Reliability is expressed as the quotient of true variance over observed variance and shows the level of reproducibility of the measures (Peter, 1979). The method used for estimating the true variance will produce different reliability index. We report in our results the following reliability coefficient:

- the KR-20 (Kuder and Richardson, 1937), which is a special case of Cronbach's α for dichotomies, based on raw score variance;
- the person separation reliability r_θ, virtually equivalent to the KR-20, but based on person abilities variance;
- the item separation reliability r_β, based on item difficulties variance.

All basic statistics were computed through SPSS release 20.0.0, Rasch model estimates and tests were computed either through WINSTEPS 3.80.1 or the eRm package v0.15-6 for R release 3.2.3. Differences in parameter estimation between WINSTEPS and R comes from different estimation methods: the first one estimates simultaneously item and person parameters using a normal approximation method followed by a Joint Maximum Likelihood and the second one uses Conditional Maximum Likelihood for item parameters and Joint Maximum Likelihood for person parameters. This will not interfere with our analysis as parameter estimates for both methods are linearly related (figure 7).

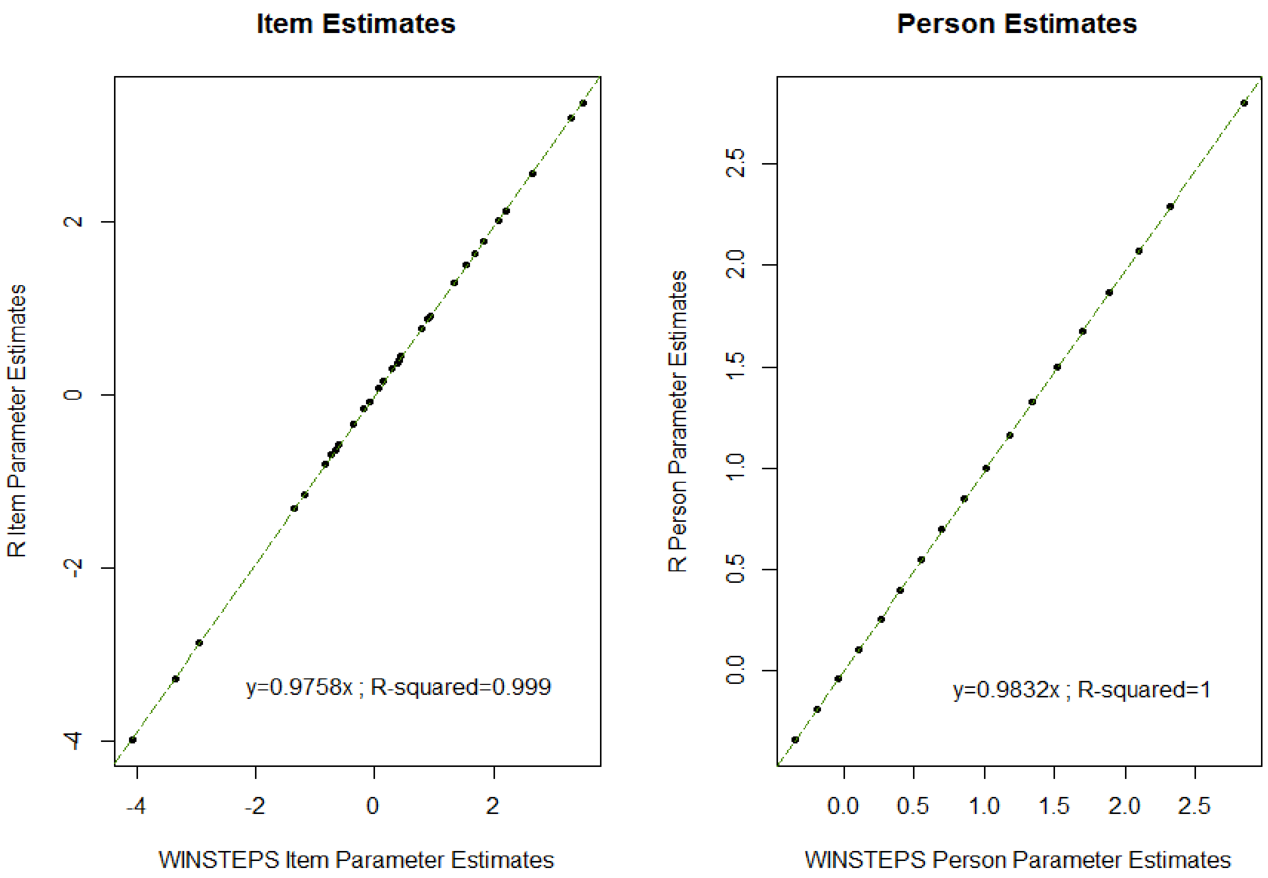


Figure 7: Winsteps vs eRm estimates of item and person parameters

2.4 Selection of psycho-social models and psychological constructs measurements.

This step makes use of the general framework of Structural Equation Modelling (SEM) that merges a set of techniques that allows to conduct together confirmatory factor analysis, linear and logistic regressions, path analysis and more. SEM are especially appropriate for theory testing (Savalei and Bentler, 2010) and are widely used in marketing research. Three different models, derived from social-psychology will be tested: 1) the Norm-Activation Theory; 2) the Theory of Planned Behaviour with the general measure of Attitude toward the environment; 3) the Theory of Interpersonal Behaviour, from which habits will be excluded. Finally, our own composite model that will take into account transport-related values will be tested, together with various variables mediation hypothesis.

The three theories are compared with the aim of: a) explaining people's behaviour; b) evaluating if the estimates of the general attitude (according to Campbell), produced by the Rasch measures, can replace the specific attitudes generally used within the Theory of planned Behaviour; c) testing some hypothesis about psychological constructs interaction and extracting the most important factors that can explain travel behaviour.

2.4.1 Variable selection and construction

In order to highlight the different psycho-social factors behind modal choice, we used logistic and linear regressions of various psychological constructs (independent variables) on three different measures of observed behaviour (dependent variables).

Dependent variables

Observed dependent behaviours included in the models will take three forms, all based on self-reported behaviour:

- one binomial modal choice for the most frequent trip, labelled as "ModBin", which provides two modes: (1) "private", for people using a motorized two-wheeler or a car – either as driver or passenger – and (2) "pt/soft" for people using public transport or soft mode;
- one trinomial modal choice for the most frequent trip, labelled as "ModTrin", which provides three modes: (1) "private", for people using a motorized two-wheeler or a car – either as driver or passenger – (2) "pt" for people using public transport and (3) "soft", for people riding a bicycle or walking for their most frequent trip;
- one continuous variable representing a sustainable personal mobility index, labelled as "SusMobIndex", which ranges from 0 to 1 and has been built as a weighted mean of self-reported frequencies of use of the different modes. The formal definition is given by equation 12:

$$SusMobInd = 1 - \frac{\sum w_m f_m}{\sum f_m} \quad (12)$$

where w_m is the weight for mode m and f_m the weekly frequency of mode m. Table 5 summarises each mode m and their corresponding weight.The weight is related to the gross estimation of CO_2 emissions produced by the different modes: 104 grams of CO_2/p*km for car, 72 grams CO_2/p*km for two-wheelers and 35 grams of CO_2/p*km for public transport (EEA, TERM report, 2014 ; Kenworthy, 2003)

Table 5:Values of the weighting parameters used in SusMobInd

m	w_m
Car	1
Two-wheeler	0.66
Public transport	0.33
Bicicle/walk	0

It is worthy to note that this index does not consider the distance travelled nor the exact number of trips actually made. However, it is a gross indicator of environmentally-friendly trips per individual for a typical week, according to the his/her mobility habits.

Psychological constructs

Latent psychological constructs were produced using Confirmatory Factor Analysis (CFA) on questionnaire items. Three constructs are exclusive to the NAT: Problem Awareness (PA); Adverse Consequences (AC) and Ascription of Responsibility (AR). The TPB and TIB have both one exclusive construct: Attitude (ATT) for the TPB and Affect (AFF) for the TIB. The Personal Norms construct is common to NAT and TIB whereas the Perceived Behavioural Control (PBCb & PBCpt) and the Subjective Norms constructs are common to the TPB and the TIB.

The **Personal norms (PN)** construct was assessed with two items: (PN1) "People should be allowed to use their car as much as they like, even if it causes damage to the environment" and (PN2) "A sustainable mobility would allow an improvement of the quality of life in the city of Torino". The answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree". Moreover, PN1 has been recoded using reverse-scoring, to reflect a positive statement toward the environment.

The **Problem Awareness (PA)** construct was assessed using three items: (PA1) "Air pollution is a real problem for the city of Torino"; (PA2) "Noise pollution is a real problem for the city of Torino"; and (PA3) "Road accidents are a real problem for the city of Torino". Answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The **Adverse Consequences (AC)** construct was assessed using two items: (AC1) "Traffic jams are a real problem for the city of Torino" and (AC2) "Traffic jams worsen air pollution". Answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The **Ascription of Responsibility (AR)** construct was assessed with two items: (AR1) "Respect toward the environment" which was assessed by asking the respondents the level of importance for choosing the mode of transport for their most frequent trip and (AR2) "It is my personal responsibility to reduce the emission of greenhouse gases that induce climate-change". Answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The **Subjective Norms (SN)** construct was assessed with two items: (SN1) "I expect public policy makers put pressure on me to reduce the environmental impacts of my travels" and (SN2) "I expect my family and friends put pressure on me to reduce the environmental impacts of my travels". Answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The **Affect (AFF)** construct towards cars was assessed using one item: (AFF1) "I like travelling by car" which was measured using a 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The **Perceived Accessibility (PAC)** construct was assessed using four items: (PAC1) "Public Transport is available for my most frequent trip"; (PAC2) "My personal bike is available for my most frequent trip"; (PAC3) "The bike-sharing service is available for my most frequent trip"; and (PAC4) "I can walk for my most frequent trip". Answers were collected on 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

The Perceived Behavioural Control has been split into two independent constructs. Firstly, the **Perceived Behavioural Control toward bicycle use (PBCb)** was constructed using two items: (PBCb1) “I would use the bike more frequently if the cycling infrastructures were better” and (PBCb2) “I would use the bike sharing service more frequently if I had real time information on their availability and on the stalls' occupation”. Secondly, the **Perceived Behavioural Control toward public transport use (PBCpt)** was constructed using three items: (PBCpt1) “I would use the public transport more frequently if the vehicles (bus, metro, Tram) were better”; (PBCpt2) “I would use the public transport more frequently if the stops were better equipped”; and (PBCpt3) “I would use public transport more frequently if I had real time information about arrival times at all the stops”. Answers were collected on 5-points Likert scale where 1 was labelled “I totally disagree” and 5 “I totally agree”.

Transport related **Values** were explored using an Exploratory Factor Analysis (EFA) on items where respondents were asked, on a 5-point Likert scale (where 1 was labelled “Not important at all” and 5 “Extremely important”), the level of importance of choosing their mode of transport for their most frequent trip, according to different reasons. Such reasons were “Cost”, “Speed”, “Comfort”, “Pleasure (I like this mode of transport)”, “Flexibility and independence”, “Respect towards the environment” and “Reliability of travel time”. The Exploratory Factor Analysis (EFA) was conducted using the Maximum Likelihood method and the rotation of the factor was performed using the oblique Quartimin criterion that allows correlation between latent factors (Fabrigar, 1999). The EFA produced a 2 factors solutions which have been named **Utilitarian (U)** and **Convenience (C)** values

Another independent variable included in our analysis is the **Home localisation (Home)** which was divided into three categories: Urban (U), SubUrban (SU) and Rural (R).

2.4.2 Data analysis and modelling

In the following section, path diagrams for each model computed is presented. Manifest variables (observed or measured) are represented in rectangular boxes; latent Variables (psychological constructs) are represented in elliptic boxes and estimated variances of questionnaire items are represented by the error terms in circled boxes. Arrows linking latent constructs to questionnaire items indicates that a CFA was computed whereas all other arrows indicates a regression that may be linear if the dependent variable is continuous or logistic if the dependent variable is ordinal.

Norm-Activation Theory

The path diagram of the Norm-Activation Theory is represented in figure 8. We chose a linear model, as proposed by Steg and DeGroot (2010). As explained in section 1.2.1, the Norm-Activation Theory states that that pro-social behaviour depends on the activation of personal moral (PN) norms, which are activated once individuals expect a negative outcome to a given situation (problem awareness [PA] and adverse consequences [AC]) and when they believe that their action may have a role in reducing this threat (ascription of responsibility [AR]).

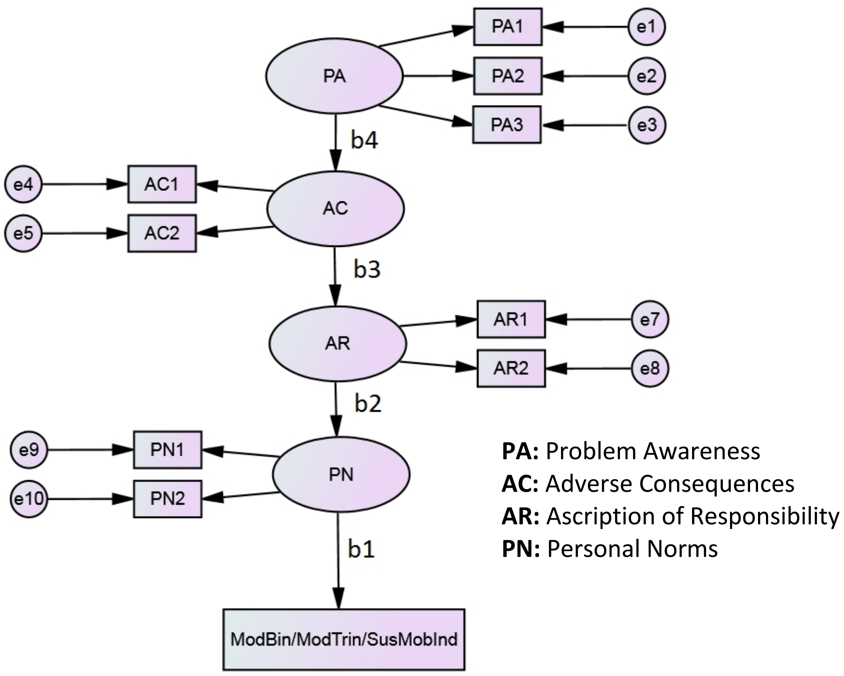


Figure 8: Path diagram of the NAT

Thus, 4 Confirmatory Factor Analysis (CFA) will be performed to load latent variables. These factors will be regressed in sequence: PA on AC, AC on AR, AR on PN and finally PN on our three measures of observed behaviours. We expect all regression coefficient to be positive and with a medium-to high size effect.

Theory of Planned Behaviour

The representation of the path diagram for the Theory of Planned Behaviour (TPB) is represented in figure 9. In our model, we replaced the specific attitude construct with the general attitude toward environment as measured by the GEB (section 2.3), thus violating the principle of compatibility of Ajzen (1985). Moreover, we regressed our latent variables directly on behaviour, without considering the role of Intention: as explained in Chapter 1: the attitude in Campbell's sense links directly attitude and behaviour, as, in practice within the Rasch Model, attitude itself is derived from a set of transitively ordered behaviours. So, our model postulates that travel behaviour (ModBin, ModTrin and SusMobInd) is driven by the Perceived Behavioural Control, the general attitude toward the environment (ATT) and subjective norms (SN).

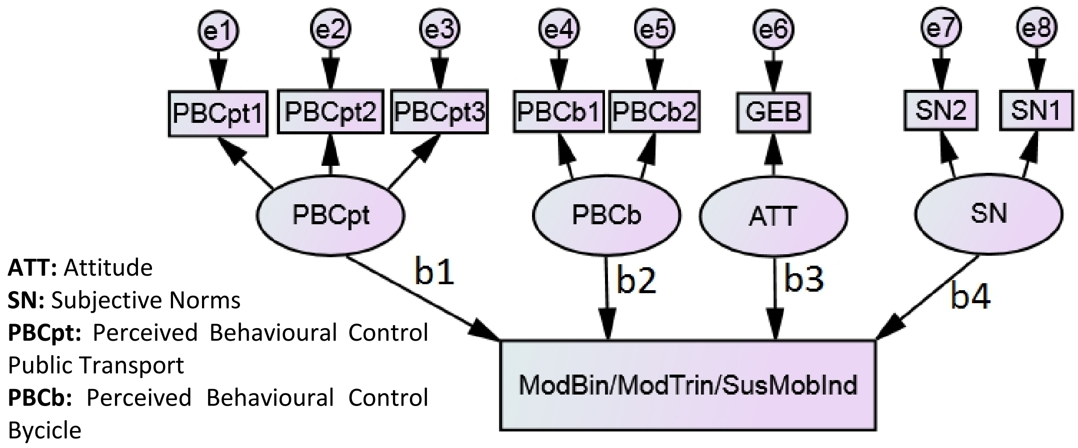


Figure 9: Path diagram of the TPB

Three Confirmatory Factor Analysis (CFA) will be performed to load three latent variables (PBCpt, PBCb and SN). The Rasch Measure of attitude will serve as the fourth variable (ATT). All factors will be regressed in our three measures of observed behaviours. We expect all regression coefficients to be positive.

Theory of Interpersonal Behaviour

The path diagram of the Theory of Interpersonal Behaviour (TIB) is represented in figure 10. In our model, Personal Norms and Subjective Norms are both used to produce a second order latent variable, namely Personal Factors (PF). So, this model postulates that observed travel behaviour (ModBin, ModTrin and SusMobInd) is driven by the Perceived Behavioural Control (PBCpt and PBCb), the Affect toward car-use (AFF) and social factors (SF). Also, we did not include habits as a predictor of the behaviour as, in our opinion, habitual routine, even if it correlates well with actual behaviour, does not help us in our understanding of psychological drivers of behaviours (cf. section 1.3.2).

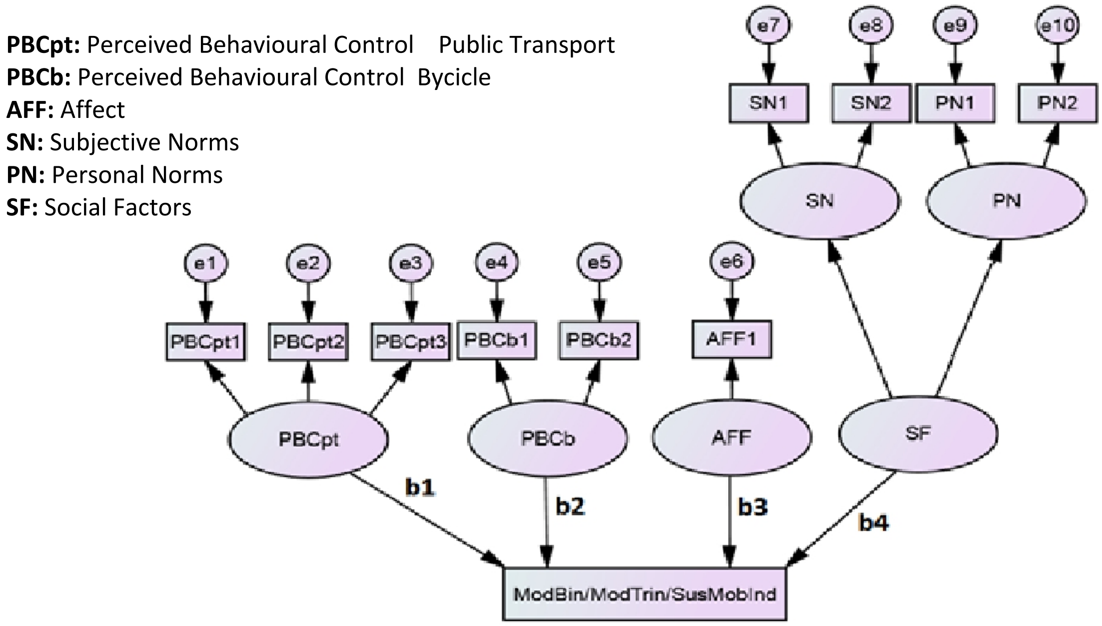


Figure 10: Path diagram for the TIB

Five Confirmatory Factor Analysis (CFA) will be performed to load five latent variables (PBCpt, PBCb, SN and PN). Affect toward car-use will be assessed thanks to the measure on item (AFF1) "I like travelling by car". A sixth factor analysis will allow the construction of a second order latent variable (SF). All factors will be regressed in on our three measures of observed behaviours. We expect all regression coefficients to be positive except for the affect toward car-use, which should have a negative coefficient.

Composite model

We decided to create a model that would take into considerations the general attitude toward the environment, the affect toward car-use, the perceived accessibility and transport-related values as factors to understand travel behaviour. Attitude and affect are known to have an influence on travel behaviour (Chapter 1), perceived accessibility will allow us to control for external constraints and, finally, although theoretical values are important in decision making, a specific construct of transport related values has, as far as we know, never been integrated in a psycho-social model aiming at explaining travel behaviour.

The model will be built step by step, in order to measure the additional variance explained at each step. The general path diagram of the model is presented in Figure 11. The first step will introduce the Perceived Accessibility (PAC), the general attitude toward the environment (ATT) and the Affect toward car-use (AFF) as explaining factors of behaviour.

The second step will introduce a variable of the participants' home localisation (Home), which, as we hypothesized, should be mediated by PAC. Indeed, the home localisation (Urban, SubUrban or rural) should explain a major part of PAC. In figure 11, direct paths are represented with thicker arrows and mediation paths with thinner arrows. The third step will test the mediation of AFF by ATT: indeed, although someone may like to drive cars, his/her attitude toward environment may act as a mediator factor that could limit him/her in car-use. Finally, the fourth and final step will introduce transport related values, namely Utilitarian (U) and Convenience (C), and hypotheses about their mediation by PAC and ATT. We hypothesize that the convenience value (C) is mediated by ATT because we think that values are more stable, influencing a wide spectrum of behaviours and should be reflected on general attitude toward the environment as measured by the GEB. Finally, we suggest that both transport-related (U and C) are mediated by perceived accessibility (PAC): although one may have preferences, his/her perceived available options, which we think are reflected by PAC, may act as a refraining factor of mode choice purely-led by values.

So, the final model postulates that home localisation, perceived accessibility, general attitude toward the environment, affect toward car-use, and transport related values all have an influence on travel behaviour. Morover, it postulates that: a) home localisation is mediated by the perceived accessibility; b) the affect toward car-use is mediated by the general attitude toward environment; c) the utilitarian value is mediated by the perceived accessibility; and d) the convenience value is mediated by both perceived accessibility and attitude toward the environment.

Looking at the model on the final step, three Confirmatory Factor Analysis (CFA) will be performed in order to load three latent variables (PAC, U and C). Affect toward car-use will be assessed thanks to the measure on item (AFF1) "I like travelling by car". Attitude toward the environment is measured thanks to the Rasch Measure. All the factors (Home, PAC, U, C, ATT and AFF) will be regressed on our three measures of travel behaviour (ModBin, ModTrin and SusMobInd). Home, U and C will be regressed on PAC and AFF and C on ATT. We expect ATT, U and PAC to have positive regression coefficients, AFF, Home and U to have negative regression coefficients.

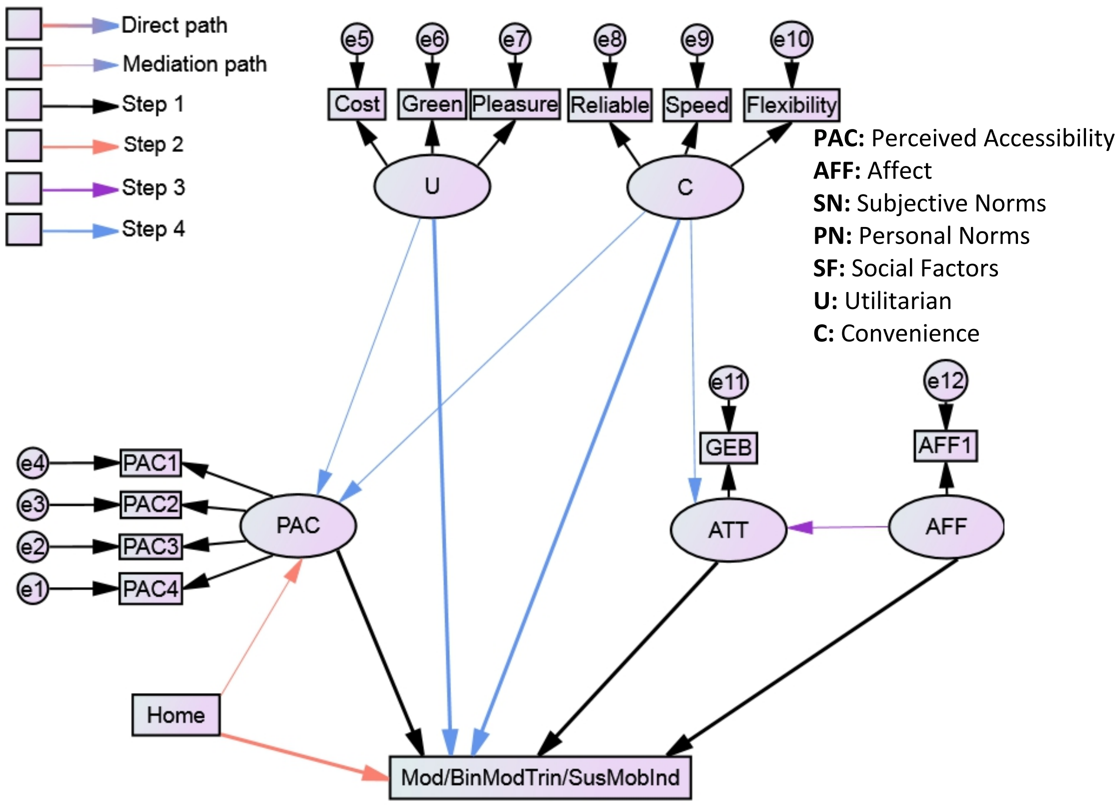


Figure 11: Path diagram of the Composite model

2.4.3 Statistics

The scale reliability for the latent constructs was evaluated using: a) Cronbach's α when the latent variable was assessed using more than two items; b) half-split Sperman-Brown (ρ^*) formula when the latent construct was assessed using only two items. Indeed, in case of a two-item scale, the Spearman-Brown formula seems to be less biased and to be the most appropriate measure of reliability (Eisinga, Grotenhuis and Pelzer, 2012).

For SEM techniques, **Diagonal Weighted Least Squares (DWLS)** estimator has been adopted when using categorical dependent variable. DWLS has been proven to perform well and better than other categorical data estimator for small samples (Rhemtullaet al., 2012).The **Maximum Likelihood (ML)** method has been adopted when using continuous dependent variables. Although ML implies a multivariate normality assumption, it is "considerably more insensitive than [Generalized Least Squares and Weighted Least Squares] to variations in sample size and kurtosis" (Olsson et al., 2000)

The model goodness of fit will be checked by looking at different test statistics:

- **the Satorra-Bentler χ^2 scaled test statistics** (Satorra and Bentler, 1994), which is a corrected χ^2 approximation of goodness-of-fit test for small samples and non-normal data;
- **the Root Mean Square Error of Approximation (RMSEA)**. We will use threshold of 0.01, 0.05 and 0.08 to indicate excellent, good and poor fit respectively, as proposed by MacCallum et al. (1996);
- **the Comparative Fit Index (CFI)**, that is acceptable when it is greater than 0.93 (Byrne, 1994);
- **Bollen's Incremental Fit Index (IFI)** (Bollen, 1989), which should exceed 0.90 (Hu and Bentler, 1999).

RMSEA, CFI and IFI have been chosen for their relative insensitivity to the sample size, so that fit is not overestimated when the sample size is small (Fan, Thompson and Wang, 1999).

All SEM-related statistics have been computed through the lavaan package[9] v0.5-20 for R release 3.2.5.

2.5 ATIS user segmentation

The last step of the methodology focuses on group segmentation: a range of psychological constructs is used to define different sub-groups of potential ATIS users and to compare them in terms of socio-economics, travel behaviour and expectations toward the use of ATIS.

A two-step clustering method has been used in order to classify the sample within different sub-groups of potential ATIS users. The psychological constructs that in the SEM analysis were powerful in explaining observed behaviour (AFF, U, C and ATT), together with a construct of enthusiasm toward technology (TechEnt), have been used in this step. The TechEnt variable was built using 6 items (Cronbach's α = 0.908): (1) "I like to try out new technological devices"; (2) "I am enchanted by the potential of the new technologies"; (3) "I

[9]"lavaan" stands for LAtent VAriable ANalysis : https://cran.r-project.org/web/packages/lavaan/index.html

am interested in new technology”; (4) “Apps are helping me in my daily life”; (5) “Some apps are fun to use”; and (6) “I enjoy coming across new apps”.

Factor scores for U, C and TechEnt were computed as Bartlett Scores, a refined method that produces unbiased estimates of the true factor score (Hershberger, 2005, cited by DiStefano, Zhu and Mîndrilă, 2009). The measure of ATT was the output score from the Rasch model estimates and, finally, as the AFF construct is given by only one item (AFF1), the score of this item was used. All variables were standardised, and, after having checked the correlation, AFF was removed from the analysis as it was too strongly correlated with ATT (Spearman’s $\rho = -0.395$). A descriptive analysis was then conducted, by checking significant differences among the clusters related to socio-economic variables (Gender, Home localisation, Age and Income), to personal mobility details (mode used for the most frequent trip, the sustainable mobility index and the scope of the most frequent trip) and to different expectations toward the use of the multi-modal trip navigator, TUeTO. The χ^2 statistics was used for categorical descriptive variables while a non-parametric ANOVA – using Kruskall-Wallis test followed by Dunn’s test for ordinal and continuous descriptive variable – was used. All analyses were conducted using SPSS release 20.0.0.

III. Results

This chapter describes the results obtained in our study. After a brief description of socio-economic attributes and mobility pattern of the final sample (§3.1) – composed by participants who answered both questionnaires – we will present the results of the Rasch Analysis (fits, parameter estimation and tests) conducted on the GEB questionnaire (§3.2 and §3.3), the results (scale reliability, regression coefficients, and fits) of the different models presented above (§2.4.2) which were computed through Structural Equation Modelling technique (§3.4) and, finally, the results of the cluster analysis (groups description), of the χ^2 test of independence and of the Analysis of Variance (ANOVA) (§3.5).

3.1 Sample description

The sample who answered the ex-ante survey of the Opticities project was composed of 159 participants. Medium age of respondents was 40.47 years (Median = 40 years, range from 20 to 75 years), 43% were women (N = 69) and 56% were men (N = 90). From the original 159 participants, 130 accepted to answer the GEB questionnaire. Medium age of respondents was 41.4 years (Median = 41.0 years, range from 20 to 75 years), 42% were women (N = 55) (Figure 12), showing no significant difference with the original sample.

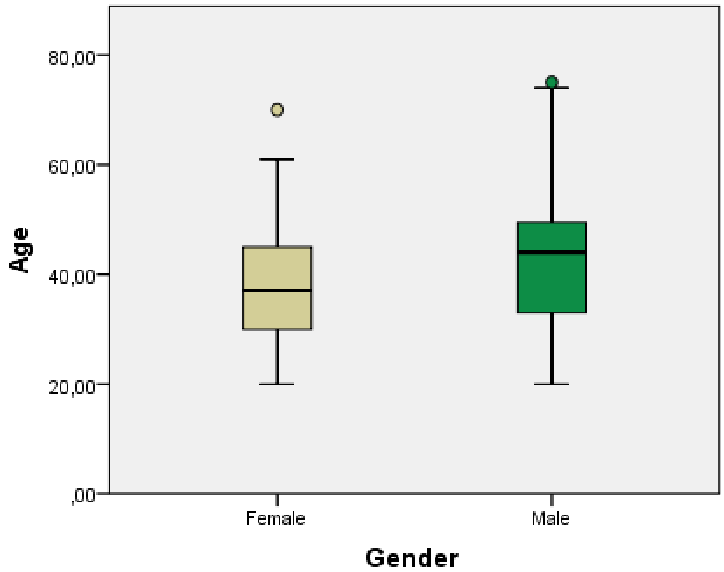


Figure 12: Boxplot of respondents Age by Gender

Figure 13 shows the highest educational qualification obtained by the participants. 3% (N=4) do not own a diploma and 25% (N=33) possess a high school degree. All others respondents attended university: 15% (N=20) have an undergraduate level, 51% (N=66) have a Master Degree and 5% (N=7) have a PhD degree.

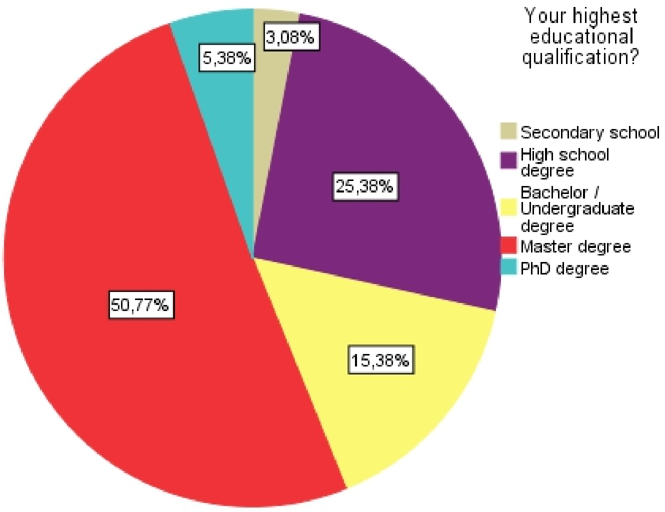


Figure 13: Pie Chart of respondents' level of Instruction

Concerning the household size of the respondents: 27 live alone, 33 live with someone else, 23 live with two other people and 47 live with more than two people (figure 14). There are 68 households without children and 62 with at least on child (31 households with one child, 37 households with two children and four households with three children). The average age of the children is 10 years, with a minimum age of less than one year old and a maximum age of 24 years old.

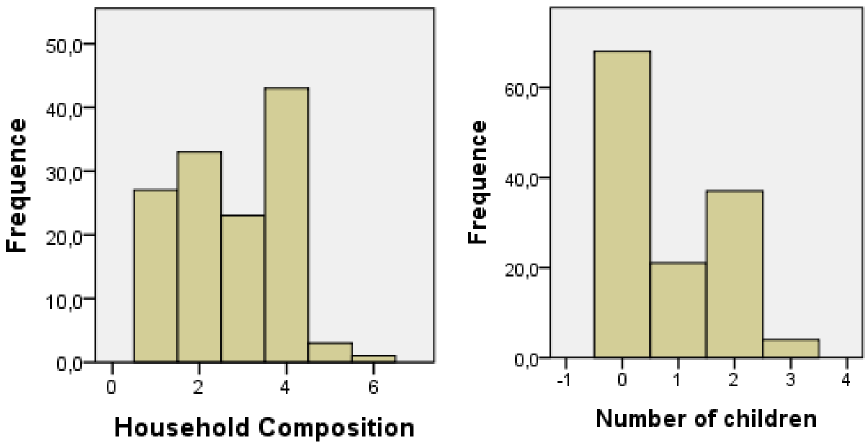


Figure 14: Histograms of respondents' household composition

Out of the 130 respondents, only 6 (4.6%) do not have a driving license. 18 of them (13.8%) do not have their own car, 50 (38.5%) have one car available for their use and 62 (47.7%) have two cars or more at disposition. 51% of the sample (N=66) do not have a public transport subscription whereas 49% (N=64) possess either a weekly pass (N=5), a monthly pass (N=18), a yearly pass (N=39) or a lifetime pass (N=2).

Finally, the mean household monthly income is close to 3 000 Euros, its median value is 2 750 Euros. According to the Italian's National Statistic Institute[10], in metropolitan areas, the Italian average household income is about 2 720 Euros/month and its median is around 2 150 Euros/month. A t-test of equal means returned a significance value of p=0.376, meaning that the mean measured is not different form the general population. However the Mann-Whitney U-test on median values returned a highly significant level: our sample is globally richer than the metropolitan Italian population.

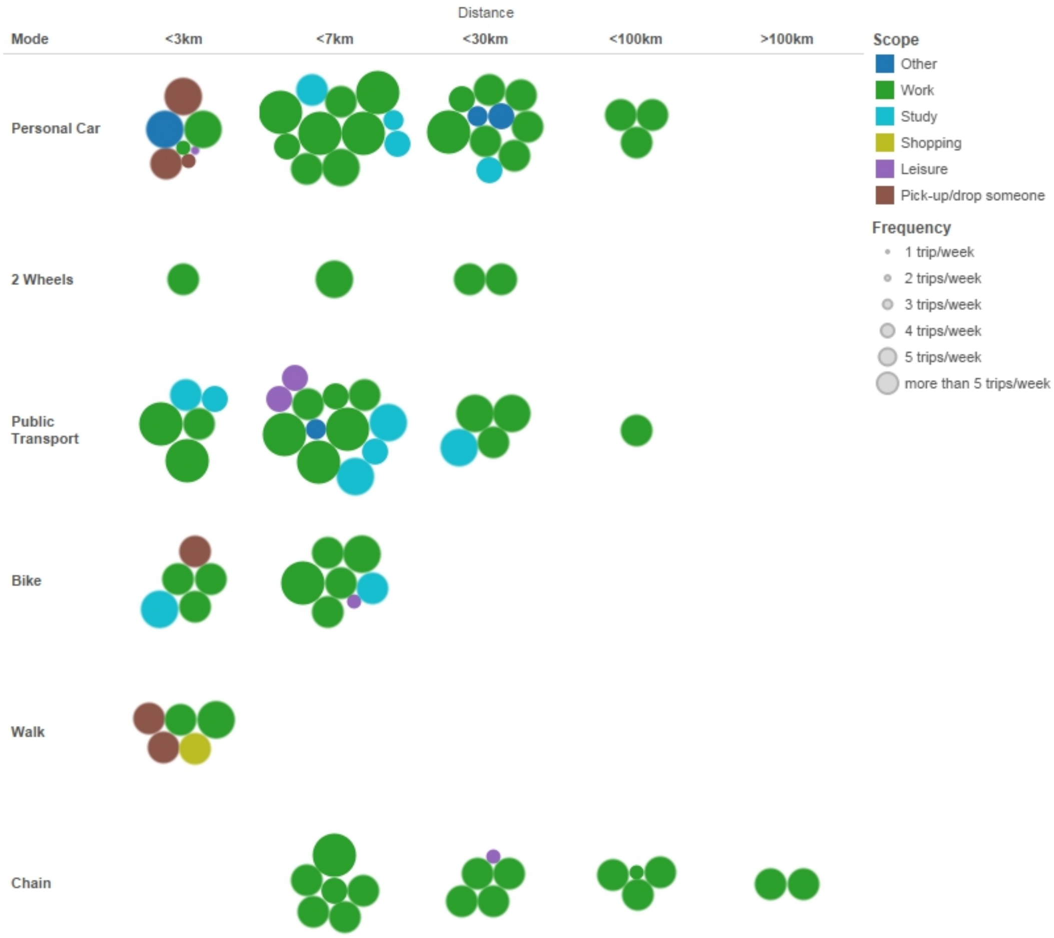


Figure 15: Most frequent trips attributes (mode, distance , scope and frequency).

Figure 15 shows different information about respondents' most frequent trip: the mode used to travel (Personal car, two-wheeled vehicles, Public Transport, Bike, Walk, Chain

[10] http://dati.istat.it

of transport); the distance travelled for one-way trip to the most frequent destination; the scope (Work, Study, Shopping, Leisure, pick-up/drop someone and other reasons) and finally the weekly frequency of the most frequent trip (from 1 trip/week to more than 5 trips/week). We can make some observations: chain of transport are used for the longest trips and never for travelling distance below 3 kilometres; walking for the most frequent trip is performed for distance which are inferior to 3 kilometres whereas the bicycles are used for distance below 7 kilometres. The most frequent trip is mainly performed to go to work (79%) or to study (9%). All trips with the scope of picking-up or dropping someone are within 3 kilometres of distance, regardless of the mode used. In total, 34% (N=44) of participants drive for their most frequent trip, 32 % (N=41) use Public Transport, 16% (N=22) make use of different mode in a transport chain and 14% (N=14) go either walking or by bicycle. Almost 80% (N=103) travel to their most frequent destinations at least five times a week, 9% four times a week and 11% three times/week or less.

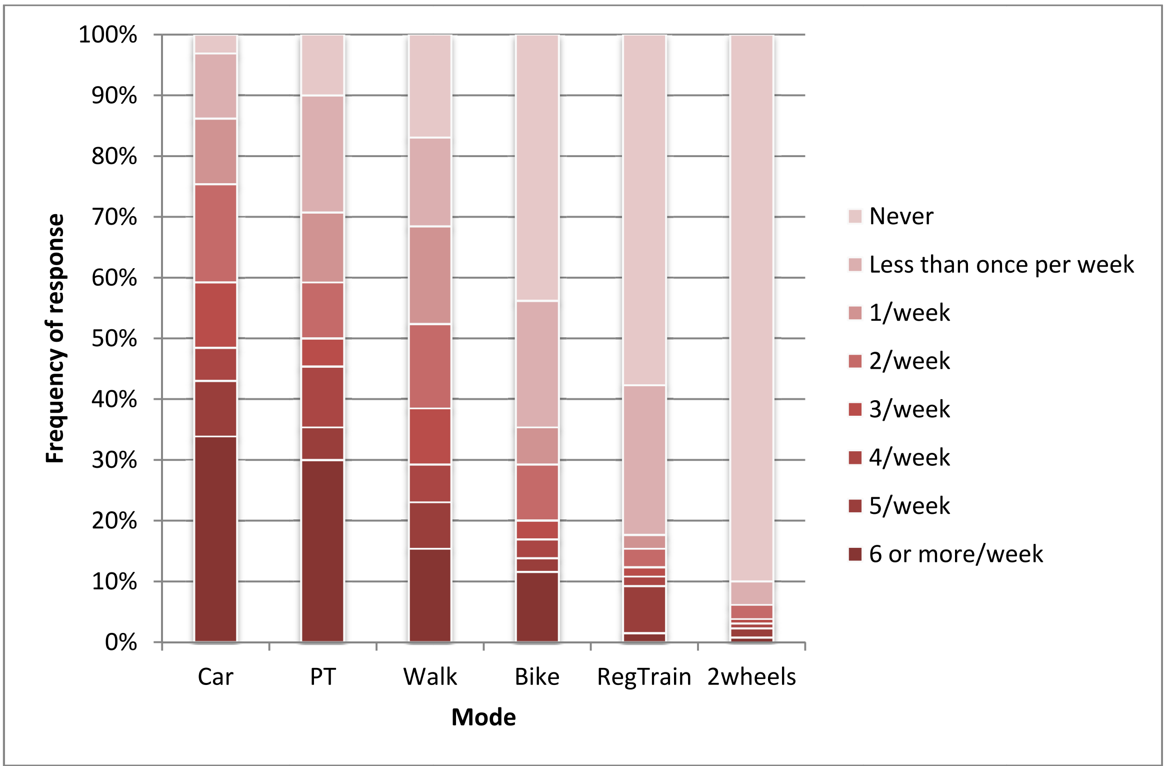


Figure 16: Mode usage frequency

Finally, we see that, considering all trips within a week, car is the most used travel mode: almost 50% of the respondents claimed using it at least four times a week. The second most used mode is Public Transport (metro, tram, bus), 50% of the respondents use them at least 3 times a week. Walking to destination is performed at least 2 times a week for half of participants. The bicycle is never used by almost 45% of respondents, as for the regional trains, which is never used by almost 60% of them and, finally, two-wheeled vehicles are barely used in general, as 90% of the sample never use this mode. Figure 16 shows the weekly use of the sample for each mode of transport.

3.2 Rasch model fitting and estimation.

Table 6 presents the estimates of item parameter ("MEASURE") from WINSTEPS together with their corresponding observed and expected point-biserial correlation, INFIT and OUTFIT statistics. Additional information includes the raw score on items ("SCORE") as well as the percentage of observed and expected positive answers for each item ("EXACT MATCH"). In table 6, items are ordered by increasing observed point-biserial correlation.

As showed on the table 6 some items are problematic, as explained hereafter:

Item 27-RR1 ("I re-use plastic bag from the groceries.") shows a high mean square OUTFIT value of 2.02 and a negative correlation with person measures (-0.07). It is estimated to be one of the easiest behaviour to engage into (MEASURE = -4.06) and has been answered "Yes" by all except one respondent (TOTAL SCORE = 130, TOTAL COUNT = 131), which caused the observed misfit. An explanation may be the semantic ambiguity of the item; indeed, perhaps this person does not use plastic bags to carry groceries home and, therefore, answered "No" to this specific task of re-using them. Considering the acceptable Z-standardised (1.1), and the fact that, although negative, the observed correlation is close to the expected one, we decided to keep this item in the final model;

Item 5-CS5 ("If a friend or a relative had to stay in the hospital for a week or two for minor surgery I would visit him or her") shows a value of mean square OUTFIT of 1.65, that is, "unproductive but not degrading for the measurement" (Table 4). The observed correlation with person measure is negative (CORR. = -0.03) but close to the expected one (EXP. = 0.07). Similarly to the item 27-RR1, the behaviour is considered easy by the model (MEASURE = -3.35) and has been answered positively by all except two respondents. We also decided to keep this item in the final model;

Table 6: Estimates of Item parameters, infit, outift and serial correlation statistics

ENTRY N°	SCORE	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	POINT-BIS. CORR. OBS.	POINT-BIS. CORR. EXP.	EXACT MATCH OBS. %	EXACT MATCH EXP. %	ITEM NAME
27	**130**	**-4.06**	**1.01**	**1.02**	**0.35**	**2.02**	**1.08**	**-0.07**	**0.05**	**99.2**	**99.2**	**RR1**
5	**129**	**-3.35**	**0.72**	**1.03**	**0.27**	**1.65**	**0.93**	**-0.03**	**0.07**	**98.5**	**98.5**	**CS5**
14	**12**	**3.49**	**0.31**	**1.11**	**0.52**	**1.48**	**1.44**	**-0.02**	**0.20**	**90.8**	**90.8**	**AE1**
8	109	-0.72	0.24	1.10	0.71	1.38	1.72	0.03	0.22	83.2	83.2	R1
7	108	-0.66	0.24	1.09	0.68	1.26	1.29	0.05	0.23	82.4	82.5	CS7
11	129	-3.35	0.72	1.00	0.24	1.06	0.35	0.07	0.07	98.5	98.5	R4
4	36	2.08	0.2	1.13	1.39	1.15	1.22	0.09	0.28	70.2	73.5	CS4
6	107	-0.61	0.23	1.08	0.60	1.17	0.92	0.09	0.23	81.7	81.7	CS6
3	128	-2.94	0.59	0.99	0.17	0.87	0.04	0.13	0.09	97.7	97.7	CS3
12	129	-3.35	0.72	1.00	0.22	0.67	-0.18	0.13	0.07	98.5	98.5	R5
1	89	0.19	0.2	1.09	1.19	1.11	1.08	0.14	0.28	64.9	69.2	CS1
13	129	-3.35	0.72	0.99	0.22	0.60	-0.28	0.14	0.07	98.5	98.5	R6
19	102	-0.36	0.22	1.06	0.52	1.07	0.51	0.16	0.25	77.9	77.9	AE6
39	84	0.38	0.19	1.08	1.12	1.14	1.47	0.16	0.29	63.4	66.8	T4
37	24	2.65	0.23	1.04	0.33	1.15	0.82	0.17	0.25	80.9	81.9	T2
15	116	-1.19	0.28	1.01	0.10	1.03	0.18	0.18	0.19	88.6	88.6	AE2
18	118	-1.36	0.3	0.99	0.05	0.90	-0.25	0.21	0.18	90.1	90.1	AE5
22	90	0.15	0.2	1.03	0.46	1.08	0.73	0.21	0.28	67.2	69.8	CE2
9	90	0.15	0.2	1.04	0.52	1.04	0.36	0.22	0.28	68.7	69.8	R2
20	96	-0.09	0.21	1.04	0.40	1.00	0.01	0.23	0.26	73.3	73.6	AE7
33	14	3.31	0.29	1.01	0.11	0.86	-0.43	0.23	0.21	89.3	89.3	V2
17	98	-0.18	0.21	1.03	0.31	0.98	-0.12	0.23	0.26	73.3	75.0	AE4
2	92	0.07	0.2	1.00	0.00	0.99	-0.03	0.28	0.27	71.8	71.0	CS2
24	69	0.89	0.18	1.02	0.31	1.01	0.20	0.28	0.30	61.1	62.8	CE4
26	42	1.84	0.2	1.01	0.16	0.99	-0.04	0.28	0.29	68.7	69.7	CE6
40	83	0.41	0.19	0.98	-0.25	1.04	0.43	0.30	0.29	73.3	66.3	T5
34	111	-0.84	0.25	0.95	-0.27	0.86	-0.57	0.31	0.21	84.7	84.8	V3
36	72	0.79	0.18	0.99	-0.13	1.00	0.01	0.31	0.30	57.3	63.1	T1
28	56	1.33	0.19	0.99	-0.12	0.98	-0.25	0.32	0.30	64.9	64.0	RR2
31	42	1.84	0.2	0.97	-0.37	0.96	-0.40	0.34	0.29	67.2	69.7	RR5
30	68	0.93	0.18	0.97	-0.51	0.95	-0.72	0.35	0.30	61.8	62.7	RR4
23	108	-0.66	0.24	0.93	-0.47	0.84	-0.81	0.35	0.23	82.4	82.5	CE3
35	33	2.21	0.21	0.94	-0.54	0.90	-0.75	0.37	0.28	76.3	75.6	V4
21	46	1.69	0.19	0.95	-0.70	0.93	-0.76	0.37	0.30	69.5	67.4	CE1
16	90	0.15	0.2	0.94	-0.69	0.89	-1.05	0.38	0.28	68.7	69.8	AE3
10	92	0.07	0.2	0.92	-0.91	0.88	-1.08	0.39	0.27	73.3	71.0	R3
29	90	0.15	0.2	0.93	-0.91	0.87	-1.26	0.40	0.28	71.8	69.8	RR3
32	82	0.45	0.19	0.93	-1.15	0.90	-1.22	0.40	0.29	71.0	65.9	V1
38	86	0.3	0.19	0.91	-1.24	0.87	-1.39	0.42	0.28	71.0	67.7	T3
25	**50**	**1.54**	**0.19**	**0.85**	**-2.44**	**0.80**	**-2.65**	**0.53**	**0.30**	**72.5**	**65.8**	**CE5**
MEAN	84.5	0.00	0.29	1.00	0.00	1.03	0.00	-	-	77.6	77.6	-
S.D.	33.3	1.82	0.2	0.06	0.7	0.25	0.9	-	-	11.9	11.7	-

Bolded items are problematic

Item 14-AE1 ("Before taking a shower, I let the water run so it gets to the temperature I want") may show good mean square statistics (INFIT MNSQ = 1.11, ZSTD = 0.5; OUTFIT MNSQ = 1.48, ZSTD = 1.4) but a negative correlation with person measure (CORR. = -0.02), quite far from the expected one (EXP. = 0.20). This item will be excluded from the final model.

Item 25-CE5 ("I use phosphate-free laundry detergent") shows acceptable mean square values (INFIT = 0.85; OUTFIT = 0.80) but very high negative Z-standardised scores (INFIT = -2.4; OUTFIT = -2.6). We conclude that this item is very unlikely fitting the Rasch model (p = 0.016 for INFIT; p = 0.09 for OUTFIT). It will be excluded from the final model computation.

Finally, 2 out of 40 items were excluded for the aforementioned reasons. The parameters were estimated with this new set of 131 persons x 38 items where fit-statistics where satisfactory as shown in figure 17.

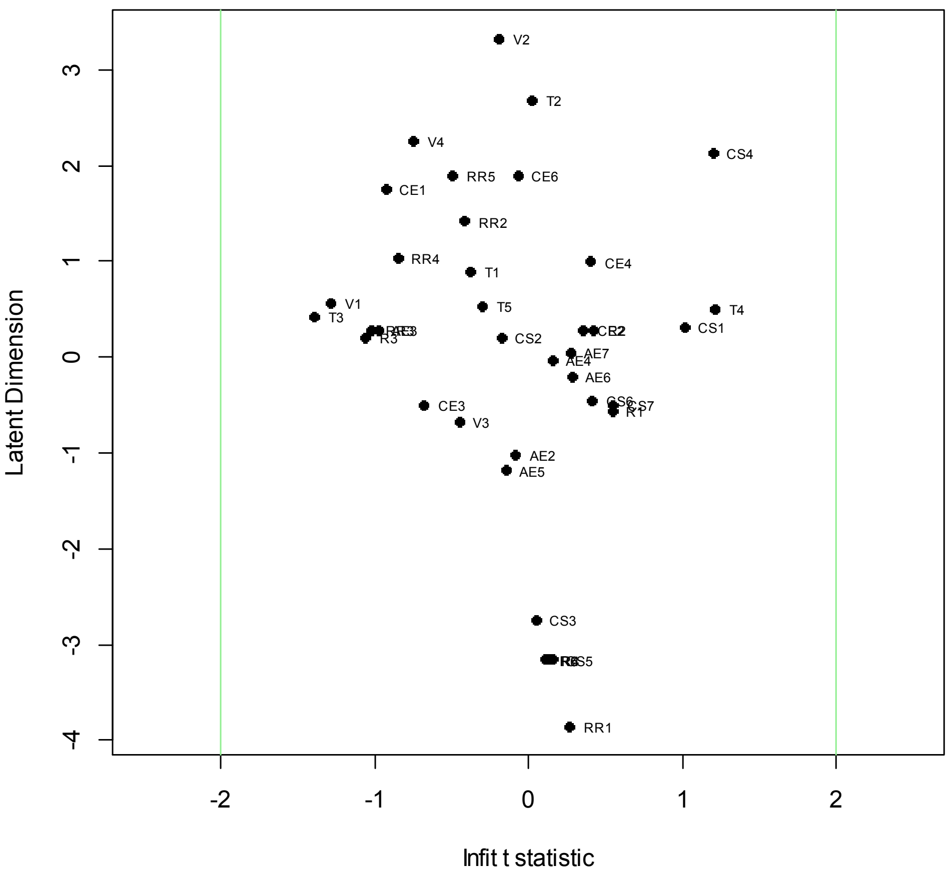


Figure 17: Item map of infit statistics for final item selection

3.3 Rasch model testing

As explained in the previous chapter, this section regards assumption testing and scale reliability assessment. The tests for one-dimensionality include a Principal Components Analysis on the residuals produced by the Rasch Model, a Martin-Löf Test and a non-parametric T_{md} test. The test for local stochastic independence is performed with the non-parametric T_{11} test. Subgroup homogeneity will be tested using two splitting criteria (Mean score and gender) and will be assessed by a graphical model check, an Andersen Likelihood-Ratio test and a non-parametric T_{10} test. Finally, the KR-20, person separation and item separation reliability statistics will be calculated. Afterward, all Item Characteristic Curves will be presented.

Check for one-dimensionality : Table 7 presents the results of the Rasch-residuals-based PCA and Figure 18 its associated scree plot.

Table 7: Results of the PCA performed on resdiuals

INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS WINSTEPS 3.80.1

Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)

	-- Empirical --			Modeled
Total raw variance in observations	55.6	100.0%		100.0%
Raw variance explained by measures	17.6	31.6%		31.6%
Raw variance explained by persons	4.3	7.8%		7.7%
Raw Variance explained by items	13.3	23.9%		23.8%
Raw unexplained variance (total)	38.0	68.4%	100.0%	68.4%
Unexplained variance in 1st contrast	2.8	5.0%	7.3%	
Unexplained variance in 2nd contrast	2.3	4.1%	6.0%	
Unexplained variance in 3rd contrast	2.1	3.8%	5.5%	
Unexplained variance in 4th contrast	1.9	3.3%	4.9%	
Unexplained variance in 5th contrast	1.7	3.1%	4.6%	

Comparing the values contained in "empirical" and "modelled" column in Table 7, we do not see any noticeable difference, confirming the good fitting of the model. The first contrast has an Eigenvalue of 2.8, explaining 5.0% of total variance. Although 2.8 as Eigenvalue is high enough to consider investigating this possible second dimension produced by the data, 5.0% of total variance explained is low enough to neglect it (Linacre, 2005). By plotting the loading of items on the 1st contrast of the residuals-based PCA (Figure 19), we clearly see that this possible dimension is produced by transport-related items. In fact, item T1 ("Usually, I do not drive my automobile in the city"), T2 ("I usually drive on freeways at speeds under 100 km/h") and T5 ("I walk, ride or take public transport to go to work/university") are quite away from the general cluster created by the other items. In figure 19, only the five items with the highest loading have been deciphered. Refer to Appendix B.1 for full information as well as similar plots for the other 4 constrasts.

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

Figure 18: Scree plot of the PCA variance component

The Martin-Löf Test for one-dimensionality was conducted by grouping in one subset all items except those related to transport, while transport-related items were grouped in a second subset. The test gave a p-value equal to 0.997, comforting the idea of an one-dimensional trait measure by the GEB questionnaire. However, the non-parametric T_{md} test conducted on 1000 sampled matrices was highly significant (p-value=0.001). This result points out that transport-related items show low discrimination and/or multidimensionality (Koller and Hatzinger, 2013).

Check for local stochastic independence. The test T_{11} produced a significant result (p-value < $10e^{-4}$) and lead us to reject the hypothesis of local independence. This does mean that some of our items in the GEB questionnaire are related to each other. Taking into account the results of dimension exploration (Figure 19), it is reasonable saying that items related to transport are subjected to other conditions, such as the fact of owning a car. In the same way, we could expect that the items concerning collecting and recycling diverse type of garbage (glass, paper and plastic) are somewhat correlated, under the influence of another factor, like living in a zone where differential garbage collection has been enacted.

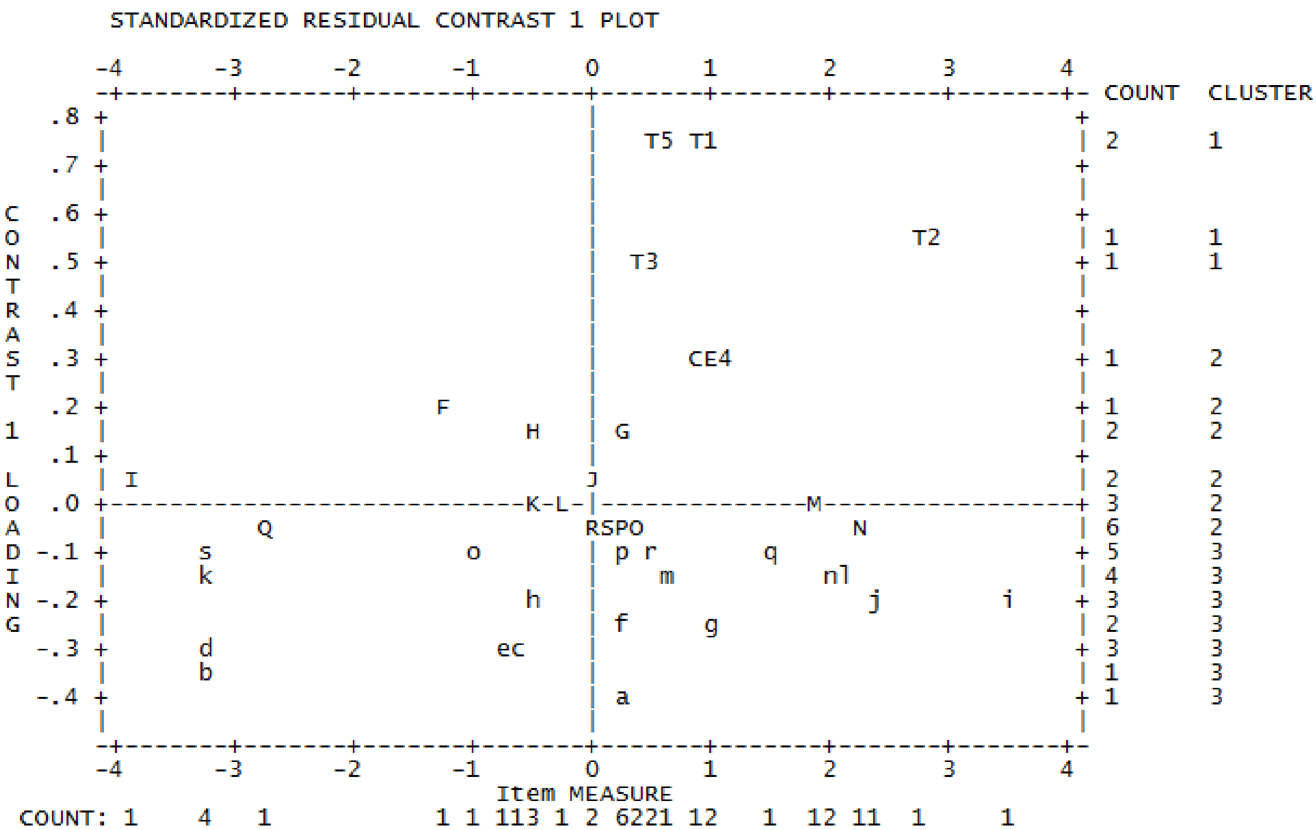


Figure 19: Item loadings on the first constrast

<u>Check for differential item functioning or subgroup homogeneity</u>. Figure 20 shows the graphical representation of the model check for both group splitting procedures, *median raw score* and *gender*. Items parameters estimates for both sub-group are plotted against each others, red ellipsoids represent the 95% confidence interval. Both Likelihood-ratio tests could not lead to reject the null hypothesis of subgroup homogeneity (p-value = 0.151 for median raw score splitting and p-value = 0.098 for gender splitting), which leads us to conclude that items are equally discriminatory for subgroups, which is a good thing for the quality of the Rasch measure. Ponocny's T_{10} test was performed using the same splitting procedure. The conclusion that can be reached is identical (p-value = 0.096 for median raw score splitting and p-value = 0.076 for gender splitting). However, examining the right-hand side graph within figure 20, although not significant at the general questionnaire level, we can see that item 37-T2 ("I usually drive on freeways at speeds under 100 km/h") is slightly

more difficult for men and that item 39-T4 (“If possible, I do not insist on my right of way and make the traffic stop before entering crossroads”) is slightly more difficult for women.

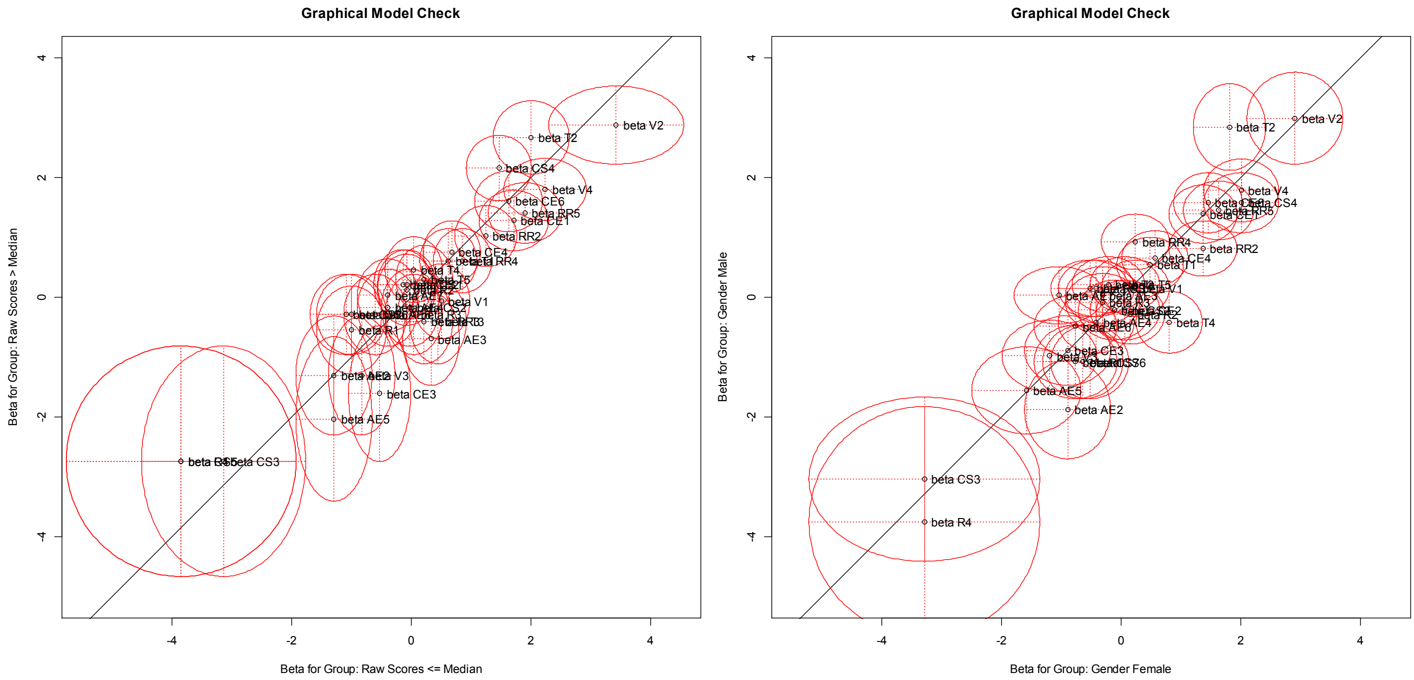


Figure 20: Graphical model check for both splitting procedure.

Reliability. The item separation reliability, equal to 0.96, shows a very good estimate of item hierarchy (Linacre, 2005) or, in other words, states that the items estimated as more difficult (vicevera more easy) are effectively more difficult (viceversa more easy). The KR-20 value was equal to 0.58 and the value of person separation reliability was equal to 0.57. This result points out that items are not very powerful to precisely estimate differences between respondents; such issue will be further discussed in the following paragraphs.

Figure 21 and 22 represent, for each item category, the joint plot of Item-Characteristic Curves. Focusing on garbage handling and transport items, we observe that ICC curves overlap for:

- R4 (“I sort paper wastes for recycling”), R5 (“I sort glass wastes for recycling”) and R6 (“I sort plastic wastes for recycling”);
- T3 (“When possible, I do not use a car for distance lower than 30km”), T4 (“If possible, I do not insist on my right of way and make the traffic stop before entering crossroads”) and T5 (“I walk, ride or take public transport to go to work/university”).

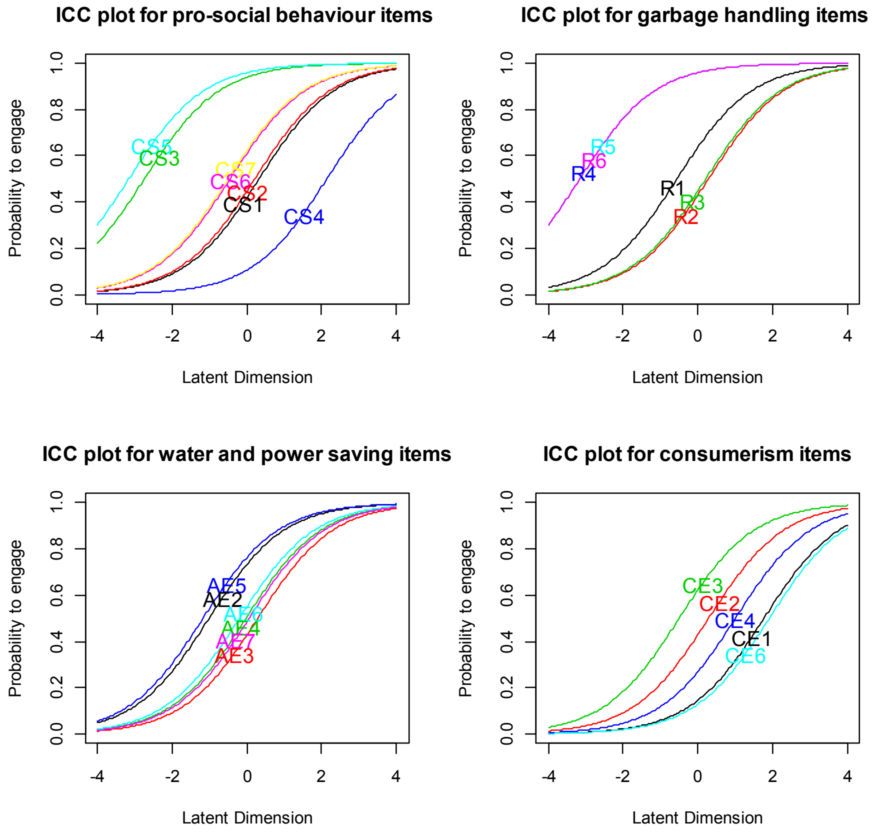


Figure 21: ICC plots for pro-social, garbage handling, power saving and consumerism items

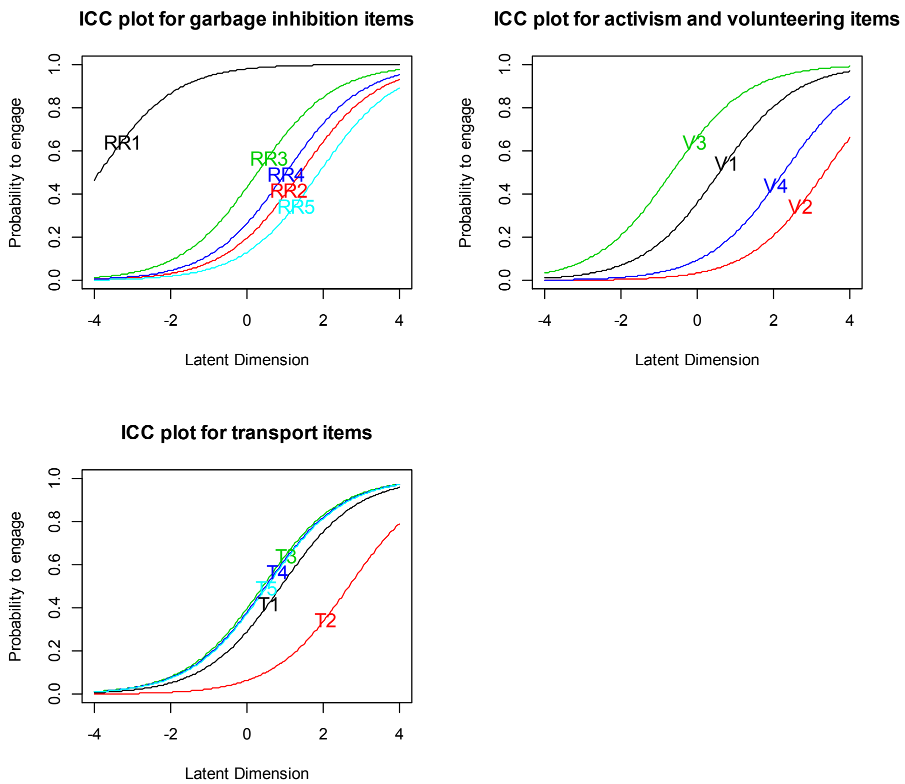


Figure 22: ICC plots for garbage inhibition, activism and volunteering and transport items

Such result reveals that these items are producing the same information. Concerning the other categories, we can observe that items are pretty well distributed on the latent dimension.

The Person-Item Map (Figure 23) is a representation, on the upper part, of the person parameter distribution and, on the lower part, of the item parameter value, sorted from the easier-to-engage item to the most difficult one. When items align, it means that they share the same level of difficulty and, thus, that all except one are superfluous. It is confirmed that items related to recycling share the same estimate of difficulty, together with CS5 ("If a friend or a relative had to stay in the hospital for a week or two for minor surgery I would visit him or her"). However, items related to transport that seemed to coincide on Figure 21 present a little difference between parameters' estimates.

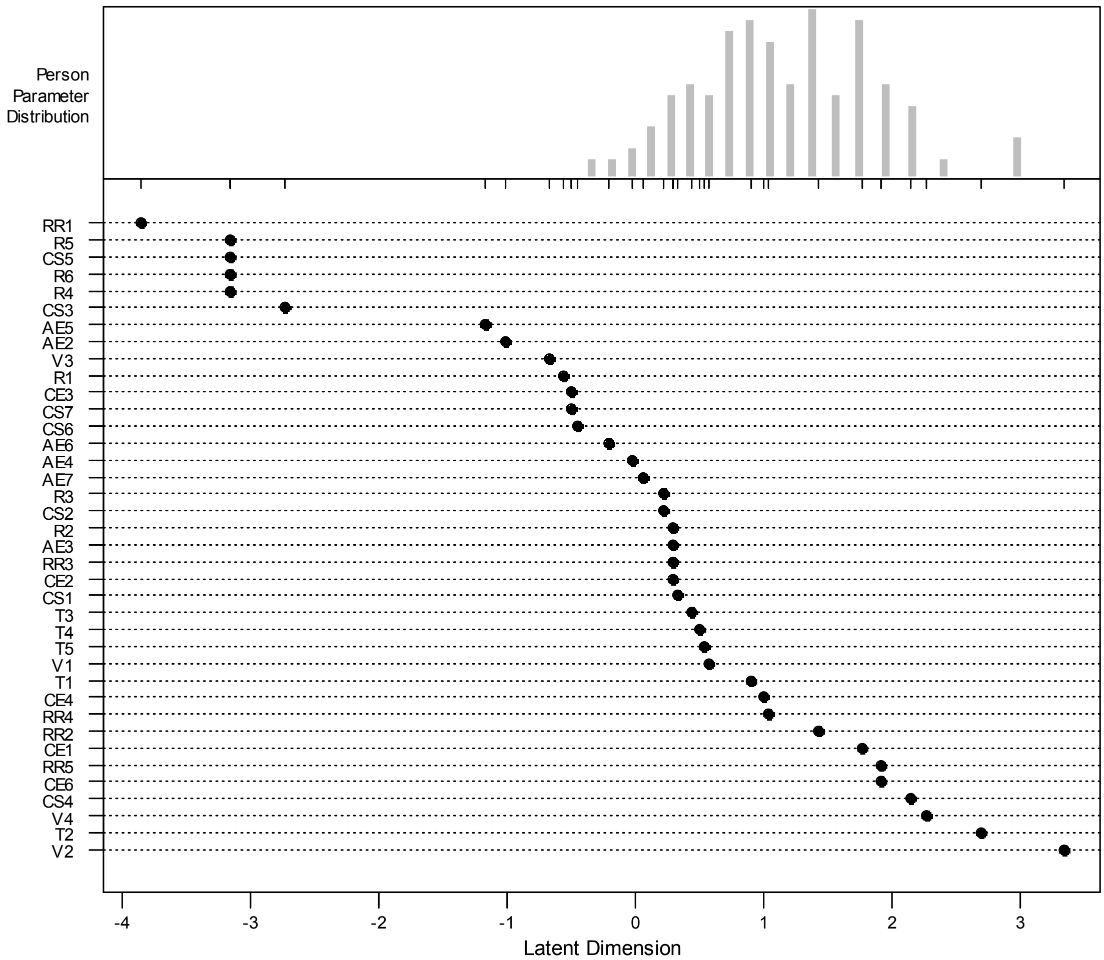
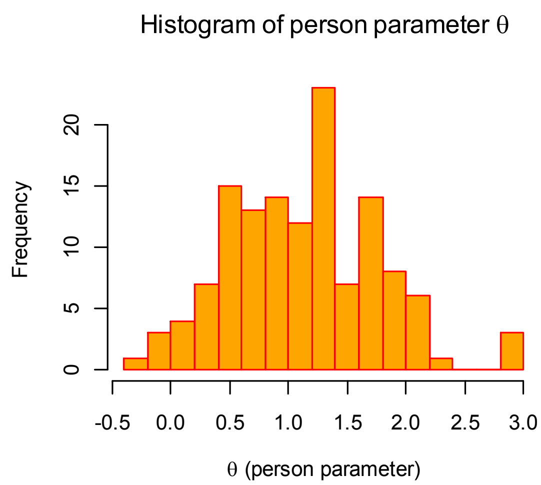


Figure 23: Person-item map of the Rasch Model

Within the Person-Item Map, when an item is aligned with a person, this person is predicted to have a 50% of engaging the behaviour. Such an item is said to be *targeted* on the person. Equivalently, when an item is 1.1 logits more difficult (or more easy) than the person ability, this person has 25% (or 75%) probability of engaging the behaviour. With these properties in mind, we can draw a few observations from Figure 23:

- first, we can see that at least the eight easiest items are too easy, not targeting anyone, and so they are not very useful for the GEB measurement;
- second, the existence of gaps between two successive parameters related to item difficulty on the horizontal scale makes difficult to *fine-tune* person estimates, especially around values of 0.7, 1.2, 1.6, 2.5 and 3 logits; this explains the relatively poor value of the person separation reliability. This issue will be further discussed in the discussion section (4.1).

Figure 24 represents the histogram of person parameter together with its kernel density plot. The distribution of θ fits a normal distribution of mean $\mu_\theta = 1.14$ and standard deviation $\sigma_\theta = 0.66$ (Jarque-Bera test p-value=0.27, skewness = 0.35, Pearson's kurtosis = 3.00).



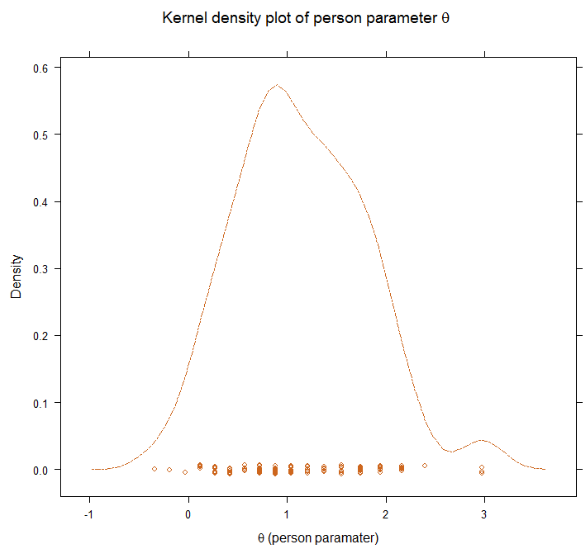


Figure 24: Histogram and Kernel density plot of the Rasch Measure

Detailed results (parameter estimates, infit and outfit statistics etc.) about person parameters θ are reported in appendix B.2.

3.4 Psychological constructs and correlational models

The **Personal norms** construct was assessed using two items (PN, $\rho^* = 0.504$). The **Problem Awareness** construct was assessed using three items (PA, $\alpha = 0.786$). The **Adverse**

Consequences construct was assessed with two items (AC, $\rho^* = 0.420$). The **Ascription of responsibility** construct was assessed with two items (AR, $\rho^* = 0.351$). The **Subjective Norms** construct was assessed with two items (SN, $\rho^* = 0.637$). The **Perceived Accessibility** construct was assessed using four items (PAC, $\alpha = 0.528$). The **Perceived Behavioural Control toward bicycle use** was assessed using two items (PBCb, $\rho^* = 0.690$). The **Perceived Behavioural Control toward public transport use** was assessed using three items (PBCpt, $\alpha = 0.740$).

The results from the Exploratory Factor Analysis (EFA) conducted on the reasons to choose a specific mode of transport for the most frequent trip gave a two-factor solution. The rotated loadings of factors on items are shown in table 8 (only loadings above 0.300 are reported), and their position on the two-dimension space is shown in Figure 25. The "Comfort" item was excluded from the final factor construction due to low loadings for both factors. Finally, "Speed", "Flexibility and independence" and "Reliability" of travel time" form the Utilitarian value (UTIL, $\alpha = 0.708$) and "Cost", "Pleasure" and "Respect toward the environment" form the Convenience value (CONV, $\alpha = 0.693$). Correlation between factors is low (r = 0.077).

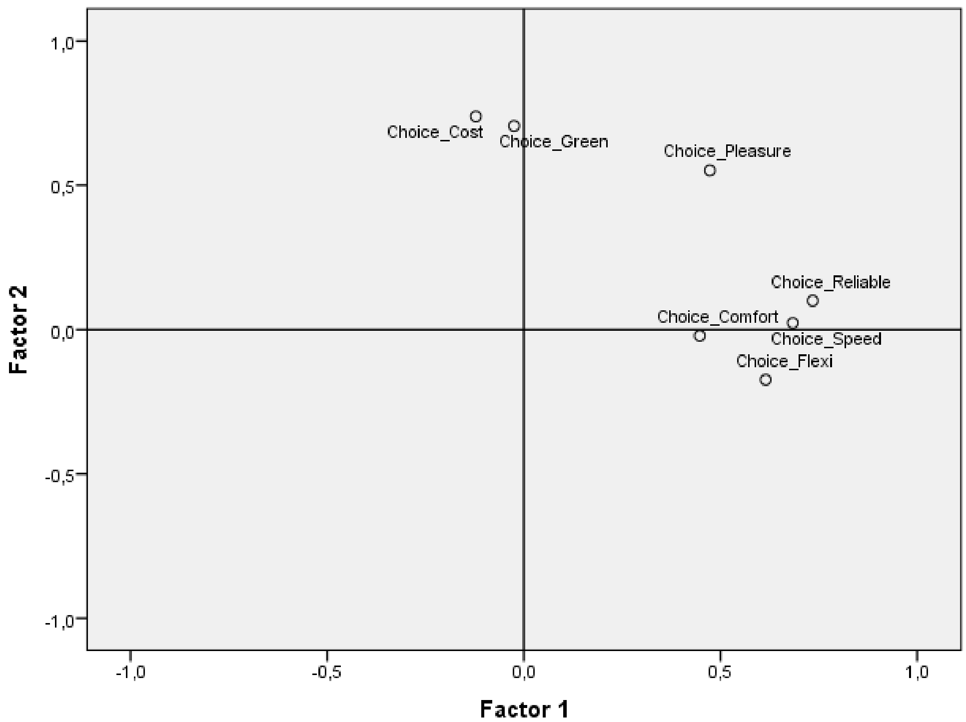


Figure 25: Factor plot in rotated factor space (transport-related Values)

Table 8: Factor loadings on transport-related values

	Factor	
	1 (UTIL)	2 (CONV)
[Cost]		,739
[Speed]	,684	
[Pleasure (I like this mode of transport)]	,472	,551
[Flexibility and independence]	,615	
[Respect towards the environment]		,706
[Reliability of the travel time]	,734	
[Comfort]	,447	

The Norm-Activation Theory.

The summary of the results obtained for the norm-activation model for all three dependent variables are shown in table 9. Detailed statistics are given in Appendix C.1.

Table 9: regression coefficients and fits statistics for the NAT

		Y:	ModBin	ModTrin	SusMobInd
	Parameter (standardized)	R^2:	0.027	0.019	0.011
Y<-PN	β1		0.166	0.139	0.106
PN<-AR	β2		0.787**	0.778**	0.825*
AR<-AC	β3		0.902**	0.902**	0.970**
AC<-PA	β4		0.650***	0.646***	0.599**
Model Fit	Robust p-value (scaled χ^2)		.000	.000	.000
	RMSEA		.081	.089	.121
	CFI		.942	.931	.808
	IFI		.943	.932	.814

Significance level: ***p<0.001 **p<0.01 *p<0.05.

We can observe that estimated regression parameters are very similar for all three models, with strong positive effects of Problem Awareness (PA) on Adverse Consequences (AC) perception (b4 ≅ 0.6), and strong positive effect of both Adverse Consequences (AC) perception on Ascription of Responsibility (AR) and of Ascription of Responsibility (AR) on Personal Norms (PN); in fact, all standardised regression parameters are greater than 0.7 and highly significant (p-value < 0.05). Personal Norms have an effect on specific behaviour (β1=0.166 [p=0.186] if regressed on ModBin and β1=0.139 [p=0.175] if regressed on ModTrin). However, the role of Personal Norms on a general behaviour, as measured by SusMobInd, is very low and may be considered null (β1=0.106, b1=0.061, se=0.057

[p=0.283]). In all cases, the variance of the behavioural measure explained by the model does not exceed 3% and the various goodness-of-fit test-statistics show unacceptable model fit to the data even if, for the specific behaviour cases, the proposed model is significantly better than the null model as the values of CFI (>0.93) and IFI (>0.90) show for both logistic regressions (MobBin and ModTrin).

We can conclude that the linear Norm-Activation Model performs well in explaining the formation of Personal Norms as already noted by Steg and de Groot (2010), who manipulated different predictors to study the causal relationship within the NAT. However, Personal Norms is having very low power on predicting actual behaviour, both specifically or generally measured.

The Theory of Planned Behaviour.

The summary of the results of the structural equation model of our modified version of the theory of planned behaviour for all three independent variables is shown in table 10. Detailed statistics are given in Appendix C.2. Firstly, we can see that, being the observed behaviour specific (ModBin and ModTrin) or general (SusMobInd), the effect of Subjective Norms (SN) is close to zero and highly not significantly different from zero (p-value=0.958 for the regression on ModBin, p-value=0.759 for the regression on ModTrin and p-value=0.545 for the regression on SusMobInd). The Perceived Behavioural Control toward Public Transport use (PBCpt) has a low significant negative influence on the general behaviour, measured by SusMobInd ($\beta 1$=-0.204, p-value=0.015), a low negative influence on specific behaviour as measured by ModTrin ($\beta 1$=-0.191, p-value=0.088) and no effect on specific behaviour as measured by ModBin ($\beta 1$=-0.038, p-value=0.753). The Perceived Behavioural Control toward bicycle use (PBCb), instead, has low positive effect on all three dependent observed behaviour ($\beta 2 \cong 0.1$ and p-value$\cong$0.15 for specific behaviour, and $\beta 2=0.204$, p-value=0.017 for general behaviour). The general attitude towards the environment as measured by the General Ecological Behaviour scale has a medium and highly significant positive influence on all three behavioural measures. We can also remark that the general attitude has a greater influence on very specific behaviour (ModBin; $\beta 3$=0.371) than on general behaviour (SusMobInd; $\beta 3$=0.291). In all cases, the variance of the observed behaviour explained by the model does not exceed 15%. As for the goodness-of-fit test-statistics, all indicators show a good model fit to the data, with better fit for the models that aim at predicting specific behaviour (p-value>0.5, RMSEA=0, CFI=1, IFI>1) in comparison with the one that aims at predicting a general behaviour (p-value=0.078, RMSEA=0.066, CFI=0.950, IFI=0.954).

Table 10:regression coefficients and fits statistics for the TPB

	Parameter	Y:	ModBin	ModTrin	SusMobInd
		R^2:	0.15	0.14	0.137
Y<-PBCpt	β1		-0.038	-0.191	-0.204*
Y<-PBCb	β2		0.108	0.098	0.178*
Y<-ATT	β3		0.371***	0.317***	0.291***
Y<-SN	β4		-0.007	-0.038	-0.067
Model Fit	Robust p-value (scaled χ^2)		.538	.513	.078
	RMSEA		.000	.000	.066
	CFI		1.000	1.000	.950
	IFI		1.091	1.087	.954

Significance level: ***p<0.001 **p<0.01 *p<0.05

We can conclude that the Theory of Planned Behaviour, in its simplest form and with a very general measure of attitude, is good in explaining both specific and general behaviour. However, it seems that, in our case, Subjective Norms (SN) construct is a superfluous predictor. The negative influence of the Perceived Behavioural Control toward Public Transport use and the positive influence toward bicycle use may be problematic. Indeed, we could expect both PBCs influence in the same direction (negatively) the observed behaviour. The opposite effect of influence may be due to a threshold effect of another kind: we can suppose that PBCb influences positively the observed behaviour because people already behaving in a pro-environmental way would be willing to do more: while people using their personal motorised vehicles would agree to do an effort (riding public transport if the vehicles/information/frequency were better), people already riding the bicycle or travelling by public transport would travel more by bicycle if infrastructures were better and real-time information on bike-sharing stalls were better-provided.

The Theory of Interpersonal Behaviour.

The summary of the results obtained for the structural equation model of the theory of interpersonal behaviour for all three independent variables are shown in table 11. Detailed statistics are given in Appendix C.3. We can see that, for the models that aim at explaining specific behaviours (ModBin and ModTrin), the affective factor (AFF) is the only significant one with a medium negative influence on behaviour (β3=-0.375, p-value=0.002 if regressed on ModBin, and β3=-0.284, p-value=0.002 if regressed on ModTrin). As for the model explaining general behaviour, we can see that both the affective factor (AFF) and the Perceived Behavioural Control toward bicycle use (PBCb) are significant predictors, PBCb influencing moderately positively SusMobInd (β2=0.299, p-value=0.033) and PBCpt influences negatively the observed behaviour (β1=-0.190, p-value=0.122). Social Factors (SF) influence may be considered as null as all p-value for β4 are greater than 0.5. The variance explained by the model ranges between 16 and 22% of total variance in dependent variables and the goodness-of-fit test-statistics shows a low fit of the model to the data for the general behavioural measure and an acceptable fit for specific behavioural measures.

Table 11: regression coefficients and fits statistics for the TIB

		Y:	ModBin	ModTrin	SusMobInd
	Parameter	R^2:	0.224	0.162	0.161
Y<-PBCpt	β1		0.055	-0.093	-0.190
Y<-PBCb	β2		0.079	0.075	0.299*
Y<-AFF	β3		-0.375**	-0.284**	-0.300*
Y<-SF	β4		0.105	0.117	-0.118
Model Fit	Robust p-value (scaled χ^2)		.017	.017	.006
	RMSEA		.032	.035	.073
	CFI		.975	.971	.907
	IFI		.977	.973	.913

Significance level: ***p<0.001 **p<0.01 *p<0.05

We can conclude that the TIB is an acceptable model for explaining behaviour. In the case of specific behaviours, the only significant predictors is the affect toward car use. As for the case of general behaviour, within the TIB, Perceived Behavioural Control seems to have similar effect than within the Theory of Planned Behaviour: i.e. a low negative influence of PBCpt on behaviour and a low positive influence of PBCb on behaviour.Refer to previous section for a possible explanation of opposite direction of influence of both PBC. However, we can see that the TIB is the model that explains at best the variance observed in behaviour, when compared with the TPB.

Composite model.

Tables 12 reports all standardised regression coefficients for all successive steps on all three dependent variables (ModBin, ModTrin and SusMobInd). Detailed statistics are given in Appendix C.4. We will first look at what we can conclude about two out of the three main variables included in our model, namely attitude (ATT) and Perceived Accessibility (PAC), before discussing our hypothesis. The role the affective construct toward car use (AFF) will be discussed when observing the mediation effect of attitude.

Table 12: regression coefficients and fits statistics for the composite model

		Y = ModBin			
	R^2	0.671	0.814	0.814	0.985
	ΔR^2	-	0.143	-	0.171
		β^1_x	β^2_x	β^3_x	β^4_x
Y<-ATT	β^Y_1	0.157	0.248**	0.248**	0.070
Y<-AFF	β^Y_2	-0.071	-0.274**	-0.274**	-0.145
Y<-PAC	β^Y_3	0.731***	0.808***	0.808***	0.460**
Y<-Home	β^Y_4	-	0.039	0.039	-0.119
PAC<-Home	β^Y_5	-	-0.443***	-0.443***	-0.433***
ATT<-AFF	β^Y_6	-	-	-0.382***	-0.446***
Y<-U	β^Y_7	-	-	-	-0.364***
Y<-C	β^Y_8	-	-	-	0.492***
PAC<-U	β^Y_9	-	-	-	-0.266*
PAC<-C	β^Y_{10}	-	-	-	0.311*
ATT<-C	β^Y_{11}	-	-	-	0.195
Model Fit	Robust p-value (scaled χ^2)	0.500	0.037		0
	RMSEA	0	0.064		0.60
	CFI	1.00	0.925		0.901
	IFI	1.05	0.931		0.908
		ModTrin			
	R2	0.560	0.655	0.656	0.786
	ΔR2	-	0.09	-	0.13
		β^1_x	β^2_x	β^3_x	β^4_x
Y<-ATT	β^Y_1	0.121	0.202*	0.202*	0.017
Y<-AFF	β^Y_2	-0.038	-0.225**	-0.225**	-0.193*
Y<-PAC	β^Y_3	0.690**	0.717**	0.717**	0.446*
Y<-Home	β^Y_4	-	-0.022	-0.022	-0.153

			β^1_x	β^2_x	β^3_x	β^4_x
	PAC<-Home	β^y_5	-	-0.464***	-0.464***	-0.454***
	ATT<-AFF	β^y_6	-	-	-0.382***	-0.458***
	Y<-U	β^y_7	-	-	-	-0.017
	Y<-C	β^y_8	-	-	-	0.513***
	PAC<-U	β^y_9	-	-	-	-0.250
	PAC<-C	β^y_{10}	-	-	-	0.340*
	ATT<-C	β^y_{11}	-	-	-	0.189
Model Fit	Robust p-value (scaled χ^2)		0.635	0.046		0.001
	RMSEA		0	0.059		0.508
	CFI		1	0.938		0.905
	IFI		1.056	0.942		0.912
			SusMobInd			
		R2	0.559	0.534	0.534	0.629
		ΔR2	-	-0.025	-	0.095
			β^1_x	β^2_x	β^3_x	β^4_x
	Y<-ATT	β^y_1	0.108	0.150*	0.150*	0.009
	Y<-AFF	β^y_2	0.047	-0.065	-0.065	-0.053
	Y<-PAC	β^y_3	0.731***	0.640***	0.640***	0.487**
	Y<-Home	β^y_4	-	-0.125	-0.125	-0.167
	PAC<-Home	β^y_5	-	-0.465***	-0.465***	-0.432***
	ATT<-AFF	β^y_6	-	-	-0.390***	-0.351***
	Y<-U	β^y_7	-	-	-	-0.146
	Y<-C	β^y_8	-	-	-	0.351***
	PAC<-U	β^y_9	-	-	-	-0.240
	PAC<-C	β^y_{10}	-	-	-	0.379**
	ATT<-C	β^y_{11}	-	-	-	0.257**
Model Fit	Robust p-value (scaled χ^2)		0.325	0.040		0
	RMSEA		0.042	0.073		0.102
	CFI		0.979	0.914		0.780
	IFI		0.981	0.919		0.792

Significance level: ***p<0.001 **p<0.01 *p<0.05

For the most simple model (first step), the role of the general attitude toward environment on observed behaviour, being either ModBin, ModTrin or SusMobInd, is positively low (β_1^1 lies between 0.10 and 0.16, p-value of 0.09, 0.185 and 0.207 for ModBin, ModTrin and SusMobInd respectively). This positive influence increases further and becomes statistically significant, when considering the two successive steps ($\beta_1^{2|3}$ between 0.15 and

0.25, p-value<0.01). Finally, the role on explaining behaviour of the most complex model, that incorporates transport-related values, becomes null ($\beta_1^4 \leq 0.07$, p-value of 0.371, 0.841 and 0.892 for ModBin, ModTrin and SusMobInd respectively). The Perceived Accessibility (PAC) shows a strong positive influence on every behavioural measure for all model until step 3 ($\beta_3^{1|2|3} > 0.6$, p-value<0.01). For the last step, that is the most complex model, this influence remains positive but lowers and is almost constant across behavioural measure it is regressed with ($\beta_3^4 \cong 0.46$, p-value<0.05).

We now have a closer look on the second step of our model, testing the hypothesis of a mediation of Home localisation by perceived accessibility. We can see that Home localisation (Home) is totally mediated by the Perceived Accessibility (PA) for specific behavioural measure (ModBin and ModTrin) as the standardized coefficients of regression on both dependent variables are close to zero and not significantly different from zero (β_4^2<0.04, p-value>0.7). Home localisation has, therefore, no influence on specific behaviour, however it has a medium negative influence on Perceived Accessibility (β_5^2 ≅0.450, p-value<0.001). This negative medium influence is also true for the case of the model that aims at explaining the general behaviour (SusMobInd) but, in this case, home localisation is only partially mediated by Perceived Accessibility. Indeed, a low negative influence (β_4^2=-0.125), however not significant (p-value=0.291), is present. Thus, we conclude that Home localisation is totally mediated by perceived accessibility for specific behaviour, and partially for general behaviour. This may be explained by the fact that the perceived accessibility is constructed as a perceived accessibility for the most frequent trip, that is the base for specific behavioural measure. Table 13 below re-assumes both indirect (i.e., mediated by PA) and total effect of Home localisation on behaviour. We observe the major part of the effect of Home localisation on behaviour is carried by the mediation of PAC. Our hypothesis is thus validated.

Table 13: Table of indirect and total effect of Home

		ModBin	ModTrin	SusMobInd
Home	Indirect effect (through PAC)	-0.357***	-0.512***	-0.100***
	Total effect	-0,483**	-0.547***	-0.142***

Significance level: ***p<0.001 **p<0.01 *p<0.05. Values at step 2.

We now focus on the third step of our model, testing the hypothesis of a mediation of the affect construct toward car use by the general attitudes. We can observe that the affective construct (AFF) toward the use of the car is mediated, for all three models, by the general attitude toward the environment. Indeed, the medium negative influence of AFF on ATT is constant for all models (β_6^3 ≅0.385) and highly significant (p-value<0.001). However, we can see an interesting difference about the direct effect of AFF on either specific behavioural measures or the general one: whereas the affective component toward the use of car has a medium negative direct influence on ModBin and ModTrin (β_2^3 ≅ -0.25, p-value<0.01), it has no direct effect on SusMobInd (β_2^3= -0.065, p-value=0.408). Table 14 below re-assume both indirect (i.e., mediated by ATT) and total effect of the affective construct toward the use of car on behaviour. We can see that one fourth to one third of the total effect of AFF on behaviour is carried by the mediation of ATT. Our hypothesis is thus validated.

Table 14: Table of indirect and total effect of AFF

		ModBin	ModTrin	SusMobInd
AFF	Indirect effect (through ATT)	-0.095*	-0.077*	-0.058*
	Total effect	-0.369***	-0.302***	-0.124

Significance level: ***p<0.001 **p<0.01 *p<0.05. Values at step 3

With regards to our transport related values, namely Convenience (C) and Utilitarian (U), we can observe that, concerning the Binomial mode choice (ModBin), U has a negative medium highly significant direct effect (β_7^4= -0.364, p-value<0.001) whereas C has a positive medium highly significant direct effect (β_8^4= 0.492, p-value<0.001), as we could expect. Indeed, it is not surprising that an utilitarian value would rather influence people to take their car whereas people valuating convenience would rather choose alternative modes to travel. However, surprisingly enough, we can notice that, with regards to the Trinomial mode choice (ModTrin), the direct effect of U on the response variable disappears (β_7^4= -0.017, p-value<0.858). To understand this, let's remind that ModBin has been constructed using two modes: personal motorised vehicles on one hand and other modes (either alone or in a sequence) on the other hand; instead, ModTrin has been constructed using three modes: the first one is the same as in ModBin, while soft modes of transport (walk and bicycle) have been extracted to form the third mode. Therefore, we suggest that U may well explains differences between the fact of choosing the car versus other modes of transport but is unable to explain differences between choosing soft modes versus public transport. Finally, in regards to the model that aims at explaining general behaviour as measured by SusMobInd, we notice that the direct effects of both U and C on ModBin are similar, but fairly lower in intensity, to the observed effects (β_7^4= -0.146, p-value<0.115; β_8^4= 0.351, p-value<0.001). If we now have a look on indirect effects of values, we observe that each model for all three behavioural measures (ModBin, ModTrin and SusMobInd) presents indirect effects of similar magnitude; this means that the utilitarian value is mediated by perceived accessibility, with a medium negative effects of U on PA ($\beta_9^4 \cong$ -0.250, p-value of 0.037, 0.054 and 0.051 for regression on ModBin, ModTrin and SusMobInd respectively). The Convenience value is, similarly, mediated by the Perceived Accessibility, with a medium positive effect of C on PAC ($\beta_{10}^4 \cong$ 0.340, p-values<0.05). This *could* mean that having an utilitarian vision of personal mobility *may* reduce the perceived accessibility and, symmetrically, that valuating convenience for personal mobility *may* increase the perceived accessibility, but, as we did not manipulate any independent variables, we cannot infer anything about causality. Lastly, we can conclude that C is also mediated by the general attitude toward environment, as C has a medium positive effect on ATT. This relation is more noticeable when considering the general behaviour (β_{11}^4= 0.257, p-values=0.008) than the specific ones ($\beta_{10}^4 \cong$ 0.190, p-values of 0.081 and 0.099 for ModBin and ModTrin respectively). Table 15 synthesizes both indirect (i.e. mediated by PAC and ATT) and total effect of U and C on behaviour. We can see that, for the case of ModBin, one fourth of the total effect of U on behaviour is carried by PAC (p-value=0.071). If we consider ModTrin as the behavioural measure, almost the entire effect of U is carried by PAC (p-value=0.101) and for the general measure of behaviour (SusMobInd), almost half of the total effect of U on behaviour is carried by PAC (p-value=0.09). The hypothesis that U is mediated by PAC is validated. Concerning the convenience value (C), in all three cases, one fifth to one third of the total effect of C on behaviour in accounted by PAC. However, absolutely none of the total effect is carried by ATT, which is consistent with the fact that the general attitude does not produce any explanation of the observed behaviour for the model related to this last step. The only validated hypothesis is that C is mediated by PAC.

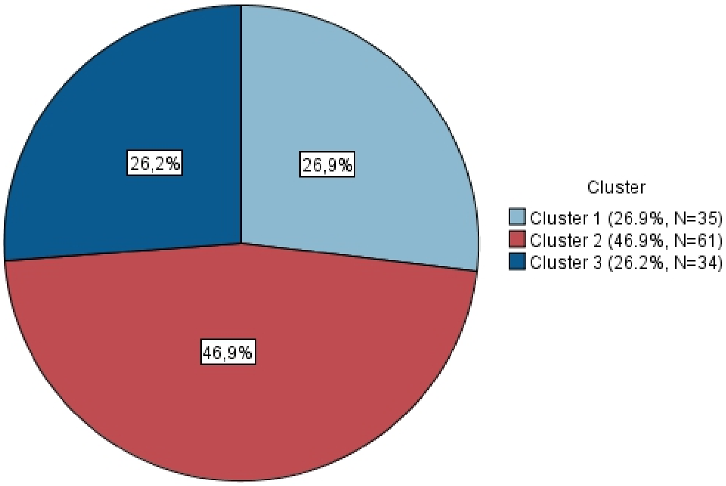
Table 15: Table of indirect and total effect of U and C

		ModBin	ModTrin	SusMobInd
U	Indirect effect (through PAC)	-0.123	-0.112	-0.117
	Total effect	-0.487***	-0.128	-0.263**
C	Indirect effect (through PAC)	0.143*	0.152*	0.185*
	Indirect effect (through ATT)	0.014	0.003	0.002
	Total effect	0.649***	0.668***	0.538***

Significance level: ***p<0.001 **p<0.01 *p<0.05

3.5 Market segmentation

Figure 26 presents the cluster dimensions, the position of the centroids on input variables as well as relative frequency of input variables for each cluster. The first cluster is composed of 35 respondents (26.9%), characterized by low scores on the enthusiasm toward technology (TechEnt) latent factor and high scores on both Utilitarian and Convenience transport related values (U and C). Their scores on the General Attitude toward the environment is neither specifically high or low. The second cluster is composed of 61 respondents (46.9%), that makes it the biggest cluster in terms of size. People in this cluster are characterized by high scores on the Convenience transport related value (C), high scores on the enthusiasm toward technology (TechEnt) and high scores on attitude toward the environment (ATT). They, however, have low score on the utilitarian transport related value (U). The third and last cluster is composed of 34 respondents (26.2%). They are characterized by low scores on the Convenience transport related value (C) and attitude toward the environment (ATT). They score higher than the first cluster but lower than the second on the enthusiasm toward technology (TechEnt); their score on Utilitarian transport-related value is neither specifically high or low (Fig. 26).



Cluster / Input	1	2	3
	C 0,45	C 0,47	C -1,37
	TechEnt -1,20	TechEnt 0,59	TechEnt 0,25
	ATT 0,04	ATT 0,28	ATT -0,54
	U 0,24	U -0,25	U 0,03

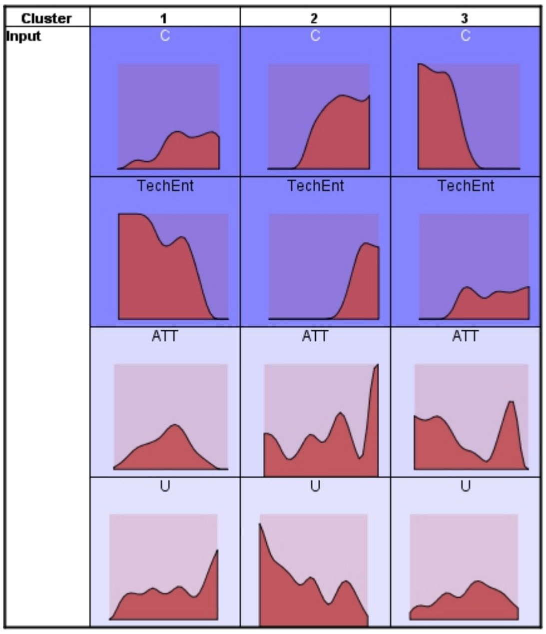


Figure 26: Cluster dimensions (up), position of cluster centroids (left) and relative frequencies (right).

Given this characteristics, we can label our clusters in the following way:

- the group formed by the first cluster will be labelled "**Neo-Luddites Opportunists**". Opportunists because their high scores on both the Utilitarian and Convenience transport related values denotes that they value whatever they can benefit from. Luddites were British textile workers who stand up protesting against the mechanization of their work at the beginning of the industrial revolution. Steve (2006) introduced the term Neo-Luddism to identify people that follows a desire for a simple life where technological tools are restrained to their minimum;

- the group formed by the second cluster will be labelled "**Hedonic Techy Ecologists**".Their high score on the technology enthusiasm dimension means they are in favour of technological use. Both high score on attitude toward the environment and on the convenience transport value make them more likely to use soft modes and public transport for urban travels. And finally, higher score on the Convenience than on the Utilitarian transport value suggests that they prefer cheap and pleasant trips than fast and efficient ones;
- the group formed by the third cluster will be labelled "**Neoclassical Agents**". Their higher score on the utilitarian over the convenience transport related value, together with their low score on the measure of attitude toward the environment make people of this group fit well the definition of *homo economicus*: an agent who will tend to maximize its own short-term utility without consideration for the others or the environment.

Table 16 presents the results of differences among groups as regards some socio-economic variables (gender, Home localisation, Age and Income), some mobility-related variables (mode chosen for the most frequent trip [ModBin and Modtrin], the sustainable mobility index [SusMobInd], the stated scope related to the most frequent trip) and some ATIS related variables which represent :

- expectation for increased reliability. The item was formulated as "If TUeTO can increase the reliability of my daily trips, I intend to use it" and answers were collected on a 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree";
- expectation of easiness of use. The item was formulated as "I expect TUeTO to be easy to use" and answer were collected on a 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree";
- willingness to pay (WTP). The item was formulated as "I am willing to pay to use the kind of service offered by TUeTO" and answer were collected on a 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree";
- behavioural change induced. The item was formulated as "I think that using TUeTO would facilitate a change in my travel behaviour" and answer were collected on a 5-points Likert scale where 1 was labelled "I totally disagree" and 5 "I totally agree".

Table 16: Results of the χ2 tests and ANOVA

	Cluster Neo-Luddites Opportunists	Hedonic Techy Ecologists	Neoclassical Agents	Total
Socio-economic				
gender				
Female	20	23	12	55
Male	15	38	22	75
Home localisation				
Urban	22	42	20	84
SubUrban	10	9	12	31
Rural	3	10	2	15
Age				
observed difference	=	=	=	
Income**				
observed difference	-	=	+	
Mobility Habits				
ModBin***				
PMV	6 (-)	15 (-)	27 (+)	48
Other	29 (+)	46 (+)	7 (-)	82
ModTrin***				
PMV	6 (-)	15 (-)	27 (+)	48
PT	20 (+)	36 (+)	7 (-)	62
Soft	9 (+)	10 (+)	0 (-)	19
SusMobInd***				
observed difference	+	+	-	
Reason for most frequent trip				
Work	26	48	28	102
Study	3	7	2	12
Other	6	4	2	12
TUeTO				
Reliability*				
Mean	-	=	=	
Easy to use*				
Mean	+	=	=	
WTP*				
Mean	=	+	=	
Behavioural change*				
Mean	=	+	=	

Significance level (χ2 for categorical, Kruskall-Wallis for continous) : ***p<0.001 **p<0.01 *p<0.05

We can observe that, concerning socio-economic variables, the only statically significant differences between groups lies in Household Income, where people in the Neo-Luddites Opportunists cluster have relatively lower income than people in the Neoclassical

Agents cluster, no significant differences appear concerning the age or the level of education. Not surprisingly – because we chose our cluster analysis input variables in accordance - differences are highly significant for travel behaviour. We observe that Neoclassical Agents are using cars more often than people in the other two groups, they also have a sustainable mobility index lower than the others. However, we do not see any statistically significant differences concerning the scope stated for the most frequent trip. Finally, concerning the multimodal navigator related items, we observe that Neo-Luddites Opportunists are asking more for user-friendliness for their interaction with the application, and they are also less demanding toward an increase of reliability for their trips. Hedonic Techy Ecologists are the ones that are the most ready to pay for the kind of service offered by TUeTO and they are also the ones that think this technology could help them to change their mobility habits.

Table 17 presents, for each cluster, the five most requested features for the multimodal trip navigator. There is, cross-cutting the cluster, an overall consensus about the wish to be able to pay transport fees directly within the app. Traffic prediction remains also a must-have feature. Generally speaking, the first group (Neo-luddites Opportunists) is less interested in having parking real-time availability and it is the only one asking for the point of interests in the top five requested features.

Table 17: Most requestesd features

Neo-Luddites Opportunists		Hedonic Techy Ecologists		Neoclassical Agents	
25%	Paying through the smartphone	26%	Paying through the smartphone	25%	Paying through the smartphone
16%	One hour traffic prediction	20%	One hour traffic prediction	19%	One hour traffic prediction
13%	Balance on your PT card	13%	Balance on your PT card	13%	Parking real-time availability
10%	Parking real-time availability	12%	Parking real-time availability	13%	Balance on your PT card
10%	Points of interest along the selected route	12%	Real-time bike sharing spots and bike availability in the city	10%	Real-time bike sharing spots and bike availability in the city

IV. Discussion

In this analysis, we presented the theoretical foundation for (1) fitting the Rasch Model; (2) estimating the model parameters with two different approaches and (3) testing the model assumptions. We then applied it in practice to obtain a measure of general attitude toward the environment and to understand if the General Ecological Behaviour questionnaire is a good tool for this scope. We saw that we had to eject some items from the analysis and that items parameters were well defined. However, even though the one-dimensionality of the measurement was proved to be good enough, the results obtained from our sample showed a violation of the local stochastic dependence. We understood that this may be due to questions inside the GEB questionnaire that are correlated by an independent structural factor (the fact of owning or not a car, of living in a neighbourhood where differential garbage disposal facilities exists). The influence of independent structural factors on general attitude is not a problem, being this aspect part of Campbell's paradigm of attitude: some behaviour may be more difficult in certain contexts than in other ones. However, retaining items that are related to each other's through independent structural factors is a violation of assumptions made by the Rasch Model formal definition. Furthermore, we saw that person's ability estimates could not be fine-tuned: at least eight items are useless in producing estimates because they have too low difficulties, and some intermediate to high difficulty items are missing. Filling the gaps between difficulties (evidenced in figure 23) could highly benefit to the procurement of better estimates of person's measures of attitude.

All that considered, as a new emerging method for measuring attitude within the Item Response Theory framework, the General Ecological Behaviour may be considered as a *good enough* questionnaire: there are no discrepancies between pro-social behaviour and factual ecological behaviour; one-dimensionality, item reliability, and the absence of simple differential item functioning are all good indicators for a good model functioning. Some further research may be needed to remove, replace and add some items that could produces better person estimates. In fact, since the first development of the GEB questionnaire (Kaiser, 1998) some alternative ones have been used (Kaiser and Wilson, 2000; Kaiser, Oerke, and Bogner, 2007). Moreover, in our opinion, a such measure of attitude is far more convincing than the traditional one: its mathematical model is well defined and respond to some requirements we expect from a measurement tool, such as specific objectivity (the fact that the measure is sample-free for the agents and test-free for the items), additive measurement (adding one more unit means the same amount extra, no matter how much there is already), hypocrisy insensitive (we measure self-reported relevant behaviour instead of wills).

Pursuing the analysis, we aimed, firstly, at defining if general measure of attitude – obtained thanks to person estimates on the General Ecological Behaviour measured by the Rasch model – is compelling within traditional frameworks derived from social psychology theories. In practice the classical Attitude psychological construct has been replaced by the general attitude toward environment into the Theory of Planned Behaviour. The second scope was to compare diverse theories that aim at explaining people's behaviour (the Norm-Activation Theory, the Theory of Planned Behaviour and the Theory of Interpersonal Behaviour) with our data in order to understand which behavioural constructs are determinant for explaining observed travel behaviour.

The analysis performed on the Norm-Activation Theory were very conclusive: the structural path of the so called norm activation performs well: Problem Awareness (PA) explains identification of Adverse Consequences (AC), which in turn, explains the self Ascription of Responsibility (AR) and this activate the Personal Norms (PN). But Personal Norms are useless in explaining the observed behaviour: in our analysis, only 1 to 3% of variance observed in behaviour could be explained by the Personal Norms construct (Table 9). These results are in line with various previous studies: Bamberg et al. (2007) conducted a two-field study in order to assess the effect of personal norms on public transport use. In one of them, the variance of observed behaviour did not exceed 3% with a standardised regression coefficient of 0.17; Harland et al.(1999), studying different types of pro-environmental behaviour, found that Personal Norms explained the 1% of variance of observed use of other-than-car mode of transport with a standardised regression coefficient of 0.16.

We saw that within the theory of planned behaviour framework, a general measure of attitude may be a good predictor of both specific and general measure of behaviour. In our case, it is even the only significant factor that explains specific behaviour as measured by ModBin and ModTrin. Tonglet et al. (2004), applying the TPB in its formal definition on the intention to recycle, also concluded that "these three components [of the Theory of Planned Behaviour] collectively explained 26.1% of the variance in *recycling intentions*, with attitude being the only statistically significant predictor". Similarly, Harland et al. (1999), applying TPB to four different pro-environmental behaviour ([1] use of unbleached paper, [2] use other transport forms than the car, [3] use energy saving light bulb and [4]Turn-off faucet while brushing teeth), concluded:

- for the TPB explaining *behavioural intention,* that "attitude and PBC contributed most strongly to behavioural intention and that subjective norm was less influential and, in one case, did not reach significance";
- for the TPB explaining *past-behaviour,* that "subjective norm was the weakest contributor to the explanation of past behaviour and, in two cases, did not reach significance [from which the case of not using the car]".

Harland et al. (1999) continue by stating that "Attitude, subjective norm, and PBC together accounted for a percentage of explained variance in the four past behaviours that ranges between 13% and 39%". Finally, Forward (2008) also found the subjective norms were not significant at explaining driving violations.

Although we cannot conclude about the relative effectiveness of substituting the classical attitude measure with the Campbellian general attitude measure – because we would need more measures of attitudes (at a general and specific level) as Ajzen (1989) conceived them – the results presented so far suggest that it is a valid approach which shall be deeper examined.

The analysis carried out on the Theory of Interpersonal Behaviour demonstrated that, within this framework, the affective construct plays a significant role in travel decision making. Our analysis did not include the role of habitual behaviour, as suggested by the theory (Triandis, 1977) because arguments in favour of habits explaining decision making fail to convince us as a valid understanding of psychological drivers of choices. Overall we saw that the TIB was able to explain more variance (up to 7 points more) in behaviour than did the TPB, but has overall a lower goodness-of-fit to data.

The analysis performed on the three models taken from social-psychology research gives us three points of view of the same observed phenomenon. These are neither exclusive nor incompatible. We understood the importance of attitude and affect in travel-related decision making. We saw that personal norms (how we think it should be) did not explain variations in behaviour, although we understood how they seem to emerge from problem awareness. Subjective norms, representing the belief of how others think a person should behave, have also a virtually influence near zero. By comparing side by side the theory of planned behaviour and the theory of interpersonal behaviour, we saw that affect and attitude are competing in explaining behaviour. This led us to propose a composite model that would integrate both constructs and test their co-interactions. Perceived accessibility has been integrated, in order to account for structural urban factors, and its relationship with the objective localisation of households has been studied. Finally, we integrated what we thought was missing in theories but that was proved to be determinant as independent variables. That is, what do people value the most in travel: speed, flexibility and reliability? or cheap, pleasant and impactless mode? We constructed two dimensions of transport-related value to further integrate them in our composite model.

Its analysis, conducted in successive steps, revealed that attitude and affect, together with perceived accessibility, are determinant for travel behaviour: depending on which measure was used for its assessment, the models could explain from 50 to 81% of its variance. Moreover, the path analysis that aimed at revealing the mediation role of perceived accessibility on home localisation led us to conclude that any effect of home localisation is, for the most part, already accounted by perceived accessibility. Inversely, when studying the mediation effect of attitude on affect, we observed that they mainly have different influence on travel behaviour: only a low share of the explaining power of affect is accounted by attitude, favouring models which can take both into consideration. When inserting values into the regression, we observed that the role of attitude and affect dropped drastically, even becoming insignificant for someone. The influence of perceived accessibility also dropped down but within a range of medium effect size and still significant. Values themselves were shown to have a significant influence, especially for explaining mode choice on a binomial dependent variable. But, comprehensively, the value for convenience was much more indicative than the utilitarian one.

The study made so far allowed us to highlight psychological constructs that are able to explain travel behaviour. With the final aim of understanding the potential modal shift induced by the introduction of innovative advanced traveller information systems, we used our psychological constructs (values, attitude and affect) together with a construct on technology enthusiasm to conduct a cluster analysis on our sampled population. We obtained three sub-populations: (1) Neo-Luddites Opportunists, who are unlikely to use the multimodal navigator because of their reluctance toward the technology; (2) Neoclassical Agents, who have little consideration for the environment and favour their own benefits over others. Even if they may benefit from the multimodal navigator, it is unlikely that they will shift from their most favoured mode until economical constraints will force them to do so; (3) Hedonic Techy Ecologists, they are people that are in line with the Zeitgest. They are enthusiast about technologies (if not addicted) and take care about the environment. They clearly expect that technology will solve many problems, including transport-related ones, and are aware of the need to pay to benefit from a service such as the multimodal navigator we presented to them. They can represent the main source of revenue in a business model assessment. Out of 130 respondents, half belongs to Hedonic Techy Ecologists and, within this group of 63 people, nine drive their car to go to work, four use a two-wheeled vehicle and two are car passengers, scoring 15 people who actually use a personal motor vehicle for their most frequent trip. 11 out 15 declared their intention to reduce their car-use in the following months. If the multimodal navigator will fulfil the expectations we could expect (according to our analysis) that this group could be induced to a modal shift ranging between 5 and 10% of our sample.

V. Conclusions

This research was conducted with the scope of: 1) assessing the validity of a general attitude measures, in the sense of Campbell, (2) understanding if the generally adopted measure of attitude is compelling within traditional frameworks derived from social psychology theories; (3) make use of psychological determinants influencing modal choice to highlight which participants are more likely to perform a modal shift from cars to public transport or soft modes. Thus, the contribution of this research is twofold. On one side, a theoretical assessment of state of the art highlighted some problems with current psycho-social research as applied in transport and allowed for the integration of methodological tools barely used in this field. On the other side, a direct application of marketing techniques has been performed to identify the segment of the population that would be induced to shift from car to alternative modes of transport thanks to the advanced traveller information systems. So, either at the theorical, methodological or empirical level, we have showed that:

1) the GEB questionnaire is a valid tool, even if it may need some adjustments, to measure the attitude (in the sense of Campbell) toward the environment. The one–dimension scale is behaviour-based and the Rasch Model adds some desirable properties to the scale;
2) a such measure of attitude performs well inside the Theory of Planned Behaviour, which, as regards to goodness of fit, outperformed both the Norm-Activation Theory and the Theory of Interpersonal Behaviour;
3) travel behaviour is, generally speaking, not influenced by either personal or subjective norms. However, values related to transport explain a great part of the observed behaviour;
4) half of our sample population form the consumer pool to which address the diffusion of Advanced Traveller Information Systems. Given that these kind of technological tools are able to integrate in app payment services for transport services fees, their diffusion is guaranteed;
5) up to 10% of modal shift induced by the development of multimodal navigator is possible.

This research contributed, firstly, in gathering evidence that a wider use of IRT for psychological measurement may be a benefit for the scientific community. Secondly, some newly developed psychological constructs, based on specific values, have been shown to have a significant influence on travel behaviour. We hope that this contribution will allow some other use of specific values and innovative factors research. Finally, we suggest that up to 10% of our sample population may be induced toward a greener urban mobility.

The design of this research took into account the different aspects that can contribute to affect the internal and external validity of the study. Although we have attempted to control the factors that could be a limitation to this research, it should be noted that the generalization of the results should be carefully made. This is due mainly to the relatively small sample size of the participants which are not representative of the general population. Despite the above limitations, we consider that the study can give a valid and pertinent contribution to the knowledge of the subject studied and may be seen as a relevant reference for its wide literature review, its aggregation of Rasch-based methodological features and for its study on how ATIS influence a transport modal shift.

As the Opticities research project – within this thesis has been conducted – is still ongoing, further investigation will be made in the near future. The analysis of *in-itinere* and *ex-post* dataset will allow us to understand whether or not people have modified their mobility patterns using the multimodal navigator TUeTO.

Defining attitude in sense of Campbell, and measuring it with mathematically refined tools that are Item Response Theory in general, and the Rasch Model in particular, should be the norm instead of the exception from now. Also, the research for psychological determinants behind decision making should not be limited to reproducing long-living theories. We saw the important role of transport related values in our composite model, specific values that are, at our knowledge, never taken into consideration in similar research project.

The power of affect toward car-use remains one main drawback for modal shift. The question is not new, Steg (2005) pointed out that the car in modern societies represent much more than a transport vehicle and carries myth, symbols and strong affective constructs. This is why, for the greater benefit of the population, suggestive advertisement, car-company organized tours, car exhibitions and car races should not be allowed anymore, in order to stop the reinforcement of self identity with a damaging industrial product.

Investment in transport-related services and infrastructure should be developed in order to increase the accessibility in all urban areas. In order to induce a modal shift, or to better accompany it when it will become necessary, all concerned parties should invest in the development of ATIS as well as in enhancing their functionalities, especially concerning payment integration. Moreover, with the development of sensors that follow individuals, we can imagine a real-time responsive transport system and owning critical data has become an important economic factor.

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Appendices

A. Rasch estimation procedures

A.1 Winsteps procedure

A.1.1 PROX

The WINSTEPS procedure begins with the Normal Approximation Estimation Algorithm (PROX), described by Linacre (1994).

We recall the general equation for Rasch model (equation 2, p.44) :

$$P(x_{ni}) = \frac{e^{x_{ni}(\theta_n - \beta_i)}}{1 + e^{(\theta_n - \beta_i)}} = \Psi\,(\theta_n - \beta_i). \tag{2}$$

For each item i, we define S_i, the raw score of success on item i across persons, and for each person n, R_n, the raw score of success of person n across items which are defined by equations (A.1):

$$\begin{cases} S_i = \sum_{n=1}^{N} x_{ni} \\ R_n = \sum_{i=1}^{k} x_{ni} \end{cases} \tag{A.1}$$

Summing $P(x_{ni})$ across all N persons for each item, we obtain equation (A.2):

$$\sum_{n=1}^{N} P(x_{ni}) = \sum_{n=1}^{N} \Psi\,(\theta_n - \beta_i) = E(S_i) = S_i. \tag{A.2}$$

Assuming θ follows a normal distribution with mean μ_i and standard deviation σ_i, summing across $\theta_n$is approximated by integrating across N_i normal distribution of θ , thus we obtain equation (A.3):

$$S_i \;\approx\; N_i \int_{-\infty}^{+\infty} \Psi\,(\theta_n - \beta_i)\,\frac{d}{d\theta}\left\{\Phi\left(\frac{\theta - \mu_i}{\sigma_i}\right)\right\} d\theta, \tag{A.3}$$

where Φ is the *normal cumulative distribution function*. Following Camilli's equivalence (Camilli, 1994) between the logistic function and the normal ogive given by equation (A.4):

$$\Psi\,(\mathrm{x}) \approx \Phi\left(\frac{\mathrm{x}}{1.702}\right), \tag{A.4}$$

we obtain equation (A.5):

$$S_i \;\approx\; N_i \int_{-\infty}^{+\infty} \Phi\,\left(\frac{\theta - \beta_i}{1.702}\right)\frac{d}{d\theta}\left\{\Phi\left(\frac{\theta - \mu_i}{\sigma_i}\right)\right\}d\theta. \tag{A.5}$$

Moreover, we have for Φ the property given by equation (A.6):

$$\int_{-\infty}^{+\infty} \Phi\,(a + bt)\,\Phi'(\mathrm{t})dt = \;\Phi\,\left(\frac{\mathrm{a}}{\sqrt{(1 + \mathrm{b}^2)}}\right). \tag{A.6}$$

It follows that equation (A.5) reduces to equation (A.7):

$$\frac{S_i}{N_i} \approx \;\Phi\,\left(\frac{\mu_\mathrm{i} - \beta_\mathrm{i}}{\sqrt{\sigma^2 + 2.9}}\right) \approx \Psi\left(\frac{\mu_\mathrm{i} - \beta_\mathrm{i}}{\sqrt{1 + \frac{\sigma_\mathrm{i}^2}{2.9}}}\right), \tag{A.7}$$

from which we can estimate $\widehat{\beta_i}$ that becomes equation (A.8)

$$\widehat{\beta_i} \approx \mu_i - \sqrt{\left(1 + \frac{\sigma_i^2}{2.9}\right)} \, ln\left(\frac{S_i}{(N_i - S_i)}\right). \tag{A.8}$$

And, similarly for person abilities estimates, we have equation (A.9)

$$\widehat{\theta_n} \approx \mu_n - \sqrt{\left(1 + \frac{\sigma_n^2}{2.9}\right)} \, ln\left(\frac{R_n}{(N_n - S_n)}\right) \tag{A.9}$$

The iteration starts with all parameters set to 0, then $\widehat{\beta_i}$are calculated for every item. The mean, $\bar{\beta}$, is subtracted from every $\widehat{\beta_i}$in order to maintain the sum of item difficulties at 0, in order to force an origin for the scale of estimated item difficulties. $\widehat{\theta_n}$are then calculated for every person before the next step of iteration with new estimations of β_i. When the differences between two successive estimates, for both β_i and θ_n, is no larger than 0.5 logits, the convergence is considered reached.

A.1.2 JMLE

Final estimates of PROX will serve for the successive iteration procedure using Unconditional Joint Maximum Likelihood Estimation (JMLE or UCON). Wright and Douglas (1977) formulated it as follow:

the likelihood of the data matrix is given by the continued product of P(x_{ni}), i.e., equation (A.10):

$$\Lambda = \prod_{n=1}^{N}\prod_{i=1}^{k} P(x_{ni}) = \frac{e^{\sum_{n=1}^{N}\sum_{i=1}^{k} x_{ni}(\theta_n-\beta_i)}}{\prod_{n=1}^{N}\prod_{i=1}^{k}(1+e^{(\theta_n-\beta_i)})}, \tag{A.10}$$

and its log-form is as in equation (A.10)

$$\lambda = \ln(\Lambda) = \sum_{n=1}^{N} R_n\,\theta_n - \sum_{i=1}^{k} S_i\,\beta_i - \sum_{n=1}^{N}\sum_{i=1}^{k} ln\left(1+e^{(\theta_n-\beta_i)}\right). \tag{A.11}$$

With the help of a condition on the origin for item difficulty ($\sum \beta_i = 0$), we can partially derive λ with respect to θ_n and β_i. The first and second partial derivative become are described by system of equation (A.12)

$$\begin{cases} \begin{cases} \dfrac{\partial\lambda}{\partial\theta_n} = R_n - \sum_{i=1}^{k}\pi_{ni} \\ \dfrac{\partial^2\lambda}{\partial{\theta_n}^2} = -\sum_{i=1}^{k}\pi_{ni}\,(1-\pi_{ni}) \end{cases} \\ \begin{cases} \dfrac{\partial\lambda}{\partial\beta_i} = -S_i + \sum_{i=n}^{N}\pi_{ni} \\ \dfrac{\partial^2\lambda}{\partial{\beta_i}^2} = -\sum_{n=1}^{N}\pi_{ni}\,(1-\pi_{ni}) \end{cases} \end{cases} ,with\;\pi_{ni} = \frac{e^{(\theta_n-\beta_i)}}{1+e^{(\theta_n-\beta_i)}}. \tag{A.12}$$

Solutions for $\frac{\partial^x\lambda}{\partial{\beta_i}^x}$ depend on the presence of values for person ability estimates and, as un-weighted test score are assumed to be sufficient statistics, persons with identical raw scores will obtain identical ability estimates. Therefore, we can group them letting

- $\widehat{\theta_r}$ be the ability estimate for person with raw score r,
- n_r be the number of person with raw score r,

then the probability that a person with raw score r succeed on item i is given by equation (A.13)

$$P_{ri} = \frac{e^{(\widehat{\theta_r} - \beta_i)}}{1 + e^{(\widehat{\theta_r} - \beta_i)}}. It\ follows\ that\ \sum_{n=1}^{N} P_{ni} = \sum_{r=1}^{L-1} n_r\, P_{ri}. \qquad \text{(A.13)}$$

From there, and using the lasts outputs from PROX for $m = 0$, we can apply the Newton-Raphson iteration method to improve each estimate, i.e., we follow equation (A.14):

$$\begin{aligned} \widehat{\beta_i^{(m+1)}} &= \widehat{\beta_i^{(m)}} - \frac{f(\beta_i)}{f'(\beta_i)} \\ &= \widehat{\beta_i^{(m)}} + \frac{Observed\ Score - Modeled\ Expected\ Score}{Modeled\ Variance} \\ &= \ \widehat{\beta_i^{(m)}} - \left(\frac{-S_i + \sum_{r=1}^{k-1} n_r P_{ri}^{(m)}}{-\sum_{r=1}^{k-1} n_r P_{ri}^{(m)} \left(1 - P_{ri}^{(m)}\right)} \right), i \in [1; k]. \end{aligned} \qquad \text{(A.14)}$$

And, in the same way for person ability estimates, we obtain the iteration given by equation (A.15):

$$\widehat{\theta_r^{(m+1)}} = \widehat{\theta_r^{(m)}} - \left(\frac{R + \sum_i^k P_{ri}^{(m)}}{-\sum_{i=1}^{k} P_{ri}^{(m)} \left(1 - P_{ri}^{(m)}\right)} \right), r \in [1; k[\,, \qquad \text{(A.15)}$$

until stability is reached.

A.2 eRm procedure-JML

The *RM* method of the eRm package for R estimates item difficulties using Conditional Maximum Likelihood (CML) for item estimates. The equations of CML, as described by Mair and Hatzinger (2007) are derived from equation 2 (p.44). We write the conditional probability of a given response pattern $x_n$for a given person n in equation (A.16):

$$P(x_n|\theta_n, \beta) = \prod_{i=1}^{k} P(x_{ni}). \tag{A.16}$$

All possible response pattern for a given raw score R_n, such that $\sum_{i=1}^{k} x_{ni} = R_n$, leads us to formulate the conditional probability of getting R_n, i.e., equation (A.17)

$$\begin{aligned} P(R_n|\theta_n, \beta) &= \sum_{\sum_{i=1}^{k} x_{ni}=R_n} P(x_n|\theta_n, \beta) \\ &= \sum_{\sum_{i=1}^{k} x_{ni}=R_n} \prod_{i=1}^{k} \frac{e^{x_{ni}(\theta_n-\beta_i)}}{1+e^{(\theta_n-\beta_i)}} \\ &= \frac{e^{R_n\theta_n}\gamma_r}{\prod_{i=1}^{k}(1+e^{(\theta_n-\beta_i)})}, \end{aligned} \tag{A.17}$$

where γ_r is the *elementary symmetric function of order r in the parameter* β, which represents the combinatorial aspect of possible response patterns for a given raw score r (Gustafsson, 1980). γ_r is described by equation (A.18):

$$\gamma_r = \sum\nolimits_{\sum_{i=1}^{k} x_i=r} e^{-\sum_{i=1}^{k}\beta_i x_i}. \tag{A.18}$$

Finally, the conditional probability of observing a given pattern x_n given the raw score R_n is given by equation (A.19):

$$P(x_n|R_n, \beta) = \frac{P(x_n|\theta_n, \beta)}{P(R_n|\theta_n, \beta)}. \tag{A.19}$$

The conditional likelihood expression for the whole sample is found by taking the product of equation (A.19) over the persons, where n_r is the number of person with score R. We obtain equation (A.20):

$$\Lambda(\beta|R) = P(x|R,\beta) = \frac{e^{\sum_{i=1}^{k} -\beta_i x_i}}{\prod_{r=0}^{k} {\gamma_r}^{n_r}}. \tag{A.20}$$

Regarding estimates of person abilities, the *person.parameter* method of the eRm package makes use of the Newton-Raphson iteration to solve the Maximum Likelihood formulation, as expressed by equation (A.15).

B. Winsteps output

B.1 Residuals-based PCA

```
TABLE 23.0
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
----------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%
    Unexplned variance in 2nd contrast =          2.3   4.1%   6.0%
    Unexplned variance in 3rd contrast =          2.1   3.8%   5.5%
    Unexplned variance in 4th contrast =          1.9   3.3%   4.9%
    Unexplned variance in 5th contrast =          1.7   3.1%   4.6%

       STANDARDIZED RESIDUAL VARIANCE SCREE PLOT

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

VARIANCE COMPONENTS

Approximate relationships between the Person measures

PCA Contrast	Item Clusters	Pearson Correlation	Disattenuated Correlation	Pearson+Extr Correlation	Disattenuated+Extr Correlation
1	1 - 3	-0.0889	-0.1944		
1	1 - 2	0.2405	0.6545		
1	2 - 3	0.2655	0.5821		
2	1 - 3	0.0023	0.0050		
2	1 - 2	0.3087	0.8194		
2	2 - 3	0.3546	0.8521		
3	1 - 3	-0.1915	-0.4341		
3	1 - 2	0.2152	0.4755		
3	2 - 3	0.3435	0.6947		
4	1 - 3	-0.0968	-0.4135		
4	1 - 2	0.3093	0.6095		
4	2 - 3	0.2388	0.9748		
5	1 - 3	0.0398	0.1540		
5	1 - 2	0.3147	0.7909		
5	2 - 3	0.2770	0.8677		

```
TABLE 23.1 GEB_Answer_Anagrafe_Recoded_Changed.x ZOU128WS.TXT  Mar 23
19:28 2016
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
------------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%

       STANDARDIZED RESIDUAL CONTRAST 1 PLOT

      -4      -3      -2      -1       0       1       2       3
4
      -+-------+-------+-------+-------+-------+-------+------+-------
+- COUNT  CLUSTER
   .8 +                                |
+
      |                                |   A  B
| 2      1
   .7 +                                |
+
      |                                |
|
C  .6 +                                |
+
O     |                                |                     C
| 1      1
N  .5 +                                |  D
+ 1      1
T     |                                |
|
R  .4 +                                |
+
A     |                                |
|
S  .3 +                                |       E
+ 1      2
T     |                                |
|
   .2 +                      F         |
+ 1      2
1     |                            H   | G
| 2      2
   .1 +                                |
+
```

```
L     | I                             J
| 2       2
O  .0 +----------------------------K-L-|--------------M----------------
-+ 3      2
A     |          Q                   RSPO              N
| 6       2
D -.1 +      s                o       | p r       q
+ 5       3
I     |      k                        |    m          nl
| 4       3
N -.2 +                           h   |                  j        i
+ 3       3
G     |                               | f     g
| 2       3
  -.3 +      d                  ec    |
+ 3       3
      |      b                        |
| 1       3
  -.4 +                               | a
+ 1       3
      |                               |
|
      -+-------+-------+-------+-------+-------+-------+-------+-------
+-
      -4      -3      -2      -1       0       1       2       3
4
                                 Item MEASURE
 COUNT: 1    4   1           1 1 113 1 2 6221 12   1  12 11  1     1

                                                111  1  1
Person                                 11 2478 7342 85 74 8 61    3
                                         T    S    M     S    T
%TILE                                  0   10 20 50 70 80 90     99
```

Approximate relationships between the Person measures

PCA Contrast	Item Clusters	Pearson Correlation	Disattenuated Correlation	Pearson+Extr Correlation	Disattenuated+Extr Correlation
1	1 - 3	-0.0889	-0.1944		
1	1 - 2	0.2405	0.6545		
1	2 - 3	0.2655	0.5821		

TABLE 23.2
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

CONTRAST 1 FROM PRINCIPAL COMPONENT ANALYSIS
STANDARDIZED RESIDUAL LOADINGS FOR Item (SORTED BY LOADING)

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER Ite	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER Ite
1	.77	.54	.98	1.04	A 40 T5	-.41	.28	1.04	1.03	a 9 R2
1	.73	.92	.98	.99	B 36 T1	-.34	-3.22	.99	.63	b 13 R6
1	.55	2.78	1.04	1.12	C 37 T2	-.30	-.59	1.10	1.38	c 8 R1
1	.48	.43	.91	.86	D 38 T3	-.29	-3.22	1.00	.70	d 12 R5
1	.28	1.03	1.02	1.02	E 24 CE4	-.29	-.71	.95	.88	e 34 V3
1	.22	-1.22	.99	.88	F 18 AE5	-.26	.20	.99	.97	f 2 CS2
1	.16	.28	.93	.87	G 16 AE3	-.25	1.06	.96	.94	g 30 RR4
1	.16	-.53	.92	.84	H 23 CE3	-.21	-.53	1.10	1.28	h 7 CS7
1	.06	-3.92	1.02	1.87	I 27 RR1	-.19	3.45	1.01	.88	i 33 V2
1	.03	.04	1.03	1.00	J 20 AE7	-.19	2.34	.95	.90	j 35 V4
1	.02	-.48	1.07	1.17	K 6 CS6	-.16	-3.22	1.00	1.00	k 11 R4
1	.02	-.22	1.04	1.06	L 19 AE6	-.16	1.97	.98	.96	l 31 RR5
1	.00	1.82	.95	.93	M 21 CE1	-.15	.58	.92	.89	m 32 V1
						-.13	1.97	1.01	.99	n 26 CE6
						-.12	-1.05	1.01	1.03	o 15 AE2
						-.11	.20	.92	.88	p 10 R3
						-.11	1.47	.98	.97	q 28 RR2
						-.11	.51	1.09	1.17	r 39 T4
						-.08	-3.22	1.02	1.53	s 5 CS5
						-.06	.28	.93	.86	S 29 RR3

```
|      |        |                    |           | |  -.05 |    -.04 1.03
.97 |R   17 AE4 |
|      |        |                    |           | |  -.04 |   -2.80  .99
.94 |Q    3 CS3 |
|      |        |                    |           | |  -.04 |     .28 1.03
1.05 |P   22 CE2 |
|      |        |                    |           | |  -.03 |     .32 1.08
1.11 |O    1 CS1 |
|      |        |                    |           | |  -.03 |    2.21 1.14
1.15 |N    4 CS4 |
------------------------------------------------ ---------------------
-------------------
```

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY	NUMBER	Ite
1 1	.77	.54	.98	1.04	A	40	T5
1 1	.73	.92	.98	.99	B	36	T1
1 1	.55	2.78	1.04	1.12	C	37	T2
1 1	.48	.43	.91	.86	D	38	T3
1 2	.28	1.03	1.02	1.02	E	24	CE4
1 2	.22	-1.22	.99	.88	F	18	AE5
1 2	.16	.28	.93	.87	G	16	AE3
1 2	.16	-.53	.92	.84	H	23	CE3
1 2	.06	-3.92	1.02	1.87	I	27	RR1
1 2	.03	.04	1.03	1.00	J	20	AE7
1 2	.02	-.48	1.07	1.17	K	6	CS6
1 2	.02	-.22	1.04	1.06	L	19	AE6
1 2	.00	1.82	.95	.93	M	21	CE1
1 3	-.41	.28	1.04	1.03	a	9	R2
1 3	-.34	-3.22	.99	.63	b	13	R6
1 3	-.30	-.59	1.10	1.38	c	8	R1
1 3	-.29	-3.22	1.00	.70	d	12	R5
1 3	-.29	-.71	.95	.88	e	34	V3
1 3	-.26	.20	.99	.97	f	2	CS2
1 3	-.25	1.06	.96	.94	g	30	RR4
1 3	-.21	-.53	1.10	1.28	h	7	CS7
1 3	-.19	3.45	1.01	.88	i	33	V2
1 3	-.19	2.34	.95	.90	j	35	V4
1 3	-.16	-3.22	1.00	1.00	k	11	R4
1 3	-.16	1.97	.98	.96	l	31	RR5
1 3	-.15	.58	.92	.89	m	32	V1
1 3	-.13	1.97	1.01	.99	n	26	CE6
1 3	-.12	-1.05	1.01	1.03	o	15	AE2
1 3	-.11	.20	.92	.88	p	10	R3
1 3	-.11	1.47	.98	.97	q	28	RR2
1 3	-.11	.51	1.09	1.17	r	39	T4
1 2	-.08	-3.22	1.02	1.53	s	5	CS5
1 2	-.06	.28	.93	.86	S	29	RR3
1 2	-.05	-.04	1.03	.97	R	17	AE4
1 2	-.04	-2.80	.99	.94	Q	3	CS3
1 2	-.04	.28	1.03	1.05	P	22	CE2
1 2	-.03	.32	1.08	1.11	O	1	CS1
1 2	-.03	2.21	1.14	1.15	N	4	CS4

TABLE 23.3
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

Item CONTRAST 1 CONTRASTING RESPONSES BY Person

Person FAVORS TOP

TOP 4 Item			BOTTOM 4 Item				
HIGH	EXP.	LOW	HIGH	EXP.	LOW		
4	0	0	0	3	1	38	218
2	2	0	0	1	3	100	78
4	0	0	0	4	0	5	153
2	2	0	0	2	2	7	173
3	1	0	0	3	1	65	217
2	2	0	0	2	2	77	114
2	2	0	0	3	1	11	207
2	1	1	0	2	2	12	263
2	2	0	0	3	1	87	202
3	1	0	0	4	0	93	45
1	3	0	0	2	2	107	133
1	3	0	0	2	2	109	149

Person FAVORS BOTTOM

TOP 4 Item			BOTTOM 4 Item				
HIGH	EXP.	LOW	HIGH	EXP.	LOW		
0	1	3	0	4	0	45	70
0	1	3	0	4	0	48	100
0	1	3	0	4	0	68	48
0	1	3	0	4	0	76	107
0	1	3	0	4	0	95	54
0	1	3	0	4	0	128	231
0	2	2	0	4	0	14	72
0	2	2	0	4	0	30	156
0	2	2	0	4	0	43	51
0	2	2	0	4	0	55	162
0	2	2	0	4	0	64	215
0	2	2	0	4	0	69	55
0	2	2	0	4	0	71	67
0	2	2	0	4	0	73	82
0	2	2	0	4	0	75	104
0	2	2	0	4	0	83	145
0	2	2	0	4	0	90	257
0	2	2	0	4	0	110	150
0	2	2	0	4	0	111	151
0	2	2	0	4	0	116	184
0	2	2	0	4	0	125	219
0	2	2	0	4	0	127	229

```
TABLE 23.11
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
-----------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%
    Unexplned variance in 2nd contrast =          2.3   4.1%   6.0%

       STANDARDIZED RESIDUAL CONTRAST 2 PLOT

      -4      -3      -2      -1       0       1       2       3
4
      -+-------+-------+-------+-------+-------+-------+-------+-------
+- COUNT  CLUSTER
       |                               |
|
C  .5 +                               |           q
+ 1      1
O      |                            L |
| 1      1
N  .4 +                               |
+
T      |                               |
|
R  .3 + I                             J f     E
+ 4      1
A      |        Q               H   R
| 3      1
S  .2 +                         h   |                 j
+ 2      1
T      |                       c    |
| 1      2
   .1 +                               | p            M
+ 2      2
2      |                    o       |                 N
| 2      2
   .0 +--------------------------K---|------B-----------------------
-+ 2      2
L      |      s                        |  OA   g       l
| 5      2
O -.1 +                               | G
+ 1      2
A      |                               | aPr           n
| 4      3
```

```
D -.2 +                                |                     C
+ 1      3
I      |      b              F         |
| 2      3
N -.3 +       kd                       |
+ 2      3
G      |                         e     |    m
| 2      3
  -.4 +                                | SD                        i
+ 3      3
       |                               |
|
      -+-------+-------+-------+-------+-------+-------+-------+-------
+-
      -4      -3      -2      -1       0       1       2       3
4
                                 Item MEASURE
 COUNT: 1    4   1           1 1 113 1 2 6221 12   1  12 11  1     1

                                             111  1  1
Person                               11 2478 7342 85 74 8 61    3
                                       T    S    M     S    T
%TILE                                0   10 20 50 70 80 90      99

Approximate relationships between the Person measures
 PCA      Item      Pearson       Disattenuated Pearson+Extr
Disattenuated+Extr
Contrast  Clusters  Correlation   Correlation   Correlation
Correlation
 2        1 - 3     0.0023        0.0050
 2        1 - 2     0.3087        0.8194
 2        2 - 3     0.3546        0.8521
```

TABLE 23.12
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

CONTRAST 2 FROM PRINCIPAL COMPONENT ANALYSIS
STANDARDIZED RESIDUAL LOADINGS FOR Item (SORTED BY LOADING)

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER	Ite	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER	Ite
2	.52	1.47	.98	.97	q 28	RR2	-.41	.43	.91	.86	D 38	T3
2	.43	-.22	1.04	1.06	L 19	AE6	-.39	.28	.93	.86	S 29	RR3
2	.32	.20	.99	.97	f 2	CS2	-.39	3.45	1.01	.88	i 33	V2
2	.30	.04	1.03	1.00	J 20	AE7	-.34	.58	.92	.89	m 32	V1
2	.30	-3.92	1.02	1.87	I 27	RR1	-.33	-.71	.95	.88	e 34	V3
2	.29	1.03	1.02	1.02	E 24	CE4	-.32	-3.22	1.00	1.00	k 11	R4
2	.24	-2.80	.99	.94	Q 3	CS3	-.30	-3.22	1.00	.70	d 12	R5
2	.24	-.53	.92	.84	H 23	CE3	-.26	-1.22	.99	.88	F 18	AE5
2	.23	-.04	1.03	.97	R 17	AE4	-.25	-3.22	.99	.63	b 13	R6
2	.22	-.53	1.10	1.28	h 7	CS7	-.22	2.78	1.04	1.12	C 37	T2
2	.18	2.34	.95	.90	j 35	V4	-.16	.28	1.04	1.03	a 9	R2
2	.13	-.59	1.10	1.38	c 8	R1	-.16	.28	1.03	1.05	P 22	CE2
2	.11	1.82	.95	.93	M 21	CE1	-.15	.51	1.09	1.17	r 39	T4
2	.09	.20	.92	.88	p 10	R3	-.13	1.97	1.01	.99	n 26	CE6
2	.04	-1.05	1.01	1.03	o 15	AE2	-.10	.28	.93	.87	G 16	AE3
2	.03	2.21	1.14	1.15	N 4	CS4	-.07	.54	.98	1.04	A 40	T5
2	.01	-.48	1.07	1.17	K 6	CS6	-.04	-3.22	1.02	1.53	s 5	CS5
							-.04	1.97	.98	.96	l 31	RR5
							-.03	.32	1.08	1.11	O 1	CS1
							-.03	1.06	.96	.94	g 30	RR4

```
|       |        |                   |           | |  -.01 |      .92  .98
.99 |B   36 T1  |
------------------------------------------------ ----------------------
-------------------
```

CONTRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ		ENTRY NUMBER	Ite
2 1	.52	1.47	.98	.97	q	28	RR2
2 1	.43	-.22	1.04	1.06	L	19	AE6
2 1	.32	.20	.99	.97	f	2	CS2
2 1	.30	.04	1.03	1.00	J	20	AE7
2 1	.30	-3.92	1.02	1.87	I	27	RR1
2 1	.29	1.03	1.02	1.02	E	24	CE4
2 1	.24	-2.80	.99	.94	Q	3	CS3
2 1	.24	-.53	.92	.84	H	23	CE3
2 1	.23	-.04	1.03	.97	R	17	AE4
2 1	.22	-.53	1.10	1.28	h	7	CS7
2 1	.18	2.34	.95	.90	j	35	V4
2 2	.13	-.59	1.10	1.38	c	8	R1
2 2	.11	1.82	.95	.93	M	21	CE1
2 2	.09	.20	.92	.88	p	10	R3
2 2	.04	-1.05	1.01	1.03	o	15	AE2
2 2	.03	2.21	1.14	1.15	N	4	CS4
2 2	.01	-.48	1.07	1.17	K	6	CS6
2 3	-.41	.43	.91	.86	D	38	T3
2 3	-.39	.28	.93	.86	S	29	RR3
2 3	-.39	3.45	1.01	.88	i	33	V2
2 3	-.34	.58	.92	.89	m	32	V1
2 3	-.33	-.71	.95	.88	e	34	V3
2 3	-.32	-3.22	1.00	1.00	k	11	R4
2 3	-.30	-3.22	1.00	.70	d	12	R5
2 3	-.26	-1.22	.99	.88	F	18	AE5
2 3	-.25	-3.22	.99	.63	b	13	R6
2 3	-.22	2.78	1.04	1.12	C	37	T2
2 3	-.16	.28	1.04	1.03	a	9	R2
2 3	-.16	.28	1.03	1.05	P	22	CE2
2 3	-.15	.51	1.09	1.17	r	39	T4
2 2	-.13	1.97	1.01	.99	n	26	CE6
2 2	-.10	.28	.93	.87	G	16	AE3
2 2	-.07	.54	.98	1.04	A	40	T5
2 2	-.04	-3.22	1.02	1.53	s	5	CS5
2 2	-.04	1.97	.98	.96	l	31	RR5
2 2	-.03	.32	1.08	1.11	O	1	CS1
2 2	-.03	1.06	.96	.94	g	30	RR4
2 2	-.01	.92	.98	.99	B	36	T1

```
TABLE 23.21
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
------------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%
    Unexplned variance in 2nd contrast =          2.3   4.1%   6.0%
    Unexplned variance in 3rd contrast =          2.1   3.8%   5.5%

       STANDARDIZED RESIDUAL CONTRAST 3 PLOT

      -4      -3      -2      -1       0       1       2       3
4
      -+-------+-------+-------+-------+-------+-------+-------+-------
+- COUNT  CLUSTER
   .5 +                                |
+
C     |                                J                 N
| 2      1
O  .4 +                                |  O
+ 1      1
N     |                                |   r
| 1      1
T  .3 +      s                         |
+ 1      1
R     |                                |               n     C
| 2      1
A  .2 + I                          K   | f
+ 3      1
S     |          Q                     |       g
| 2      1
T  .1 +                                | PS                j
+ 3      2
      |                                |  D
| 1      2
3  .0 +------k-------------------------|-p----------------------------
-+ 2      2
      |                       o e     R a
| 4      2
L -.1 +                            H L |   Am
+ 4      2
O     |      d               F         |               l
| 3      2
```

```
A -.2 +                              h    |                            i
+ 2       3
D     |                                   |      BE
| 2       3
I -.3 +      b                            |
+ 1       3
N     |                                   | G          q  M
| 3       3
G -.4 +                                   |
+
      |                             c     |
| 1       3
      -+-------+-------+-------+-------+-------+-------+-------+-------
+-
      -4      -3      -2      -1       0       1       2       3
4
                                  Item MEASURE
 COUNT: 1    4   1           1 1 113 1 2 6221 12   1  12 11  1     1

                                          111  1  1
Person                           11 2478 7342 85 74 8 61    3
                                   T    S    M     S    T
%TILE                            0   10 20 50 70 80 90     99

Approximate relationships between the Person measures
 PCA      Item      Pearson       Disattenuated Pearson+Extr
Disattenuated+Extr
Contrast  Clusters  Correlation   Correlation   Correlation
Correlation
 3        1 - 3     -0.1915       -0.4341
 3        1 - 2     0.2152        0.4755
 3        2 - 3     0.3435        0.6947
```

TABLE 23.22
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

CONTRAST 3 FROM PRINCIPAL COMPONENT ANALYSIS
STANDARDIZED RESIDUAL LOADINGS FOR Item (SORTED BY LOADING)

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER Ite	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER Ite
3	.46	2.21	1.14	1.15	N 4 CS4	-.45	-.59	1.10	1.38	c 8 R1
3	.46	.04	1.03	1.00	J 20 AE7	-.36	.28	.93	.87	G 16 AE3
3	.41	.32	1.08	1.11	O 1 CS1	-.35	1.82	.95	.93	M 21 CE1
3	.35	.51	1.09	1.17	r 39 T4	-.33	1.47	.98	.97	q 28 RR2
3	.30	-3.22	1.02	1.53	s 5 CS5	-.31	-3.22	.99	.63	b 13 R6
3	.27	1.97	1.01	.99	n 26 CE6	-.26	1.03	1.02	1.02	E 24 CE4
3	.23	2.78	1.04	1.12	C 37 T2	-.26	.92	.98	.99	B 36 T1
3	.20	.20	.99	.97	f 2 CS2	-.21	-.53	1.10	1.28	h 7 CS7
3	.20	-3.92	1.02	1.87	I 27 RR1	-.20	3.45	1.01	.88	i 33 V2
3	.19	-.48	1.07	1.17	K 6 CS6	-.15	-3.22	1.00	.70	d 12 R5
3	.17	-2.80	.99	.94	Q 3 CS3	-.15	-1.22	.99	.88	F 18 AE5
3	.17	1.06	.96	.94	g 30 RR4	-.15	1.97	.98	.96	l 31 RR5
3	.09	2.34	.95	.90	j 35 V4	-.08	-.22	1.04	1.06	L 19 AE6
3	.08	.28	1.03	1.05	P 22 CE2	-.08	-.53	.92	.84	H 23 CE3
3	.08	.28	.93	.86	S 29 RR3	-.08	.58	.92	.89	m 32 V1
3	.05	.43	.91	.86	D 38 T3	-.08	.54	.98	1.04	A 40 T5
						-.07	-.71	.95	.88	e 34 V3
						-.06	.28	1.04	1.03	a 9 R2
						-.06	-1.05	1.01	1.03	o 15 AE2
						-.03	-.04	1.03	.97	R 17 AE4

```
|       |       |                    |            | |  -.02 |   -3.22 1.00
1.00 |k   11 R4  |
|       |       |                    |            | |  -.01 |     .20  .92
.88 |p   10 R3  |
------------------------------------------------ ----------------------
-------------------
```

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ		ENTRY NUMBER	Ite
3 1	.46	2.21	1.14	1.15	N	4	CS4
3 1	.46	.04	1.03	1.00	J	20	AE7
3 1	.41	.32	1.08	1.11	O	1	CS1
3 1	.35	.51	1.09	1.17	r	39	T4
3 1	.30	-3.22	1.02	1.53	s	5	CS5
3 1	.27	1.97	1.01	.99	n	26	CE6
3 1	.23	2.78	1.04	1.12	C	37	T2
3 1	.20	.20	.99	.97	f	2	CS2
3 1	.20	-3.92	1.02	1.87	I	27	RR1
3 1	.19	-.48	1.07	1.17	K	6	CS6
3 1	.17	-2.80	.99	.94	Q	3	CS3
3 1	.17	1.06	.96	.94	g	30	RR4
3 2	.09	2.34	.95	.90	j	35	V4
3 2	.08	.28	1.03	1.05	P	22	CE2
3 2	.08	.28	.93	.86	S	29	RR3
3 2	.05	.43	.91	.86	D	38	T3
3 3	-.45	-.59	1.10	1.38	c	8	R1
3 3	-.36	.28	.93	.87	G	16	AE3
3 3	-.35	1.82	.95	.93	M	21	CE1
3 3	-.33	1.47	.98	.97	q	28	RR2
3 3	-.31	-3.22	.99	.63	b	13	R6
3 3	-.26	1.03	1.02	1.02	E	24	CE4
3 3	-.26	.92	.98	.99	B	36	T1
3 3	-.21	-.53	1.10	1.28	h	7	CS7
3 3	-.20	3.45	1.01	.88	i	33	V2
3 2	-.15	-3.22	1.00	.70	d	12	R5
3 2	-.15	-1.22	.99	.88	F	18	AE5
3 2	-.15	1.97	.98	.96	l	31	RR5
3 2	-.08	-.22	1.04	1.06	L	19	AE6
3 2	-.08	-.53	.92	.84	H	23	CE3
3 2	-.08	.58	.92	.89	m	32	V1
3 2	-.08	.54	.98	1.04	A	40	T5
3 2	-.07	-.71	.95	.88	e	34	V3
3 2	-.06	.28	1.04	1.03	a	9	R2
3 2	-.06	-1.05	1.01	1.03	o	15	AE2
3 2	-.03	-.04	1.03	.97	R	17	AE4
3 2	-.02	-3.22	1.00	1.00	k	11	R4
3 2	-.01	.20	.92	.88	p	10	R3

```
TABLE 23.31
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
-----------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%
    Unexplned variance in 2nd contrast =          2.3   4.1%   6.0%
    Unexplned variance in 3rd contrast =          2.1   3.8%   5.5%
    Unexplned variance in 4th contrast =          1.9   3.3%   4.9%

       STANDARDIZED RESIDUAL CONTRAST 4 PLOT

      -4      -3      -2      -1       0       1       2       3
4
      -+-------+-------+-------+-------+-------+-------+-------+-------
+- COUNT  CLUSTER
      |                                |
|
   .5 +                                |                           i
+ 1      1
C     |                                |
|
O  .4 +                                |
+
N     |                                |
|
T  .3 +                                | f               j
+ 2      1
R     |                     F     H L | P  m          n
| 6      1
A  .2 +                                |   r
+ 1      1
S     |                                |
|
T  .1 +                       o        |                 N
+ 2      2
      |      s                   e     | G
| 3      2
4  .0 +-I------------------------------R--D----E---q-------------------
-+ 5      2
      |                                |   A  B
| 2      2
L -.1 +      b                         | pO          M
+ 4      2
```

```
O     |                              | aS    g
| 3       2
A -.2 +                         h    |              l     C
+ 3       3
D     |      d   Q              c    |
| 3       3
I -.3 +                              |
+
N     |                              J
| 1       3
G -.4 +      k                       |
+ 1       3
      |                              |
|
  -.5 +                         K    |
+ 1       3
      -+-------+-------+-------+-------+-------+-------+-------+-------
+-
      -4      -3      -2      -1       0       1       2       3
4
                                Item MEASURE
 COUNT: 1    4   1           1 1 113 1 2 6221 12   1  12 11  1     1

                                            111  1  1
Person                            11 2478 7342 85 74 8 61     3
                                    T    S    M     S    T
%TILE                             0   10 20 50 70 80 90     99

Approximate relationships between the Person measures
 PCA      Item      Pearson       Disattenuated Pearson+Extr
Disattenuated+Extr
Contrast  Clusters  Correlation   Correlation   Correlation
Correlation
 4        1 - 3     -0.0968       -0.4135
 4        1 - 2     0.3093        0.6095
 4        2 - 3     0.2388        0.9748
```

TABLE 23.32
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

CONTRAST 4 FROM PRINCIPAL COMPONENT ANALYSIS
STANDARDIZED RESIDUAL LOADINGS FOR Item (SORTED BY LOADING)

CON- TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER	Ite	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY NUMBER	Ite
4	.50	3.45	1.01	.88	i 33	V2	-.50	-.48	1.07	1.17	K 6	CS6
4	.32	2.34	.95	.90	j 35	V4	-.40	-3.22	1.00	1.00	k 11	R4
4	.30	.20	.99	.97	f 2	CS2	-.35	.04	1.03	1.00	J 20	AE7
4	.27	1.97	1.01	.99	n 26	CE6	-.27	-3.22	1.00	.70	d 12	R5
4	.26	-1.22	.99	.88	F 18	AE5	-.26	-.59	1.10	1.38	c 8	R1
4	.26	-.53	.92	.84	H 23	CE3	-.25	-2.80	.99	.94	Q 3	CS3
4	.25	-.22	1.04	1.06	L 19	AE6	-.21	-.53	1.10	1.28	h 7	CS7
4	.23	.28	1.03	1.05	P 22	CE2	-.20	1.97	.98	.96	l 31	RR5
4	.23	.58	.92	.89	m 32	V1	-.18	2.78	1.04	1.12	C 37	T2
4	.20	.51	1.09	1.17	r 39	T4	-.16	.28	1.04	1.03	a 9	R2
4	.11	2.21	1.14	1.15	N 4	CS4	-.16	.28	.93	.86	S 29	RR3
4	.10	-1.05	1.01	1.03	o 15	AE2	-.16	1.06	.96	.94	g 30	RR4
4	.05	-.71	.95	.88	e 34	V3	-.11	.32	1.08	1.11	O 1	CS1
4	.03	-3.22	1.02	1.53	s 5	CS5	-.11	.20	.92	.88	p 10	R3
4	.03	.28	.93	.87	G 16	AE3	-.10	1.82	.95	.93	M 21	CE1
4	.02	-.04	1.03	.97	R 17	AE4	-.09	-3.22	.99	.63	b 13	R6
4	.02	1.03	1.02	1.02	E 24	CE4	-.07	.54	.98	1.04	A 40	T5
4	.01	1.47	.98	.97	q 28	RR2	-.05	.92	.98	.99	B 36	T1
4	.00	-3.92	1.02	1.87	I 27	RR1						
4	.00	.43	.91	.86	D 38	T3						

CON- TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ		ENTRY NUMBER	Ite
4 1	.50	3.45	1.01	.88	i	33	V2
4 1	.32	2.34	.95	.90	j	35	V4
4 1	.30	.20	.99	.97	f	2	CS2
4 1	.27	1.97	1.01	.99	n	26	CE6
4 1	.26	-1.22	.99	.88	F	18	AE5
4 1	.26	-.53	.92	.84	H	23	CE3
4 1	.25	-.22	1.04	1.06	L	19	AE6
4 1	.23	.28	1.03	1.05	P	22	CE2
4 1	.23	.58	.92	.89	m	32	V1
4 1	.20	.51	1.09	1.17	r	39	T4
4 2	.11	2.21	1.14	1.15	N	4	CS4
4 2	.10	-1.05	1.01	1.03	o	15	AE2
4 2	.05	-.71	.95	.88	e	34	V3
4 2	.03	-3.22	1.02	1.53	s	5	CS5
4 2	.03	.28	.93	.87	G	16	AE3
4 2	.02	-.04	1.03	.97	R	17	AE4
4 2	.02	1.03	1.02	1.02	E	24	CE4
4 2	.01	1.47	.98	.97	q	28	RR2
4 2	.00	-3.92	1.02	1.87	I	27	RR1
4 2	.00	.43	.91	.86	D	38	T3
4 3	-.50	-.48	1.07	1.17	K	6	CS6
4 3	-.40	-3.22	1.00	1.00	k	11	R4
4 3	-.35	.04	1.03	1.00	J	20	AE7
4 3	-.27	-3.22	1.00	.70	d	12	R5
4 3	-.26	-.59	1.10	1.38	c	8	R1
4 3	-.25	-2.80	.99	.94	Q	3	CS3
4 3	-.21	-.53	1.10	1.28	h	7	CS7
4 3	-.20	1.97	.98	.96	l	31	RR5
4 3	-.18	2.78	1.04	1.12	C	37	T2
4 2	-.16	.28	1.04	1.03	a	9	R2
4 2	-.16	.28	.93	.86	S	29	RR3
4 2	-.16	1.06	.96	.94	g	30	RR4
4 2	-.11	.32	1.08	1.11	O	1	CS1
4 2	-.11	.20	.92	.88	p	10	R3
4 2	-.10	1.82	.95	.93	M	21	CE1
4 2	-.09	-3.22	.99	.63	b	13	R6
4 2	-.07	.54	.98	1.04	A	40	T5
4 2	-.05	.92	.98	.99	B	36	T1

```
TABLE 23.41
INPUT: 131 Person  40 Item  REPORTED: 131 Person  38 Item  2 CATS
WINSTEPS 3.80.1
------------------------------------------------------------------------
----------

     Table of STANDARDIZED RESIDUAL variance (in Eigenvalue units)
                                                 -- Empirical --
Modeled
Total raw variance in observations     =         55.6 100.0%
100.0%
  Raw variance explained by measures   =         17.6  31.6%
31.6%
    Raw variance explained by persons  =          4.3   7.8%
7.7%
    Raw Variance explained by items    =         13.3  23.9%
23.8%
  Raw unexplained variance (total)     =         38.0  68.4% 100.0%
68.4%
    Unexplned variance in 1st contrast =          2.8   5.0%   7.3%
    Unexplned variance in 2nd contrast =          2.3   4.1%   6.0%
    Unexplned variance in 3rd contrast =          2.1   3.8%   5.5%
    Unexplned variance in 4th contrast =          1.9   3.3%   4.9%
    Unexplned variance in 5th contrast =          1.7   3.1%   4.6%

       STANDARDIZED RESIDUAL CONTRAST 5 PLOT

      -4      -3      -2      -1       0       1       2       3
4
      -+-------+-------+-------+-------+-------+-------+-------+-------
+- COUNT  CLUSTER
C     | I    b                         |
| 2      1
O  .4 +      d                         |
+ 1      1
N     |                                | f
| 1      1
T  .3 +      k                      L  |
+ 2      1
R     |                                | p    B          j
| 3      1
A  .2 +                                J
+ 1      1
S     |                          e     |              n
| 2      2
T  .1 +                      F         | G
+ 2      2
      |                                | S  m         M  N   C
| 5      2
5  .0 +--------------------------------R---A-------q-------------------
-+ 3      2
      |      s   Q               K     |  D
| 4      2
L -.1 +                         cH     | a                         i
+ 4      2
O     |                                |  O
| 1      3
```

```
A -.2 +                        o       |       g
+ 2       3
D     |                                | P r   E
| 3       3
I -.3 +                                |
+
N     |                                |              l
| 1       3
G -.4 +                            h   |
+ 1       3
      -+-------+-------+-------+-------+-------+-------+-------+-------
+-
      -4      -3      -2      -1       0       1       2       3
4
                                 Item MEASURE
 COUNT: 1    4   1          1 1 113 1 2 6221 12   1  12 11  1     1

                                                111  1  1
Person                              11 2478 7342 85 74 8 61    3
                                      T    S    M     S    T
%TILE                               0   10 20 50 70 80 90     99

Approximate relationships between the Person measures
 PCA      Item      Pearson       Disattenuated Pearson+Extr
Disattenuated+Extr
Contrast  Clusters  Correlation   Correlation   Correlation
Correlation
 5        1 - 3     0.0398        0.1540
 5        1 - 2     0.3147        0.7909
 5        2 - 3     0.2770        0.8677
```

TABLE 23.42
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

CONTRAST 5 FROM PRINCIPAL COMPONENT ANALYSIS
STANDARDIZED RESIDUAL LOADINGS FOR Item (SORTED BY LOADING)

CON-TRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ		ENTRY NUMBER	Ite	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ		ENTRY NUMBER	Ite
5	.44	-3.92	1.02	1.87	I	27	RR1	-.38	-.53	1.10	1.28	h	7	CS7
5	.43	-3.22	.99	.63	b	13	R6	-.33	1.97	.98	.96	l	31	RR5
5	.39	-3.22	1.00	.70	d	12	R5	-.26	.51	1.09	1.17	r	39	T4
5	.36	.20	.99	.97	f	2	CS2	-.25	.28	1.03	1.05	P	22	CE2
5	.32	-3.22	1.00	1.00	k	11	R4	-.25	1.03	1.02	1.02	E	24	CE4
5	.30	-.22	1.04	1.06	L	19	AE6	-.19	1.06	.96	.94	g	30	RR4
5	.26	.92	.98	.99	B	36	T1	-.18	-1.05	1.01	1.03	o	15	AE2
5	.24	.20	.92	.88	p	10	R3	-.17	.32	1.08	1.11	O	1	CS1
5	.23	2.34	.95	.90	j	35	V4	-.12	-.59	1.10	1.38	c	8	R1
5	.18	.04	1.03	1.00	J	20	AE7	-.12	.28	1.04	1.03	a	9	R2
5	.13	1.97	1.01	.99	n	26	CE6	-.12	3.45	1.01	.88	i	33	V2
5	.13	-.71	.95	.88	e	34	V3	-.10	-.53	.92	.84	H	23	CE3
5	.11	-1.22	.99	.88	F	18	AE5	-.07	.43	.91	.86	D	38	T3
5	.09	.28	.93	.87	G	16	AE3	-.06	-2.80	.99	.94	Q	3	CS3
5	.07	.58	.92	.89	m	32	V1	-.05	-.48	1.07	1.17	K	6	CS6
5	.05	1.82	.95	.93	M	21	CE1	-.03	-3.22	1.02	1.53	s	5	CS5
5	.05	.28	.93	.86	S	29	RR3	-.02	-.04	1.03	.97	R	17	AE4
5	.03	2.21	1.14	1.15	N	4	CS4							
5	.03	2.78	1.04	1.12	C	37	T2							
5	.02	.54	.98	1.04	A	40	T5							

```
|  5   |   .01 |    1.47  .98  .97 |q   28 RR2 | |       |
|          |
------------------------------------------------ ----------------------
-------------------
```

CONTRAST	LOADING	MEASURE	INFIT MNSQ	OUTFIT MNSQ	ENTRY	NUMBER	Ite
5 1	.44	-3.92	1.02	1.87	I	27	RR1
5 1	.43	-3.22	.99	.63	b	13	R6
5 1	.39	-3.22	1.00	.70	d	12	R5
5 1	.36	.20	.99	.97	f	2	CS2
5 1	.32	-3.22	1.00	1.00	k	11	R4
5 1	.30	-.22	1.04	1.06	L	19	AE6
5 1	.26	.92	.98	.99	B	36	T1
5 1	.24	.20	.92	.88	p	10	R3
5 1	.23	2.34	.95	.90	j	35	V4
5 1	.18	.04	1.03	1.00	J	20	AE7
5 2	.13	1.97	1.01	.99	n	26	CE6
5 2	.13	-.71	.95	.88	e	34	V3
5 2	.11	-1.22	.99	.88	F	18	AE5
5 2	.09	.28	.93	.87	G	16	AE3
5 2	.07	.58	.92	.89	m	32	V1
5 2	.05	1.82	.95	.93	M	21	CE1
5 2	.05	.28	.93	.86	S	29	RR3
5 2	.03	2.21	1.14	1.15	N	4	CS4
5 2	.03	2.78	1.04	1.12	C	37	T2
5 2	.02	.54	.98	1.04	A	40	T5
5 2	.01	1.47	.98	.97	q	28	RR2
5 3	-.38	-.53	1.10	1.28	h	7	CS7
5 3	-.33	1.97	.98	.96	l	31	RR5
5 3	-.26	.51	1.09	1.17	r	39	T4
5 3	-.25	.28	1.03	1.05	P	22	CE2
5 3	-.25	1.03	1.02	1.02	E	24	CE4
5 3	-.19	1.06	.96	.94	g	30	RR4
5 3	-.18	-1.05	1.01	1.03	o	15	AE2
5 3	-.17	.32	1.08	1.11	O	1	CS1
5 2	-.12	-.59	1.10	1.38	c	8	R1
5 2	-.12	.28	1.04	1.03	a	9	R2
5 2	-.12	3.45	1.01	.88	i	33	V2
5 2	-.10	-.53	.92	.84	H	23	CE3
5 2	-.07	.43	.91	.86	D	38	T3
5 2	-.06	-2.80	.99	.94	Q	3	CS3
5 2	-.05	-.48	1.07	1.17	K	6	CS6
5 2	-.03	-3.22	1.02	1.53	s	5	CS5
5 2	-.02	-.04	1.03	.97	R	17	AE4

TABLE 23.99
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS
WINSTEPS 3.80.1

LARGEST STANDARDIZED RESIDUAL CORRELATIONS
USED TO IDENTIFY DEPENDENT Item

CORREL-ATION	ENTRY NUMBER Ite	ENTRY NUMBER Ite
.63	36 T1	40 T5
.33	2 CS2	35 V4
.32	12 R5	13 R6
.30	36 T1	37 T2
.29	5 CS5	6 CS6
.28	38 T3	40 T5
.27	11 R4	13 R6
.26	36 T1	38 T3
.26	11 R4	12 R5
.24	13 R6	34 V3
-.29	28 RR2	38 T3
-.29	9 R2	40 T5
-.28	6 CS6	33 V2
-.28	20 AE7	33 V2
-.25	30 RR4	36 T1
-.25	10 R3	22 CE2
-.24	16 AE3	39 T4
-.24	28 RR2	29 RR3
-.24	27 RR1	33 V2
-.24	9 R2	36 T1

B.2 Person parameter estimates

TABLE 17.1 GEB_Answer_Anagrafe_Recoded_Changed.x ZOU640WS.TXT Mar 25 11:30 2016
INPUT: 131 Person 40 Item REPORTED: 131 Person 38 Item 2 CATS WINSTEPS 3.80.1

Person: REAL SEP.: 1.15 REL.: .57 ... Item: REAL SEP.: 4.75 REL.: .96

Person STATISTICS: MEASURE ORDER

ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	PTMEASURE-A CORR.	PTMEASURE-A EXP.	EXACT MATCH OBS%	EXACT MATCH EXP%	Person
59	34	38	3.02	.59	.77	-.5	.52	-.2	.44	.34	92.1	90.1	179
76	34	38	3.02	.59	1.11	.4	.74	.1	.32	.34	86.8	90.1	107
86	34	38	3.02	.59	.92	-.1	1.22	.6	.34	.34	92.1	90.1	199
105	32	38	2.43	.51	.90	-.2	.66	.0	.44	.39	84.2	85.9	110
30	31	38	2.19	.48	1.04	.2	.73	.0	.42	.42	81.6	84.0	156
36	31	38	2.19	.48	1.05	.3	.99	.3	.39	.42	81.6	84.0	204
52	31	38	2.19	.48	.70	-1.1	.46	-.4	.55	.42	92.1	84.0	143
106	31	38	2.19	.48	1.10	.4	1.18	.5	.36	.42	81.6	84.0	126
119	31	38	2.19	.48	.85	-.5	.63	-.1	.49	.42	81.6	84.0	196
123	31	38	2.19	.48	.97	.0	.90	.2	.42	.42	81.6	84.0	212
8	30	38	1.97	.46	1.12	.6	.78	.1	.41	.43	78.9	82.4	40
23	30	38	1.97	.46	1.02	.2	1.03	.3	.41	.43	89.5	82.4	144
33	30	38	1.97	.46	.86	-.5	.63	-.1	.51	.43	84.2	82.4	186
47	30	38	1.97	.46	1.06	.3	1.12	.4	.40	.43	78.9	82.4	97
74	30	38	1.97	.46	1.14	.6	1.09	.4	.37	.43	84.2	82.4	95
94	30	38	1.97	.46	.80	-.7	.96	.3	.50	.43	89.5	82.4	53
124	30	38	1.97	.46	1.09	.4	1.09	.4	.38	.43	84.2	82.4	216
131	30	38	1.97	.46	.82	-.6	.58	-.2	.52	.43	84.2	82.4	299
18	29	38	1.77	.44	1.24	1.0	1.12	.4	.35	.45	73.7	81.3	251

24	29	38	1.77	.44	1.02	.1	4.56	2.6	.35	.45	84.2	81.3	203
28	29	38	1.77	.44	.88	-.4	.69	-.1	.51	.45	84.2	81.3	91
35	29	38	1.77	.44	.88	-.4	.63	-.2	.52	.45	84.2	81.3	200
49	29	38	1.77	.44	1.32	1.3	1.27	.6	.30	.45	73.7	81.3	127
70	29	38	1.77	.44	.99	.1	.92	.2	.45	.45	84.2	81.3	63
73	29	38	1.77	.44	.93	-.2	.70	-.1	.49	.45	78.9	81.3	82
78	29	38	1.77	.44	1.00	.1	1.12	.4	.43	.45	84.2	81.3	116
81	29	38	1.77	.44	.80	-.8	.85	.1	.52	.45	89.5	81.3	125
83	29	38	1.77	.44	.75	-1.1	.50	-.4	.58	.45	84.2	81.3	145
103	29	38	1.77	.44	1.08	.4	.97	.3	.41	.45	78.9	81.3	94
107	29	38	1.77	.44	1.03	.2	1.03	.3	.42	.45	84.2	81.3	133
109	29	38	1.77	.44	1.17	.8	1.02	.3	.38	.45	73.7	81.3	149
117	29	38	1.77	.44	.86	-.6	.65	-.2	.52	.45	89.5	81.3	189
21	28	38	1.57	.43	1.02	.1	.84	.1	.46	.46	81.6	80.2	112
29	28	38	1.57	.43	.98	.0	.84	.0	.48	.46	81.6	80.2	128
44	28	38	1.57	.43	.73	-1.3	.56	-.4	.59	.46	86.8	80.2	66
61	28	38	1.57	.43	1.21	1.0	7.31	3.9	.27	.46	76.3	80.2	193
62	28	38	1.57	.43	.98	.0	1.06	.3	.45	.46	81.6	80.2	210
64	28	38	1.57	.43	1.32	1.4	3.11	2.0	.25	.46	76.3	80.2	215
90	28	38	1.57	.43	1.03	.2	.87	.1	.46	.46	76.3	80.2	257
9	27	38	1.39	.42	1.03	.2	.84	.0	.48	.48	76.3	79.0	52
10	27	38	1.39	.42	1.46	2.0	1.42	.8	.27	.48	65.8	79.0	206
39	27	38	1.39	.42	1.28	1.3	1.13	.4	.36	.48	71.1	79.0	278
42	27	38	1.39	.42	.67	-1.8	.51	-.6	.63	.48	92.1	79.0	47
45	27	38	1.39	.42	.90	-.4	.66	-.3	.54	.48	76.3	79.0	70
51	27	38	1.39	.42	1.00	.1	.75	-.1	.49	.48	76.3	79.0	139
53	27	38	1.39	.42	1.20	1.0	1.12	.4	.38	.48	76.3	79.0	147
55	27	38	1.39	.42	.93	-.3	.69	-.2	.52	.48	76.3	79.0	162
58	27	38	1.39	.42	.92	-.3	.73	-.2	.52	.48	81.6	79.0	174

```
|    71      27      38    1.39      .42| .96   -.1| .88     .1|  .49
.48| 81.6  79.0|  67   |
|    80      27      38    1.39      .42|1.41   1.8|3.65   2.5|  .24
.48| 65.8  79.0| 121   |
|    95      27      38    1.39      .42|1.54   2.3|1.31     .6|  .26
.48| 60.5  79.0|  54   |
|   101      27      38    1.39      .42| .82   -.8| .62    -.4|  .57
.48| 81.6  79.0|  86   |
|   116      27      38    1.39      .42| .75  -1.3| .53    -.5|  .60
.48| 81.6  79.0| 184   |
|   128      27      38    1.39      .42|1.11    .6| .83     .0|  .45
.48| 71.1  79.0| 231   |
|     6      26      38    1.22      .41|1.05    .3|1.02     .3|  .46
.49| 78.9  77.8| 180   |
|    27      26      38    1.22      .41| .91   -.4| .90     .1|  .52
.49| 84.2  77.8|  75   |
|    31      26      38    1.22      .41| .80  -1.0| .61    -.5|  .59
.49| 84.2  77.8| 171   |
|    56      26      38    1.22      .41|1.08    .5| .95     .1|  .46
.49| 73.7  77.8| 167   |
|    57      26      38    1.22      .41|1.04    .3| .88     .0|  .48
.49| 78.9  77.8| 170   |
|   110      26      38    1.22      .41| .80  -1.0| .59    -.5|  .59
.49| 78.9  77.8| 150   |
|   125      26      38    1.22      .41| .85   -.7| .63    -.4|  .57
.49| 78.9  77.8| 219   |
|   126      26      38    1.22      .41|1.08    .5| .89     .0|  .46
.49| 73.7  77.8| 225   |
|    14      25      38    1.05      .40|1.14    .8|1.10     .4|  .43
.50| 68.4  76.5|  72   |
|    46      25      38    1.05      .40|1.08    .5| .83    -.1|  .48
.50| 73.7  76.5|  79   |
|    48      25      38    1.05      .40|1.02    .2| .95     .1|  .49
.50| 73.7  76.5| 100   |
|    66      25      38    1.05      .40|1.09    .5|1.10     .4|  .45
.50| 78.9  76.5| 314   |
|    67      25      38    1.05      .40|1.16    .9|1.05     .3|  .43
.50| 73.7  76.5| 999   |
|    68      25      38    1.05      .40| .61  -2.5| .45   -1.0|  .68
.50| 84.2  76.5|  48   |
|    84      25      38    1.05      .40| .98    .0| .76    -.2|  .52
.50| 73.7  76.5| 152   |
|    89      25      38    1.05      .40| .95   -.2| .77    -.2|  .53
.50| 78.9  76.5| 226   |
|    97      25      38    1.05      .40| .98   -.1| .74    -.3|  .53
.50| 73.7  76.5|  68   |
|   104      25      38    1.05      .40|1.06    .4| .91     .0|  .48
.50| 78.9  76.5| 105   |
|   113      25      38    1.05      .40|1.21   1.1|1.02     .2|  .42
.50| 68.4  76.5| 161   |
|   122      25      38    1.05      .40| .95   -.2| .82    -.1|  .52
.50| 78.9  76.5| 211   |
|     3      24      38     .89      .40|1.06    .4| .89     .0|  .49
.51| 76.3  75.4|  85   |
|    11      24      38     .89      .40|1.22   1.2|1.16     .5|  .41
.51| 71.1  75.4| 207   |
|    12      24      38     .89      .40|1.12    .8|2.44   2.0|  .40
.51| 71.1  75.4| 263   |
```

15	24	38	.89	.40	1.16	1.0	.95	.1	.45	.51	65.8	75.4	108
20	24	38	.89	.40	.85	-.9	.69	-.4	.58	.51	81.6	75.4	84
34	24	38	.89	.40	.91	-.5	.76	-.3	.56	.51	76.3	75.4	194
37	24	38	.89	.40	1.26	1.4	1.13	.4	.40	.51	71.1	75.4	209
43	24	38	.89	.40	1.05	.4	.98	.2	.48	.51	76.3	75.4	51
60	24	38	.89	.40	.79	-1.3	.59	-.7	.62	.51	76.3	75.4	187
77	24	38	.89	.40	1.10	.6	.99	.2	.46	.51	71.1	75.4	114
82	24	38	.89	.40	.70	-1.9	.54	-.8	.65	.51	86.8	75.4	130
92	24	38	.89	.40	1.16	1.0	1.04	.3	.44	.51	71.1	75.4	44
112	24	38	.89	.40	.86	-.8	.67	-.5	.58	.51	81.6	75.4	160
127	24	38	.89	.40	.86	-.8	.88	.0	.56	.51	81.6	75.4	229
7	23	38	.73	.40	1.21	1.3	2.43	2.2	.36	.52	73.7	74.4	173
41	23	38	.73	.40	1.07	.5	.90	.0	.50	.52	73.7	74.4	43
54	23	38	.73	.40	.85	-.9	.66	-.6	.60	.52	73.7	74.4	155
63	23	38	.73	.40	.79	-1.3	.62	-.7	.62	.52	84.2	74.4	213
69	23	38	.73	.40	1.04	.3	.86	-.1	.51	.52	73.7	74.4	55
75	23	38	.73	.40	1.12	.8	.97	.1	.47	.52	68.4	74.4	104
87	23	38	.73	.40	1.06	.4	.97	.1	.49	.52	73.7	74.4	202
96	23	38	.73	.40	1.19	1.2	1.14	.4	.43	.52	68.4	74.4	65
98	23	38	.73	.40	.77	-1.4	.59	-.7	.63	.52	78.9	74.4	76
99	23	38	.73	.40	1.10	.7	2.14	1.8	.43	.52	68.4	74.4	77
118	23	38	.73	.40	.92	-.4	.82	-.2	.55	.52	78.9	74.4	195
129	23	38	.73	.40	1.19	1.2	1.09	.3	.43	.52	73.7	74.4	254
130	23	38	.73	.40	.93	-.4	.81	-.2	.55	.52	78.9	74.4	281
16	22	38	.58	.39	1.14	.9	.97	.1	.47	.53	65.8	73.3	158
40	22	38	.58	.39	1.19	1.2	1.02	.2	.45	.53	60.5	73.3	41
50	22	38	.58	.39	.85	-1.0	.64	-.7	.61	.53	71.1	73.3	138
79	22	38	.58	.39	.73	-1.8	.55	-.9	.66	.53	81.6	73.3	119
85	22	38	.58	.39	.86	-.9	.73	-.5	.59	.53	76.3	73.3	168

111	22	38	.58	.39	.76	-1.6	.62	-.7	.64	.53	81.6	73.3	151
115	22	38	.58	.39	1.18	1.2	1.06	.3	.45	.53	71.1	73.3	182
4	21	38	.43	.39	.87	-.9	.67	-.7	.61	.53	78.9	72.6	118
19	21	38	.43	.39	1.26	1.6	1.16	.5	.42	.53	68.4	72.6	308
32	21	38	.43	.39	.66	-2.5	.50	-1.2	.69	.53	84.2	72.6	181
65	21	38	.43	.39	.74	-1.8	.56	-1.0	.66	.53	73.7	72.6	217
72	21	38	.43	.39	.82	-1.2	.63	-.8	.63	.53	73.7	72.6	81
91	21	38	.43	.39	.81	-1.2	.71	-.6	.62	.53	84.2	72.6	260
102	21	38	.43	.39	.93	-.4	.79	-.3	.57	.53	78.9	72.6	88
108	21	38	.43	.39	.81	-1.3	.62	-.8	.63	.53	84.2	72.6	146
5	20	38	.27	.39	1.07	.5	1.06	.3	.51	.54	68.4	72.2	153
17	20	38	.27	.39	.90	-.6	.71	-.6	.60	.54	73.7	72.2	166
25	20	38	.27	.39	1.19	1.2	1.02	.2	.47	.54	68.4	72.2	39
26	20	38	.27	.39	1.08	.6	1.00	.1	.50	.54	73.7	72.2	50
38	20	38	.27	.39	1.27	1.7	1.70	1.5	.39	.54	63.2	72.2	218
88	20	38	.27	.39	.98	-.1	.77	-.4	.57	.54	68.4	72.2	205
93	20	38	.27	.39	.90	-.7	.69	-.7	.60	.54	68.4	72.2	45
2	19	38	.12	.39	1.29	1.8	1.71	1.5	.38	.55	60.5	72.8	197
13	19	38	.12	.39	1.01	.1	.85	-.2	.55	.55	71.1	72.8	59
100	19	38	.12	.39	1.49	2.8	3.15	3.5	.23	.55	65.8	72.8	78
121	19	38	.12	.39	.75	-1.8	.56	-1.1	.67	.55	81.6	72.8	208
1	18	38	-.03	.39	1.14	.9	1.01	.2	.50	.56	71.1	73.5	169
114	18	38	-.03	.39	.86	-.9	.66	-.8	.63	.56	76.3	73.5	178
120	17	38	-.19	.40	.74	-1.7	.55	-1.2	.69	.56	81.6	74.4	201
22	16	38	-.35	.40	.78	-1.3	.61	-1.0	.67	.57	86.8	75.4	124
MEAN	25.3	38.0	1.15	.42	1.00	.0	1.02	.1			77.5	77.5	
S.D.	3.8	.0	.66	.04	.18	1.0	.80	.8			7.0	4.0	

C. R code and SEM detailed results

```
> #Packages Needed
> library(car)
> library(lavaan)
> library(semPlot)
> library(moments)
> #Data Loading
> dat<-read.csv("WorkingDB.csv", sep=";", dec=",")
```

C.1 Norm-Activation Theory

```
> #Packages Needed
> library(car)
> library(lavaan)
> library(semPlot)
> library(moments)
> #Data Loading
> dat<-read.csv("WorkingDB.csv", sep=";", dec=",")
> #Norm-Activation Model
>
> #Binomial dependent variable
> NAMbin<-'ModBin~b1*PN#regression
+  PN~b2*AR
+  AR~b3*AC
+  AC~b4*PA
+  PA=~PA1+PA2+PA3#Latent variables
+  AC=~AC1+AC2
+  AR=~AR1+AR2
+  PN=~PN1+PN2'
> NAMbin.fit<-sem(NAMbin, data=dat, ordered=c("ModBin"))
> summary(NAMbin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  51 iterations

  Number of observations                           159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               65.219     105.247
  Degrees of freedom                                32          32
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  0.686
  Shift parameter                                           10.181
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  PA =~
    PA1               1.000                               0.691
0.809
    PA2               0.932    0.143    6.528    0.000    0.645
0.700
```

```
    PA3               1.025    0.199    5.142    0.000    0.708
0.681
  AC =~
    AC1               1.000                               0.522
0.481
    AC2               0.949    0.231    4.113    0.000    0.495
0.692
  AR =~
    AR1               1.000                               0.431
0.315
    AR2               1.607    0.530    3.032    0.002    0.693
0.719
  PN =~
    PN1               1.000                               0.435
0.514
    PN2               1.091    0.212    5.151    0.000    0.474
0.691

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    PN        (b1)    0.381    0.288    1.323    0.186    0.166
0.166
  PN ~
    AR        (b2)    0.792    0.294    2.691    0.007    0.787
0.787
  AR ~
    AC        (b3)    0.746    0.256    2.914    0.004    0.902
0.902
  AC ~
    PA        (b4)    0.491    0.131    3.754    0.000    0.650
0.650

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1               4.346    0.097   45.030    0.000    4.346
5.089
    PA2               4.006    0.083   48.287    0.000    4.006
4.348
    PA3               3.610    0.083   43.247    0.000    3.610
3.473
    AC1               3.572    0.088   40.366    0.000    3.572
3.295
    AC2               4.541    0.085   53.567    0.000    4.541
6.343
    AR1               3.484    0.122   28.630    0.000    3.484
2.546
    AR2               4.252    0.109   39.044    0.000    4.252
4.408
    PN1               4.503    0.113   39.921    0.000    4.503
5.324
    PN2               4.736    0.113   42.084    0.000    4.736
6.900
    ModBin            0.000                               0.000
0.000
```

```
    PA              0.000                               0.000
0.000
    AC              0.000                               0.000
0.000
    AR              0.000                               0.000
0.000
    PN              0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1        -0.362    0.102   -3.550    0.000   -0.362   -
0.362

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1             0.251    0.046    5.409    0.000    0.251
0.345
    PA2             0.434    0.053    8.223    0.000    0.434
0.511
    PA3             0.579    0.093    6.255    0.000    0.579
0.536
    AC1             0.903    0.127    7.109    0.000    0.903
0.768
    AC2             0.267    0.036    7.423    0.000    0.267
0.522
    AR1             1.686    0.297    5.676    0.000    1.686
0.901
    AR2             0.450    0.062    7.225    0.000    0.450
0.483
    PN1             0.527    0.052   10.096    0.000    0.527
0.736
    PN2             0.246    0.039    6.272    0.000    0.246
0.523
    ModBin          0.973                               0.973
0.973
    PA              0.478    0.114    4.204    0.000    1.000
1.000
    AC              0.157    0.055    2.854    0.004    0.577
0.577
    AR              0.035    0.030    1.161    0.245    0.186
0.186
    PN              0.072    0.020    3.519    0.000    0.381
0.381

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin          1.000                               1.000
1.000

R-Square:
                   Estimate
    PA1             0.655
    PA2             0.489
    PA3             0.464
```

```
    AC1               0.232
    AC2               0.478
    AR1               0.099
    AR2               0.517
    PN1               0.264
    PN2               0.477
    ModBin            0.027
    AC                0.423
    AR                0.814
    PN                0.619

> fitMeasures(NAMbin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.081 0.942 0.943
>
> #Trinomial dependent variable
> NAMtrin<-'ModTrin~b1*PN#regression
+  PN~b2*AR
+  AR~b3*AC
+  AC~b4*PA
+  PA=~PA1+PA2+PA3#Latent variables
+  AC=~AC1+AC2
+  AR=~AR1+AR2
+  PN=~PN1+PN2'
> NAMtrin.fit<-sem(NAMtrin, data=dat, ordered=c("ModTrin"))
> summary(NAMtrin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  50 iterations

  Number of observations                           159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               72.305     114.322
  Degrees of freedom                                32          32
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  0.694
  Shift parameter                                           10.206
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  PA =~
    PA1               1.000                                0.690
0.808
    PA2               0.936    0.144    6.522    0.000    0.646
0.701
    PA3               1.027    0.200    5.136    0.000    0.709
0.682
  AC =~
    AC1               1.000                                0.521
0.481
    AC2               0.954    0.233    4.099    0.000    0.497
0.695
```

```
  AR =~
    AR1               1.000                               0.431
0.315
    AR2               1.612    0.534    3.021    0.003    0.695
0.720
  PN =~
    PN1               1.000                               0.438
0.518
    PN2               1.094    0.212    5.162    0.000    0.479
0.698

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    PN        (b1)    0.317    0.234    1.358    0.175    0.139
0.139
  PN ~
    AR        (b2)    0.790    0.295    2.680    0.007    0.778
0.778
  AR ~
    AC        (b3)    0.746    0.257    2.905    0.004    0.902
0.902
  AC ~
    PA        (b4)    0.488    0.131    3.738    0.000    0.646
0.646

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1               4.346    0.097   45.030    0.000    4.346
5.089
    PA2               4.006    0.083   48.287    0.000    4.006
4.348
    PA3               3.610    0.083   43.247    0.000    3.610
3.473
    AC1               3.572    0.088   40.366    0.000    3.572
3.295
    AC2               4.541    0.085   53.567    0.000    4.541
6.343
    AR1               3.484    0.122   28.630    0.000    3.484
2.546
    AR2               4.252    0.109   39.044    0.000    4.252
4.408
    PN1               4.503    0.113   39.921    0.000    4.503
5.324
    PN2               4.736    0.113   42.084    0.000    4.736
6.900
    ModTrin           0.000                               0.000
0.000
    PA                0.000                               0.000
0.000
    AC                0.000                               0.000
0.000
    AR                0.000                               0.000
0.000
    PN                0.000                               0.000
0.000
```

```
Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.362    0.102   -3.550    0.000   -0.362   -
0.362
    ModTrin|t2        1.032    0.122    8.487    0.000    1.032
1.032

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1               0.253    0.046    5.459    0.000    0.253
0.347
    PA2               0.432    0.053    8.175    0.000    0.432
0.508
    PA3               0.578    0.093    6.211    0.000    0.578
0.535
    AC1               0.904    0.127    7.110    0.000    0.904
0.769
    AC2               0.265    0.037    7.204    0.000    0.265
0.517
    AR1               1.687    0.297    5.672    0.000    1.687
0.901
    AR2               0.448    0.062    7.180    0.000    0.448
0.481
    PN1               0.524    0.052   10.001    0.000    0.524
0.732
    PN2               0.242    0.040    5.980    0.000    0.242
0.513
    ModTrin           0.981                               0.981
0.981
    PA                0.476    0.114    4.192    0.000    1.000
1.000
    AC                0.158    0.055    2.854    0.004    0.582
0.582
    AR                0.034    0.030    1.150    0.250    0.186
0.186
    PN                0.076    0.021    3.550    0.000    0.395
0.395

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                               1.000
1.000

R-Square:
                   Estimate
    PA1               0.653
    PA2               0.492
    PA3               0.465
    AC1               0.231
    AC2               0.483
    AR1               0.099
    AR2               0.519
    PN1               0.268
    PN2               0.487
```

```
    ModTrin           0.019
    AC                0.418
    AR                0.814
    PN                0.605

> fitMeasures(NAMtrin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.089 0.931 0.932
>
>
> #Continous dependent variable
> NAMsmi<-'SusMobInd~b1*PN#regression
+  PN~b2*AR
+  AR~b3*AC
+  AC~b4*PA
+  PA=~PA1+PA2+PA3#Latent variables
+  AC=~AC1+AC2
+  AR=~AR1+AR2
+  PN=~PN1+PN2'
> NAMsmi.fit<-sem(NAMsmi, data=dat, estimator="MLM")
> summary(NAMsmi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  54 iterations

  Number of observations                           159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic              106.977      83.131
  Degrees of freedom                                32          32
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.287
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  PA =~
    PA1               1.000                               0.654
0.766
    PA2               1.172    0.138    8.497    0.000    0.767
0.832
    PA3               1.056    0.166    6.377    0.000    0.691
0.664
  AC =~
    AC1               1.000                               0.471
0.435
    AC2               1.091    0.382    2.858    0.004    0.514
0.719
  AR =~
    AR1               1.000                               0.363
0.265
    AR2               1.843    0.576    3.202    0.001    0.669
0.693
  PN =~
```

```
    PN1               1.000                               0.417
0.493
    PN2               1.145    0.276    4.154    0.000    0.477
0.696

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    PN        (b1)    0.061    0.057    1.073    0.283    0.026
0.106
  PN ~
    AR        (b2)    0.948    0.445    2.130    0.033    0.825
0.825
  AR ~
    AC        (b3)    0.746    0.271    2.754    0.006    0.970
0.970
  AC ~
    PA        (b4)    0.431    0.166    2.602    0.009    0.599
0.599

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1               4.346    0.068   63.963    0.000    4.346
5.089
    PA2               4.006    0.073   54.653    0.000    4.006
4.348
    PA3               3.610    0.083   43.652    0.000    3.610
3.473
    AC1               3.572    0.086   41.415    0.000    3.572
3.295
    AC2               4.541    0.057   79.732    0.000    4.541
6.343
    AR1               3.484    0.109   32.007    0.000    3.484
2.546
    AR2               4.252    0.077   55.404    0.000    4.252
4.408
    PN1               4.503    0.067   66.922    0.000    4.503
5.324
    PN2               4.736    0.055   86.730    0.000    4.736
6.900
    SusMobInd         0.524    0.019   27.248    0.000    0.524
2.168
    PA                0.000                               0.000
0.000
    AC                0.000                               0.000
0.000
    AR                0.000                               0.000
0.000
    PN                0.000                               0.000
0.000

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    PA1               0.302    0.063    4.820    0.000    0.302
0.414
```

```
    PA2                  0.261     0.069     3.776     0.000     0.261
0.307
    PA3                  0.604     0.082     7.406     0.000     0.604
0.559
    AC1                  0.953     0.124     7.706     0.000     0.953
0.811
    AC2                  0.248     0.080     3.092     0.002     0.248
0.484
    AR1                  1.741     0.169    10.284     0.000     1.741
0.930
    AR2                  0.483     0.112     4.314     0.000     0.483
0.519
    PN1                  0.541     0.136     3.976     0.000     0.541
0.757
    PN2                  0.243     0.120     2.020     0.043     0.243
0.516
    SusMobInd            0.058     0.005    11.263     0.000     0.058
0.989
    PA                   0.428     0.085     5.040     0.000     1.000
1.000
    AC                   0.143     0.052     2.738     0.006     0.642
0.642
    AR                   0.008     0.024     0.326     0.744     0.060
0.060
    PN                   0.056     0.040     1.405     0.160     0.320
0.320

R-Square:
                   Estimate
    PA1               0.586
    PA2               0.693
    PA3               0.441
    AC1               0.189
    AC2               0.516
    AR1               0.070
    AR2               0.481
    PN1               0.243
    PN2               0.484
    SusMobInd         0.011
    AC                0.358
    AR                0.940
    PN                0.680

> fitMeasures(NAMsmi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.121 0.808 0.814
```

C.2 Theory of Planned Behaviour

```
> #Binomial dependent variable
> TPBbin<-'ATT=~MEASURE#Latent variables
+ SN=~SN1+SN2
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
+ ModBin~b1*PBCpt+b2*PBCb+b3*ATT+b4*SN'#regression
> TPBbin.fit<-sem(TPBbin, data=dat, ordered=c("ModBin"))
Warning messages:
```

```
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TPBbin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  90 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic                9.775      17.770
  Degrees of freedom                                19          19
  P-value (Chi-square)                           0.958       0.538
  Scaling correction factor                                  0.687
  Shift parameter                                            3.537
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                                0.667
1.000
  SN =~
    SN1               1.000                                0.899
0.801
    SN2               0.762    0.471    1.618    0.106    0.685
0.529
  PBCpt =~
    PBCpt1            1.000                                0.914
0.735
    PBCpt2            1.146    0.247    4.648    0.000    1.047
0.779
    PBCpt3            0.804    0.222    3.630    0.000    0.735
0.594
  PBCb =~
    PBCb1             1.000                                0.470
0.331
    PBCb2             4.869    5.431    0.897    0.370    2.287
1.612

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    PBCpt      (b1)   -0.041    0.131   -0.315    0.753   -0.038   -
0.038
    PBCb       (b2)    0.229    0.162    1.417    0.156    0.108
0.108
    ATT        (b3)    0.556    0.136    4.079    0.000    0.371
0.371
```

```
    SN        (b4)   -0.008    0.149   -0.052    0.958   -0.007   -
0.007

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    SN                0.151    0.069    2.192    0.028    0.251
0.251
    PBCpt            -0.024    0.063   -0.384    0.701   -0.040   -
0.040
    PBCb              0.006    0.020    0.302    0.762    0.020
0.020
  SN ~~
    PBCpt             0.087    0.097    0.895    0.371    0.106
0.106
    PBCb              0.028    0.049    0.565    0.572    0.066
0.066
  PBCpt ~~
    PBCb              0.105    0.127    0.825    0.409    0.244
0.244

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.061   19.009    0.000    1.150
1.725
    SN1               3.985    0.132   30.298    0.000    3.985
3.548
    SN2               3.031    0.115   26.369    0.000    3.031
2.341
    PBCpt1            3.869    0.139   27.857    0.000    3.869
3.113
    PBCpt2            3.200    0.119   26.881    0.000    3.200
2.381
    PBCpt3            3.769    0.139   27.189    0.000    3.769
3.046
    PBCb1             3.877    0.191   20.267    0.000    3.877
2.731
    PBCb2             3.100    0.127   24.463    0.000    3.100
2.185
    ModBin            0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    SN                0.000                               0.000
0.000
    PBCpt             0.000                               0.000
0.000
    PBCb              0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1        -0.334    0.113   -2.965    0.003   -0.334   -
0.334
```

```
Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
   MEASURE            0.000                                0.000
0.000
   SN1                0.453    0.482    0.938    0.348    0.453
0.359
   SN2                1.207    0.328    3.677    0.000    1.207
0.720
   PBCpt1             0.709    0.131    5.417    0.000    0.709
0.459
   PBCpt2             0.709    0.162    4.387    0.000    0.709
0.393
   PBCpt3             0.991    0.149    6.638    0.000    0.991
0.647
   PBCb1              1.795    0.462    3.886    0.000    1.795
0.891
   PBCb2             -3.215    5.736   -0.560    0.575   -3.215   -
1.597
   ModBin             0.850                                0.850
0.850
   ATT                0.444    0.057    7.752    0.000    1.000
1.000
   SN                 0.809    0.539    1.501    0.133    1.000
1.000
   PBCpt              0.835    0.329    2.539    0.011    1.000
1.000
   PBCb               0.221    0.263    0.838    0.402    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
   ModBin             1.000                                1.000
1.000

R-Square:
                   Estimate
   MEASURE            1.000
   SN1                0.641
   SN2                0.280
   PBCpt1             0.541
   PBCpt2             0.607
   PBCpt3             0.353
   PBCb1              0.109
   PBCb2                 NA
   ModBin             0.150

> fitMeasures(TPBbin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.000 1.000 1.091
----------------------------------------------------------------------
-----
> #Trinomial dependent variable
> TPBtrin<-'ATT=~MEASURE#Latent variables
+ SN=~SN1+SN2
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
```

```
+ ModTrin~b1*PBCpt+b2*PBCb+b3*ATT+b4*SN'#regression
> TPBtrin.fit<-sem(TPBtrin, data=dat, ordered=c("ModTrin"))
Warning messages:
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TPBtrin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  91 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               10.148      18.145
  Degrees of freedom                                19          19
  P-value (Chi-square)                           0.949       0.513
  Scaling correction factor                                  0.706
  Shift parameter                                            3.767
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  SN =~
    SN1               1.000                               0.907
0.808
    SN2               0.749    0.465    1.608    0.108    0.679
0.524
  PBCpt =~
    PBCpt1            1.000                               0.920
0.740
    PBCpt2            1.097    0.244    4.493    0.000    1.009
0.751
    PBCpt3            0.818    0.230    3.554    0.000    0.752
0.608
  PBCb =~
    PBCb1             1.000                               0.453
0.319
    PBCb2             5.236    6.336    0.826    0.409    2.371
1.671

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    PBCpt     (b1)   -0.208    0.122   -1.704    0.088   -0.191   -
0.191
```

```
    PBCb      (b2)    0.217    0.150    1.450    0.147    0.098
0.098
    ATT       (b3)    0.476    0.136    3.513    0.000    0.317
0.317
    SN        (b4)   -0.042    0.137   -0.307    0.759   -0.038   -
0.038

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    SN                0.152    0.069    2.211    0.027    0.251
0.251
    PBCpt            -0.025    0.064   -0.390    0.696   -0.041   -
0.041
    PBCb              0.006    0.019    0.300    0.764    0.019
0.019
  SN ~~
    PBCpt             0.088    0.099    0.889    0.374    0.105
0.105
    PBCb              0.026    0.048    0.539    0.590    0.063
0.063
  PBCpt ~~
    PBCb              0.100    0.131    0.764    0.445    0.240
0.240

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.061   19.009    0.000    1.150
1.725
    SN1               3.985    0.132   30.298    0.000    3.985
3.548
    SN2               3.031    0.115   26.369    0.000    3.031
2.341
    PBCpt1            3.869    0.139   27.857    0.000    3.869
3.113
    PBCpt2            3.200    0.119   26.881    0.000    3.200
2.381
    PBCpt3            3.769    0.139   27.189    0.000    3.769
3.046
    PBCb1             3.877    0.191   20.267    0.000    3.877
2.731
    PBCb2             3.100    0.127   24.463    0.000    3.100
2.185
    ModTrin           0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    SN                0.000                               0.000
0.000
    PBCpt             0.000                               0.000
0.000
    PBCb              0.000                               0.000
0.000

Thresholds:
```

```
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.334    0.113   -2.965    0.003   -0.334   -
0.334
    ModTrin|t2        1.053    0.136    7.758    0.000    1.053
1.053

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    SN1               0.439    0.494    0.888    0.374    0.439
0.348
    SN2               1.215    0.327    3.710    0.000    1.215
0.725
    PBCpt1            0.698    0.131    5.350    0.000    0.698
0.452
    PBCpt2            0.788    0.170    4.630    0.000    0.788
0.436
    PBCpt3            0.966    0.149    6.488    0.000    0.966
0.631
    PBCb1             1.811    0.469    3.857    0.000    1.811
0.898
    PBCb2            -3.610    6.708   -0.538    0.591   -3.610   -
1.793
    ModTrin           0.860                               0.860
0.860
    ATT               0.444    0.057    7.752    0.000    1.000
1.000
    SN                0.823    0.551    1.493    0.135    1.000
1.000
    PBCpt             0.846    0.342    2.476    0.013    1.000
1.000
    PBCb              0.205    0.263    0.779    0.436    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                               1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    SN1               0.652
    SN2               0.275
    PBCpt1            0.548
    PBCpt2            0.564
    PBCpt3            0.369
    PBCb1             0.102
    PBCb2                NA
    ModTrin           0.140

> fitMeasures(TPBtrin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.000 1.000 1.087
```

```
--------------------------------------------------------------------------
-----
> #Continous dependent variable
> TPBsmi<-'ATT=~MEASURE#Latent variables
+ SN=~SN1+SN2
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
+ SusMobInd~b1*PBCpt+b2*PBCb+b3*ATT+b4*SN'#regression
> TPBsmi.fit<-sem(TPBsmi, data=dat, estimator="MLM")
Warning messages:
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TPBsmi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  69 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic               29.693      28.305
  Degrees of freedom                                19          19
  P-value (Chi-square)                           0.056       0.078
  Scaling correction factor                                  1.049
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  SN =~
    SN1               1.000                               0.992
0.883
    SN2               0.626    0.410    1.529    0.126    0.621
0.480
  PBCpt =~
    PBCpt1            1.000                               0.941
0.758
    PBCpt2            1.215    0.191    6.371    0.000    1.144
0.851
    PBCpt3            0.719    0.132    5.456    0.000    0.677
0.547
  PBCb =~
    PBCb1             1.000                               0.583
0.410
    PBCb2             3.164    2.047    1.546    0.122    1.843
1.299

Regressions:
```

```
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    PBCpt     (b1)   -0.052    0.026   -1.968    0.049   -0.049   -
0.204
    PBCb      (b2)    0.073    0.031    2.396    0.017    0.043
0.178
    ATT       (b3)    0.105    0.029    3.619    0.000    0.070
0.291
    SN        (b4)   -0.016    0.027   -0.606    0.545   -0.016   -
0.067

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    SN                0.167    0.068    2.441    0.015    0.252
0.252
    PBCpt            -0.016    0.058   -0.271    0.786   -0.025   -
0.025
    PBCb              0.008    0.025    0.329    0.742    0.021
0.021
  SN ~~
    PBCpt             0.042    0.097    0.435    0.664    0.045
0.045
    PBCb              0.024    0.053    0.449    0.654    0.042
0.042
  PBCpt ~~
    PBCb              0.161    0.122    1.321    0.187    0.294
0.294

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.059   19.597    0.000    1.150
1.725
    SN1               3.985    0.099   40.297    0.000    3.985
3.548
    SN2               3.031    0.114   26.590    0.000    3.031
2.341
    PBCpt1            3.869    0.109   35.362    0.000    3.869
3.113
    PBCpt2            3.200    0.118   27.044    0.000    3.200
2.381
    PBCpt3            3.769    0.109   34.595    0.000    3.769
3.046
    PBCb1             3.877    0.125   31.015    0.000    3.877
2.731
    PBCb2             3.100    0.125   24.816    0.000    3.100
2.185
    SusMobInd         0.520    0.021   24.611    0.000    0.520
2.167
    ATT               0.000                               0.000
0.000
    SN                0.000                               0.000
0.000
    PBCpt             0.000                               0.000
0.000
```

```
    PBCb              0.000                                   0.000
0.000

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                                   0.000
0.000
    SN1               0.278    0.645    0.431    0.666    0.278
0.220
    SN2               1.290    0.263    4.903    0.000    1.290
0.770
    PBCpt1            0.658    0.164    4.021    0.000    0.658
0.426
    PBCpt2            0.497    0.184    2.704    0.007    0.497
0.275
    PBCpt3            1.073    0.144    7.466    0.000    1.073
0.701
    PBCb1             1.676    0.276    6.078    0.000    1.676
0.832
    PBCb2            -1.384    2.071   -0.668    0.504   -1.384   -
0.688
    SusMobInd         0.050    0.005   10.412    0.000    0.050
0.863
    ATT               0.444    0.055    8.071    0.000    1.000
1.000
    SN                0.983    0.661    1.487    0.137    1.000
1.000
    PBCpt             0.886    0.203    4.358    0.000    1.000
1.000
    PBCb              0.339    0.244    1.392    0.164    1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    SN1               0.780
    SN2               0.230
    PBCpt1            0.574
    PBCpt2            0.725
    PBCpt3            0.299
    PBCb1             0.168
    PBCb2                NA
    SusMobInd         0.137

> fitMeasures(TPBsmi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi 
0.066 0.950 0.954 
> 
```

C.3 Theory of Interpersonal Behaviour

```
> #Binomial dependent variable
> TIBbin<-'AFF=~AFF1#Latent variables
+ PN=~PN1+PN2
+ SN=~SN1+SN2
+ SF=~PN+SN
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
+ ModBin~b1*PBCpt+b2*PBCb+b3*AFF+b4*SF'#regression
> TIBbin.fit<-sem(TIBbin, data=dat, ordered=c("ModBin"))
Warning messages:
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TIBbin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  91 iterations

  Number of observations                           159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               39.484      53.821
  Degrees of freedom                                34          34
  P-value (Chi-square)                           0.238       0.017
  Scaling correction factor                                  0.908
  Shift parameter                                           10.316
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF =~
    AFF1              1.000                               1.276
1.000
  PN =~
    PN1               1.000                               0.491
0.581
    PN2               0.811    0.244    3.322    0.001    0.398
0.581
  SN =~
    SN1               1.000                               1.357
1.159
    SN2               0.384    0.318    1.205    0.228    0.521
0.403
  SF =~
    PN                1.000                               0.750
0.750
    SN                1.028    0.378    2.720    0.007    0.279
0.279
  PBCpt =~
    PBCpt1            1.000                               1.020
0.847
```

```
    PBCpt2            0.911    0.205    4.440    0.000    0.930
0.693
    PBCpt3            0.652    0.166    3.937    0.000    0.665
0.548
  PBCb =~
    PBCb1             1.000                               0.838
0.597
    PBCb2             1.541    0.507    3.039    0.002    1.291
0.882

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    PBCpt     (b1)    0.054    0.117    0.460    0.645    0.055
0.055
    PBCb      (b2)    0.094    0.208    0.452    0.651    0.079
0.079
    AFF       (b3)   -0.294    0.097   -3.026    0.002   -0.375   -
0.375
    SF        (b4)    0.286    0.641    0.446    0.655    0.105
0.105

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF ~~
    SF               -0.260    0.069   -3.795    0.000   -0.553   -
0.553
    PBCpt             0.122    0.125    0.968    0.333    0.093
0.093
    PBCb             -0.223    0.114   -1.952    0.051   -0.209   -
0.209
  SF ~~
    PBCpt             0.007    0.056    0.131    0.895    0.019
0.019
    PBCb              0.158    0.064    2.482    0.013    0.512
0.512
  PBCpt ~~
    PBCb              0.266    0.118    2.244    0.025    0.311
0.311

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    AFF1              2.786    0.102   27.258    0.000    2.786
2.184
    PN1               4.503    0.113   39.921    0.000    4.503
5.324
    PN2               4.736    0.113   42.084    0.000    4.736
6.900
    SN1               3.931    0.125   31.478    0.000    3.931
3.355
    SN2               3.031    0.104   29.256    0.000    3.031
2.349
    PBCpt1            3.943    0.127   31.100    0.000    3.943
3.275
```

```
    PBCpt2              3.208    0.108   29.748    0.000    3.208
2.391
    PBCpt3              3.811    0.124   30.662    0.000    3.811
3.139
    PBCb1               3.912    0.177   22.140    0.000    3.912
2.789
    PBCb2               3.138    0.120   26.187    0.000    3.138
2.143
    ModBin              0.000                               0.000
0.000
    AFF                 0.000                               0.000
0.000
    PN                  0.000                               0.000
0.000
    SN                  0.000                               0.000
0.000
    SF                  0.000                               0.000
0.000
    PBCpt               0.000                               0.000
0.000
    PBCb                0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1          -0.362    0.102   -3.550    0.000   -0.362    -
0.362

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    AFF1                0.000                               0.000
0.000
    PN1                 0.474    0.067    7.082    0.000    0.474
0.662
    PN2                 0.312    0.034    9.227    0.000    0.312
0.663
    SN1                -0.470    1.521   -0.309    0.757   -0.470    -
0.342
    SN2                 1.395    0.301    4.641    0.000    1.395
0.837
    PBCpt1              0.409    0.165    2.485    0.013    0.409
0.282
    PBCpt2              0.936    0.173    5.404    0.000    0.936
0.520
    PBCpt3              1.031    0.137    7.516    0.000    1.031
0.700
    PBCb1               1.265    0.230    5.497    0.000    1.265
0.643
    PBCb2               0.478    0.408    1.171    0.241    0.478
0.223
    ModBin              0.776                               0.776
0.776
    AFF                 1.627    0.274    5.942    0.000    1.000
1.000
    PN                  0.106    0.094    1.129    0.259    0.437
0.437
```

```
    SN                1.699    1.561    1.088    0.277    0.922
0.922
    SF                0.136    0.068    1.997    0.046    1.000
1.000
    PBCpt             1.040    0.352    2.953    0.003    1.000
1.000
    PBCb              0.702    0.319    2.199    0.028    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin            1.000                               1.000
1.000

R-Square:
                   Estimate
    AFF1              1.000
    PN1               0.338
    PN2               0.337
    SN1                  NA
    SN2               0.163
    PBCpt1            0.718
    PBCpt2            0.480
    PBCpt3            0.300
    PBCb1             0.357
    PBCb2             0.777
    ModBin            0.224
    PN                0.563
    SN                0.078

> fitMeasures(TIBbin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.032 0.975 0.977
-----------------------------------------------------------------------
----
> #Trinomial dependent variable
> TIBtrin<-'AFF=~AFF1#Latent variables
+ PN=~PN1+PN2
+ SN=~SN1+SN2
+ SF=~PN+SN
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
+ ModTrin~b1*PBCpt+b2*PBCb+b3*AFF+b4*SF'#regression
> TIBtrin.fit<-sem(TIBtrin, data=dat, ordered=c("ModTrin"))
Warning messages:
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TIBtrin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  85 iterations

  Number of observations                           159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               40.469      53.845
```

```
  Degrees of freedom                                34          34
  P-value (Chi-square)                           0.206       0.017
  Scaling correction factor                                  0.935
  Shift parameter                                           10.541
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF =~
    AFF1              1.000                               1.276
1.000
  PN =~
    PN1               1.000                               0.490
0.579
    PN2               0.817    0.240    3.404    0.001    0.400
0.583
  SN =~
    SN1               1.000                               1.485
1.268
    SN2               0.320    0.330    0.970    0.332    0.476
0.369
  SF =~
    PN                1.000                               0.789
0.789
    SN                0.946    0.365    2.587    0.010    0.246
0.246
  PBCpt =~
    PBCpt1            1.000                               1.022
0.849
    PBCpt2            0.890    0.206    4.331    0.000    0.910
0.678
    PBCpt3            0.660    0.173    3.821    0.000    0.675
0.556
  PBCb =~
    PBCb1             1.000                               0.855
0.609
    PBCb2             1.480    0.483    3.066    0.002    1.265
0.864

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    PBCpt     (b1)   -0.091    0.107   -0.849    0.396   -0.093   -
0.093
    PBCb      (b2)    0.087    0.170    0.515    0.607    0.075
0.075
    AFF       (b3)   -0.222    0.077   -2.897    0.004   -0.284   -
0.284
    SF        (b4)    0.304    0.460    0.660    0.509    0.117
0.117
```

```
Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF ~~
    SF               -0.261    0.068   -3.832    0.000   -0.530   -
0.530
    PBCpt             0.122    0.126    0.968    0.333    0.093
0.093
    PBCb             -0.230    0.116   -1.988    0.047   -0.211   -
0.211
  SF ~~
    PBCpt             0.004    0.057    0.068    0.946    0.010
0.010
    PBCb              0.167    0.065    2.569    0.010    0.505
0.505
  PBCpt ~~
    PBCb              0.272    0.121    2.250    0.024    0.312
0.312

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    AFF1              2.786    0.102   27.258    0.000    2.786
2.184
    PN1               4.503    0.113   39.921    0.000    4.503
5.324
    PN2               4.736    0.113   42.084    0.000    4.736
6.900
    SN1               3.931    0.125   31.478    0.000    3.931
3.355
    SN2               3.031    0.104   29.256    0.000    3.031
2.349
    PBCpt1            3.943    0.127   31.100    0.000    3.943
3.275
    PBCpt2            3.208    0.108   29.748    0.000    3.208
2.391
    PBCpt3            3.811    0.124   30.662    0.000    3.811
3.139
    PBCb1             3.912    0.177   22.140    0.000    3.912
2.789
    PBCb2             3.138    0.120   26.187    0.000    3.138
2.143
    ModTrin           0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PN                0.000                               0.000
0.000
    SN                0.000                               0.000
0.000
    SF                0.000                               0.000
0.000
    PBCpt             0.000                               0.000
0.000
    PBCb              0.000                               0.000
0.000

Thresholds:
```

```
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.362    0.102   -3.550    0.000   -0.362   -
0.362
    ModTrin|t2        1.032    0.122    8.487    0.000    1.032
1.032

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    AFF1              0.000                               0.000
0.000
    PN1               0.476    0.067    7.120    0.000    0.476
0.665
    PN2               0.311    0.033    9.302    0.000    0.311
0.661
    SN1              -0.834    2.262   -0.369    0.712   -0.834   -
0.607
    SN2               1.439    0.315    4.566    0.000    1.439
0.864
    PBCpt1            0.404    0.171    2.360    0.018    0.404
0.279
    PBCpt2            0.971    0.178    5.455    0.000    0.971
0.540
    PBCpt3            1.018    0.136    7.481    0.000    1.018
0.691
    PBCb1             1.237    0.227    5.439    0.000    1.237
0.629
    PBCb2             0.544    0.381    1.427    0.154    0.544
0.254
    ModTrin           0.838                               0.838
0.838
    AFF               1.627    0.274    5.942    0.000    1.000
1.000
    PN                0.090    0.094    0.958    0.338    0.377
0.377
    SN                2.073    2.299    0.902    0.367    0.939
0.939
    SF                0.149    0.074    2.009    0.045    1.000
1.000
    PBCpt             1.045    0.364    2.871    0.004    1.000
1.000
    PBCb              0.731    0.329    2.218    0.027    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                               1.000
1.000

R-Square:
                   Estimate
    AFF1              1.000
    PN1               0.335
    PN2               0.339
    SN1                  NA
    SN2               0.136
```

```
    PBCpt1            0.721
    PBCpt2            0.460
    PBCpt3            0.309
    PBCb1             0.371
    PBCb2             0.746
    ModTrin           0.162
    PN                0.623
    SN                0.061

> fitMeasures(TIBtrin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.035 0.971 0.973
------------------------------------------------------------------------
-------
> #Continous dependent variable
> TIBsmi<-'AFF=~AFF1#Latent variables
+ PN=~PN1+PN2
+ SN=~SN1+SN2
+ SF=~PN+SN
+ PBCpt=~PBCpt1+PBCpt2+PBCpt3
+ PBCb=~PBCb1+PBCb2
+ SusMobInd~b1*PBCpt+b2*PBCb+b3*AFF+b4*SF'#regression
> TIBsmi.fit<-sem(TIBsmi, data=dat, estimator="MLM")
Warning messages:
1: In lav_object_post_check(lavobject) :
  lavaan WARNING: some estimated variances are negative
2: In lav_object_post_check(lavobject) :
  lavaan WARNING: observed variable error term matrix (theta) is not
positive definite; use inspect(fit,"theta") to investigate.
> summary(TIBsmi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after 108 iterations

  Number of observations                           159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic               62.915      58.135
  Degrees of freedom                                34          34
  P-value (Chi-square)                           0.002       0.006
  Scaling correction factor                                  1.082
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF =~
    AFF1              1.000                               1.276
1.000
  PN =~
    PN1               1.000                               0.470
0.556
    PN2               0.886    0.343    2.586    0.010    0.417
0.607
  SN =~
```

```
    SN1               1.000                                1.741
1.486
    SN2               0.233    0.318    0.733    0.464    0.406
0.314
  SF =~
    PN                1.000                                0.722
0.722
    SN                1.328    0.572    2.323    0.020    0.259
0.259
  PBCpt =~
    PBCpt1            1.000                                0.959
0.797
    PBCpt2            1.061    0.159    6.667    0.000    1.018
0.759
    PBCpt3            0.695    0.122    5.692    0.000    0.666
0.549
  PBCb =~
    PBCb1             1.000                                0.779
0.555
    PBCb2             1.783    0.480    3.713    0.000    1.389
0.948

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    PBCpt      (b1)  -0.048    0.031   -1.545    0.122   -0.046   -
0.190
    PBCb       (b2)   0.093    0.044    2.130    0.033    0.072
0.299
    AFF        (b3)  -0.057    0.022   -2.557    0.011   -0.073   -
0.300
    SF         (b4)  -0.084    0.153   -0.547    0.584   -0.028   -
0.118

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  AFF ~~
    SF               -0.247    0.092   -2.685    0.007   -0.571   -
0.571
    PBCpt             0.138    0.120    1.151    0.250    0.113
0.113
    PBCb             -0.172    0.099   -1.748    0.080   -0.173   -
0.173
  SF ~~
    PBCpt            -0.036    0.052   -0.704    0.482   -0.111   -
0.111
    PBCb              0.092    0.051    1.815    0.070    0.350
0.350
  PBCpt ~~
    PBCb              0.278    0.103    2.715    0.007    0.373
0.373

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
```

AFF1	2.786	0.101	27.454	0.000	2.786	2.184
PN1	4.503	0.067	66.922	0.000	4.503	5.324
PN2	4.736	0.055	86.730	0.000	4.736	6.900
SN1	3.931	0.093	42.174	0.000	3.931	3.355
SN2	3.031	0.103	29.525	0.000	3.031	2.349
PBCpt1	3.943	0.096	41.169	0.000	3.943	3.275
PBCpt2	3.208	0.107	30.054	0.000	3.208	2.391
PBCpt3	3.811	0.097	39.462	0.000	3.811	3.139
PBCb1	3.912	0.112	35.060	0.000	3.912	2.789
PBCb2	3.138	0.116	26.939	0.000	3.138	2.143
SusMobInd	0.524	0.019	27.248	0.000	0.524	2.168
AFF	0.000				0.000	0.000
PN	0.000				0.000	0.000
SN	0.000				0.000	0.000
SF	0.000				0.000	0.000
PBCpt	0.000				0.000	0.000
PBCb	0.000				0.000	0.000

Variances:

	Estimate	Std.Err	Z-value	P(>|z|)	Std.lv	Std.all
AFF1	0.000				0.000	0.000
PN1	0.494	0.154	3.201	0.001	0.494	0.691
PN2	0.298	0.094	3.153	0.002	0.298	0.632
SN1	-1.660	4.071	-0.408	0.683	-1.660	-1.210
SN2	1.501	0.248	6.057	0.000	1.501	0.901
PBCpt1	0.530	0.145	3.660	0.000	0.530	0.365
PBCpt2	0.763	0.168	4.551	0.000	0.763	0.424
PBCpt3	1.030	0.127	8.127	0.000	1.030	0.699
PBCb1	1.361	0.206	6.605	0.000	1.361	0.692
PBCb2	0.216	0.480	0.451	0.652	0.216	0.101

```
    SusMobInd          0.049    0.005    9.372    0.000    0.049
0.839
    AFF                1.627    0.123   13.200    0.000    1.000
1.000
    PN                 0.106    0.146    0.726    0.468    0.479
0.479
    SN                 2.830    4.091    0.692    0.489    0.933
0.933
    SF                 0.115    0.083    1.392    0.164    1.000
1.000
    PBCpt              0.920    0.189    4.856    0.000    1.000
1.000
    PBCb               0.606    0.214    2.840    0.005    1.000
1.000

R-Square:
                   Estimate
    AFF1              1.000
    PN1               0.309
    PN2               0.368
    SN1                  NA
    SN2               0.099
    PBCpt1            0.635
    PBCpt2            0.576
    PBCpt3            0.301
    PBCb1             0.308
    PBCb2             0.899
    SusMobInd         0.161
    PN                0.521
    SN                0.067

> fitMeasures(TIBsmi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.073 0.907 0.913
```

C.4 Composite Model

```
> #______________________STEP1__________________#Base
>
> #Binomial dependent variable
> Mod1bin<-'ModBin~ATT+AFF+PAC
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4'
> Mod1bin.fit<-sem(Mod1bin, data=dat, ordered=c("ModBin"))
> summary(Mod1bin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  54 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic                5.059      10.345
  Degrees of freedom                                11          11
  P-value (Chi-square)                           0.928       0.500
  Scaling correction factor                                  0.567
  Shift parameter                                            1.419
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  AFF =~
    AFF1              1.000                               1.280
1.000
  PAC =~
    PAC1              1.000                               0.999
0.753
    PAC2              0.343    0.224    1.530    0.126    0.343
0.197
    PAC3              0.721    0.253    2.844    0.004    0.720
0.480
    PAC4              0.590    0.240    2.461    0.014    0.589
0.383

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    ATT               0.236    0.139    1.696    0.090    0.157
0.157
    AFF              -0.055    0.093   -0.592    0.554   -0.071   -
0.071
    PAC               0.732    0.213    3.437    0.001    0.731
0.731
```

```
Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    AFF              -0.333    0.088   -3.790    0.000   -0.390   -
0.390
    PAC               0.171    0.078    2.181    0.029    0.257
0.257
  AFF ~~
    PAC              -0.487    0.167   -2.917    0.004   -0.381   -
0.381

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.061   19.009    0.000    1.150
1.725
    AFF1              2.769    0.115   24.053    0.000    2.769
2.163
    PAC1              3.777    0.156   24.161    0.000    3.777
2.849
    PAC2              3.046    0.154   19.761    0.000    3.046
1.750
    PAC3              2.292    0.189   12.152    0.000    2.292
1.527
    PAC4              2.308    0.199   11.599    0.000    2.308
1.500
    ModBin            0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1        -0.334    0.113   -2.965    0.003   -0.334   -
0.334

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.760    0.234    3.249    0.001    0.760
0.432
    PAC2              2.911    1.022    2.848    0.004    2.911
0.961
    PAC3              1.734    0.380    4.563    0.000    1.734
0.770
    PAC4              2.020    0.481    4.195    0.000    2.020
0.853
```

```
    ModBin            0.329                               0.329
0.329
    ATT               0.444    0.057    7.752    0.000    1.000
1.000
    AFF               1.639    0.308    5.316    0.000    1.000
1.000
    PAC               0.998    0.393    2.541    0.011    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin            1.000                               1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.568
    PAC2              0.039
    PAC3              0.230
    PAC4              0.147
    ModBin            0.671

> fitMeasures(Mod1bin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
 0.00  1.00  1.05
>
> #Trinomial dependent variable
> Mod1trin<-'ModTrin~ATT+AFF+PAC
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4'
> Mod1trin.fit<-sem(Mod1trin, data=dat, ordered=c("ModTrin"))
> summary(Mod1trin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  49 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic                3.911       8.859
  Degrees of freedom                                11          11
  P-value (Chi-square)                           0.972       0.635
  Scaling correction factor                                  0.521
  Shift parameter                                            1.355
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
```

```
    MEASURE            1.000                                      0.667
1.000
  AFF =~
    AFF1               1.000                                      1.280
1.000
  PAC =~
    PAC1               1.000                                      0.918
0.693
    PAC2               0.525    0.277    1.891    0.059    0.482
0.277
    PAC3               0.734    0.264    2.784    0.005    0.674
0.449
    PAC4               0.697    0.257    2.711    0.007    0.640
0.416

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    ATT                0.181    0.137    1.325    0.185    0.121
0.121
    AFF               -0.029    0.085   -0.346    0.729   -0.038   -
0.038
    PAC                0.752    0.243    3.091    0.002    0.690
0.690

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    AFF               -0.333    0.088   -3.790    0.000   -0.390   -
0.390
    PAC                0.162    0.074    2.170    0.030    0.264
0.264
  AFF ~~
    PAC               -0.454    0.161   -2.813    0.005   -0.386   -
0.386

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE            1.150    0.061   19.009    0.000    1.150
1.725
    AFF1               2.769    0.115   24.053    0.000    2.769
2.163
    PAC1               3.777    0.156   24.161    0.000    3.777
2.849
    PAC2               3.046    0.154   19.761    0.000    3.046
1.750
    PAC3               2.292    0.189   12.152    0.000    2.292
1.527
    PAC4               2.308    0.199   11.599    0.000    2.308
1.500
    ModTrin            0.000                                      0.000
0.000
    ATT                0.000                                      0.000
0.000
```

```
    AFF               0.000                                     0.000
0.000
    PAC               0.000                                     0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.334    0.113   -2.965    0.003   -0.334   -
0.334
    ModTrin|t2        1.053    0.136    7.758    0.000    1.053
1.053

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                                     0.000
0.000
    AFF1              0.000                                     0.000
0.000
    PAC1              0.914    0.217    4.213    0.000    0.914
0.520
    PAC2              2.796    0.951    2.939    0.003    2.796
0.923
    PAC3              1.798    0.395    4.550    0.000    1.798
0.798
    PAC4              1.957    0.456    4.292    0.000    1.957
0.827
    ModTrin           0.440                                     0.440
0.440
    ATT               0.444    0.057    7.752    0.000    1.000
1.000
    AFF               1.639    0.308    5.316    0.000    1.000
1.000
    PAC               0.844    0.340    2.480    0.013    1.000
1.000

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                                     1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.480
    PAC2              0.077
    PAC3              0.202
    PAC4              0.173
    ModTrin           0.560

> fitMeasures(Mod1trin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.000 1.000 1.056
>
> #Continous dependent variable
```

```
> Mod1smi<-'SusMobInd~ATT+AFF+PAC
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4'
> Mod1smi.fit<-sem(Mod1smi, data=dat, estimator="MLM")
> summary(Mod1smi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  49 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic               13.498      12.536
  Degrees of freedom                                11          11
  P-value (Chi-square)                           0.262       0.325
  Scaling correction factor                                  1.077
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  AFF =~
    AFF1              1.000                               1.280
1.000
  PAC =~
    PAC1              1.000                               0.862
0.650
    PAC2              0.590    0.207    2.851    0.004    0.508
0.292
    PAC3              0.838    0.208    4.031    0.000    0.722
0.481
    PAC4              0.835    0.198    4.222    0.000    0.720
0.468

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    ATT               0.039    0.031    1.261    0.207    0.026
0.108
    AFF               0.009    0.021    0.426    0.670    0.011
0.047
    PAC               0.204    0.047    4.330    0.000    0.175
0.731

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
```

```
    AFF              -0.333    0.077   -4.336    0.000   -0.390   -
0.390
    PAC               0.152    0.064    2.376    0.018    0.265
0.265
  AFF ~~
    PAC              -0.437    0.138   -3.164    0.002   -0.396   -
0.396

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.059   19.597    0.000    1.150
1.725
    AFF1              2.769    0.113   24.567    0.000    2.769
2.163
    PAC1              3.777    0.117   32.354    0.000    3.777
2.849
    PAC2              3.046    0.153   19.880    0.000    3.046
1.750
    PAC3              2.292    0.132   17.345    0.000    2.292
1.527
    PAC4              2.308    0.135   17.037    0.000    2.308
1.500
    SusMobInd         0.520    0.021   24.611    0.000    0.520
2.167
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              1.016    0.170    5.958    0.000    1.016
0.578
    PAC2              2.771    0.194   14.277    0.000    2.771
0.915
    PAC3              1.732    0.230    7.540    0.000    1.732
0.769
    PAC4              1.849    0.217    8.514    0.000    1.849
0.781
    SusMobInd         0.025    0.005    4.900    0.000    0.025
0.441
    ATT               0.444    0.055    8.071    0.000    1.000
1.000
    AFF               1.639    0.138   11.878    0.000    1.000
1.000
    PAC               0.742    0.233    3.180    0.001    1.000
1.000

R-Square:
                   Estimate
```

```
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.422
    PAC2              0.085
    PAC3              0.231
    PAC4              0.219
    SusMobInd         0.559

> fitMeasures(Mod1smi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.042 0.979 0.981
>
>
> #______________________STEP2____________#Mediation of Home by PAC
>
> #Binomial dependent variable
> Mod2bin<-'ModBin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ #Indirect effet
+ Home_Die:=b1*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)'
> Mod2bin.fit<-sem(Mod2bin, data=dat, ordered=c("ModBin"))
> summary(Mod2bin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  54 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               27.657      30.018
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.067       0.037
  Scaling correction factor                                  1.055
  Shift parameter                                            3.794
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                                0.663
1.000
  AFF =~
    AFF1              1.000                                1.268
1.000
  PAC =~
    PAC1              1.000                                1.053
0.798
```

```
    PAC2              0.271    0.194    1.397    0.162    0.285
0.165
    PAC3              0.614    0.212    2.897    0.004    0.646
0.427
    PAC4              0.600    0.224    2.678    0.007    0.631
0.411

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    ATT       (a1)    0.394    0.132    2.985    0.003    0.261
0.248
    AFF       (a2)   -0.228    0.074   -3.097    0.002   -0.289   -
0.274
    PAC       (a3)    0.809    0.224    3.618    0.000    0.852
0.808
    Home_D    (a4)    0.060    0.175    0.340    0.734    0.060
0.039
  PAC ~
    Home_D    (b1)   -0.670    0.157   -4.266    0.000   -0.636   -
0.443

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    AFF              -0.322    0.085   -3.762    0.000   -0.382   -
0.382

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.089
    PAC1              4.103    0.191   21.503    0.000    4.103
3.108
    PAC2              3.210    0.195   16.435    0.000    3.210
1.858
    PAC3              2.426    0.192   12.663    0.000    2.426
1.601
    PAC4              2.502    0.189   13.255    0.000    2.502
1.627
    ModBin            0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
```

```
    ModBin|t1         -0.577    0.147   -3.924    0.000   -0.577   -
0.547

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.634    0.249    2.544    0.011    0.634
0.364
    PAC2              2.905    1.023    2.839    0.005    2.905
0.973
    PAC3              1.878    0.424    4.433    0.000    1.878
0.818
    PAC4              1.964    0.451    4.351    0.000    1.964
0.831
    ModBin            0.207                               0.207
0.186
    ATT               0.440    0.057    7.670    0.000    1.000
1.000
    AFF               1.607    0.297    5.414    0.000    1.000
1.000
    PAC               0.891    0.335    2.662    0.008    0.804
0.804

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin            1.000                               1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.636
    PAC2              0.027
    PAC3              0.182
    PAC4              0.169
    ModBin            0.814
    PAC               0.196

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.542    0.163   -3.335    0.001   -0.542   -
0.357
    Home_Dte         -0.483    0.154   -3.131    0.002   -0.483   -
0.318

> fitMeasures(Mod2bin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.064 0.925 0.931
>
> #Trinomial dependent variable
> Mod2trin<-'ModTrin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
```

```
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ #Indirect effet
+ Home_Die:=b1*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)'
> Mod2trin.fit<-sem(Mod2trin, data=dat, ordered=c("ModTrin"))
> summary(Mod2trin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  49 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               26.200      29.231
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.095       0.046
  Scaling correction factor                                  1.035
  Shift parameter                                            3.914
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                                 0.663
1.000
  AFF =~
    AFF1              1.000                                 1.268
1.000
  PAC =~
    PAC1              1.000                                 0.940
0.718
    PAC2              0.471    0.257    1.830    0.067    0.443
0.255
    PAC3              0.652    0.235    2.771    0.006    0.613
0.405
    PAC4              0.754    0.252    2.988    0.003    0.709
0.458

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    ATT       (a1)    0.325    0.132    2.453    0.014    0.216
0.202
    AFF       (a2)   -0.190    0.064   -2.984    0.003   -0.241   -
0.225
    PAC       (a3)    0.816    0.262    3.108    0.002    0.767
0.717
```

```
    Home_D    (a4)   -0.034    0.188   -0.183    0.855   -0.034   -
0.022
  PAC ~
    Home_D    (b1)   -0.628    0.152   -4.132    0.000   -0.668   -
0.464

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    AFF              -0.322    0.085   -3.762    0.000   -0.382   -
0.382

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.089
    PAC1              4.103    0.191   21.503    0.000    4.103
3.132
    PAC2              3.210    0.195   16.435    0.000    3.210
1.850
    PAC3              2.426    0.192   12.663    0.000    2.426
1.602
    PAC4              2.502    0.189   13.255    0.000    2.502
1.617
    ModTrin           0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.615    0.146   -4.210    0.000   -0.615   -
0.575
    ModTrin|t2        0.875    0.146    5.982    0.000    0.875
0.818

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.832    0.222    3.745    0.000    0.832
0.485
    PAC2              2.816    0.967    2.911    0.004    2.816
0.935
    PAC3              1.919    0.433    4.432    0.000    1.919
0.836
```

```
    PAC4              1.891    0.425    4.446    0.000    1.891
0.790
    ModTrin           0.394                               0.394
0.345
    ATT               0.440    0.057    7.670    0.000    1.000
1.000
    AFF               1.607    0.297    5.414    0.000    1.000
1.000
    PAC               0.694    0.273    2.537    0.011    0.784
0.784

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                               1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.515
    PAC2              0.065
    PAC3              0.164
    PAC4              0.210
    ModTrin           0.655
    PAC               0.216

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.512    0.156   -3.294    0.001   -0.512   -
0.333
    Home_Dte         -0.547    0.159   -3.442    0.001   -0.547   -
0.355

> fitMeasures(Mod2trin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.059 0.938 0.942
>
> #Continous dependent variable
> Mod2smi<-'SusMobInd~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ #Indirect effet
+ Home_Die:=b1*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)'
> Mod2smi.fit<-sem(Mod2smi, data=dat, estimator="MLM")
> summary(Mod2smi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  56 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                         ML      Robust
```

```
  Minimum Function Test Statistic               30.572      29.726
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.032       0.040
  Scaling correction factor                                  1.028
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  AFF =~
    AFF1              1.000                               1.280
1.000
  PAC =~
    PAC1              1.000                               0.875
0.660
    PAC2              0.572    0.216    2.641    0.008    0.500
0.287
    PAC3              0.766    0.214    3.590    0.000    0.671
0.447
    PAC4              0.853    0.210    4.057    0.000    0.746
0.485

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    ATT       (a1)    0.052    0.024    2.153    0.031    0.035
0.150
    AFF       (a2)   -0.012    0.014   -0.827    0.408   -0.015   -
0.065
    PAC       (a3)    0.171    0.043    3.947    0.000    0.149
0.640
    Home_D    (a4)   -0.042    0.040   -1.055    0.291   -0.042   -
0.125
  PAC ~
    Home_D    (b1)   -0.588    0.148   -3.963    0.000   -0.672   -
0.465

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT ~~
    AFF              -0.333    0.077   -4.336    0.000   -0.390   -
0.390

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.150    0.059   19.597    0.000    1.150
1.725
```

```
    AFF1              2.769    0.113   24.567    0.000    2.769
2.163
    PAC1              4.053    0.108   37.427    0.000    4.053
3.057
    PAC2              3.204    0.172   18.606    0.000    3.204
1.841
    PAC3              2.504    0.150   16.694    0.000    2.504
1.668
    PAC4              2.543    0.158   16.108    0.000    2.543
1.653
    SusMobInd         0.587    0.021   28.507    0.000    0.587
2.514
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.992    0.191    5.198    0.000    0.992
0.564
    PAC2              2.778    0.196   14.198    0.000    2.778
0.917
    PAC3              1.803    0.235    7.660    0.000    1.803
0.800
    PAC4              1.810    0.221    8.202    0.000    1.810
0.765
    SusMobInd         0.025    0.005    5.284    0.000    0.025
0.466
    ATT               0.444    0.055    8.071    0.000    1.000
1.000
    AFF               1.639    0.138   11.878    0.000    1.000
1.000
    PAC               0.600    0.220    2.725    0.006    0.784
0.784

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.436
    PAC2              0.083
    PAC3              0.200
    PAC4              0.235
    SusMobInd         0.534
    PAC               0.216

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
```

```
    Home_Die         -0.100    0.032   -3.182    0.001   -0.100   -
0.298
    Home_Dte         -0.142    0.034   -4.245    0.000   -0.142   -
0.423

> fitMeasures(Mod2smi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.073 0.914 0.919
>
>
> #______________________STEP3____________Mediation de AFF par ATT
>
> #Binomial dependent variable
> Mod3bin<-'ModBin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ ATT~b2*AFF
+ #Indirect effet
+ Home_Die:=b1*a3
+ AFFie:=b2*a1
+ #Total effect
+ AFFte:=a2+(b2*a1)
+ Home_Dte:=a4+(b1*a3)'
> Mod3bin.fit<-sem(Mod3bin, data=dat, ordered=c("ModBin"))
> summary(Mod3bin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  56 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               27.657      30.018
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.067       0.037
  Scaling correction factor                                  1.055
  Shift parameter                                            3.794
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.663
1.000
  AFF =~
    AFF1              1.000                               1.268
1.000
  PAC =~
    PAC1              1.000                               1.053
0.798
```

```
    PAC2              0.271    0.194    1.397    0.162    0.285
0.165
    PAC3              0.614    0.212    2.897    0.004    0.646
0.427
    PAC4              0.600    0.224    2.678    0.007    0.631
0.411

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    ATT       (a1)    0.394    0.132    2.985    0.003    0.261
0.248
    AFF       (a2)   -0.228    0.074   -3.097    0.002   -0.289   -
0.274
    PAC       (a3)    0.809    0.224    3.618    0.000    0.852
0.808
    Home_D    (a4)    0.060    0.175    0.340    0.734    0.060
0.039
  PAC ~
    Home_D    (b1)   -0.670    0.157   -4.266    0.000   -0.636   -
0.443
  ATT ~
    AFF       (b2)   -0.200    0.040   -4.994    0.000   -0.382   -
0.382

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.089
    PAC1              4.103    0.191   21.503    0.000    4.103
3.108
    PAC2              3.210    0.195   16.435    0.000    3.210
1.858
    PAC3              2.426    0.192   12.663    0.000    2.426
1.601
    PAC4              2.502    0.189   13.255    0.000    2.502
1.627
    ModBin            0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1        -0.577    0.147   -3.924    0.000   -0.577   -
0.547

Variances:
```

```
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                                0.000
0.000
    AFF1              0.000                                0.000
0.000
    PAC1              0.634    0.249    2.544    0.011    0.634
0.364
    PAC2              2.905    1.023    2.839    0.005    2.905
0.973
    PAC3              1.878    0.424    4.433    0.000    1.878
0.818
    PAC4              1.964    0.451    4.351    0.000    1.964
0.831
    ModBin            0.207                                0.207
0.186
    ATT               0.376    0.047    7.923    0.000    0.854
0.854
    AFF               1.607    0.297    5.414    0.000    1.000
1.000
    PAC               0.891    0.335    2.662    0.008    0.804
0.804

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin            1.000                                1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.636
    PAC2              0.027
    PAC3              0.182
    PAC4              0.169
    ModBin            0.814
    ATT               0.146
    PAC               0.196

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.542    0.163   -3.335    0.001   -0.542   -
0.357
    AFFie            -0.079    0.032   -2.468    0.014   -0.100   -
0.095
    AFFte            -0.307    0.070   -4.361    0.000   -0.389   -
0.369
    Home_Dte         -0.483    0.154   -3.131    0.002   -0.483   -
0.318

> fitMeasures(Mod3bin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.064 0.925 0.931
>
> #Trinomial dependent variable
```

```
> Mod3trin<-'ModTrin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ ATT~b2*AFF
+ #Indirect effet
+ Home_Die:=b1*a3
+ AFFie:=b2*a1
+ #Total effect
+ AFFte:=a2+(b2*a1)
+ Home_Dte:=a4+(b1*a3)'
> Mod3trin.fit<-sem(Mod3trin, data=dat, ordered=c("ModTrin"))
> summary(Mod3trin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  52 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               26.200      29.231
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.095       0.046
  Scaling correction factor                                  1.035
  Shift parameter                                            3.914
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                                0.663
1.000
  AFF =~
    AFF1              1.000                                1.268
1.000
  PAC =~
    PAC1              1.000                                0.940
0.718
    PAC2              0.471    0.257    1.830    0.067    0.443
0.255
    PAC3              0.652    0.235    2.771    0.006    0.613
0.405
    PAC4              0.754    0.252    2.988    0.003    0.709
0.458

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    ATT       (a1)    0.325    0.132    2.453    0.014    0.216
0.202
```

```
    AFF       (a2)   -0.190    0.064   -2.984    0.003   -0.241   -
0.225
    PAC       (a3)    0.816    0.262    3.108    0.002    0.767
0.717
    Home_D    (a4)   -0.034    0.188   -0.183    0.855   -0.034   -
0.022
  PAC ~
    Home_D    (b1)   -0.628    0.152   -4.132    0.000   -0.668   -
0.464
  ATT ~
    AFF       (b2)   -0.200    0.040   -4.994    0.000   -0.382   -
0.382

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.089
    PAC1              4.103    0.191   21.503    0.000    4.103
3.132
    PAC2              3.210    0.195   16.435    0.000    3.210
1.850
    PAC3              2.426    0.192   12.663    0.000    2.426
1.602
    PAC4              2.502    0.189   13.255    0.000    2.502
1.617
    ModTrin           0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.615    0.146   -4.210    0.000   -0.615   -
0.575
    ModTrin|t2        0.875    0.146    5.982    0.000    0.875
0.818

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.832    0.222    3.746    0.000    0.832
0.485
    PAC2              2.816    0.967    2.911    0.004    2.816
0.935
    PAC3              1.919    0.433    4.432    0.000    1.919
0.836
```

```
    PAC4              1.891    0.425    4.446    0.000    1.891
0.790
    ModTrin           0.394                               0.394
0.345
    ATT               0.376    0.047    7.923    0.000    0.854
0.854
    AFF               1.607    0.297    5.414    0.000    1.000
1.000
    PAC               0.694    0.273    2.537    0.011    0.784
0.784

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin           1.000                               1.000
1.000

R-Square:
                   Estimate
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.515
    PAC2              0.065
    PAC3              0.164
    PAC4              0.210
    ModTrin           0.655
    ATT               0.146
    PAC               0.216

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.512    0.156   -3.294    0.001   -0.512   -
0.333
    AFFie            -0.065    0.030   -2.136    0.033   -0.082   -
0.077
    AFFte            -0.255    0.060   -4.238    0.000   -0.323   -
0.302
    Home_Dte         -0.547    0.159   -3.442    0.001   -0.547   -
0.355

> fitMeasures(Mod3trin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.059 0.938 0.942
>
> #Continous dependent variable
> Mod3smi<-'SusMobInd~a1*ATT+a2*AFF+a3*PAC+a4*Home_D
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D
+ ATT~b2*AFF
+ #Indirect effet
+ Home_Die:=b1*a3
+ AFFie:=b2*a1
+ #Total effect
+ AFFte:=a2+(b2*a1)
+ Home_Dte:=a4+(b1*a3)'
```

```
> Mod3smi.fit<-sem(Mod3smi, data=dat, estimator="MLM")
> summary(Mod3smi.fit, standardized = T, rsq = T)
lavaan (0.5-20) converged normally after  53 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic               30.572      29.726
  Degrees of freedom                                18          18
  P-value (Chi-square)                           0.032       0.040
  Scaling correction factor                                  1.028
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ATT =~
    MEASURE           1.000                               0.667
1.000
  AFF =~
    AFF1              1.000                               1.280
1.000
  PAC =~
    PAC1              1.000                               0.875
0.660
    PAC2              0.572    0.216    2.641    0.008    0.500
0.287
    PAC3              0.766    0.214    3.590    0.000    0.671
0.447
    PAC4              0.853    0.210    4.057    0.000    0.746
0.485

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    ATT       (a1)    0.052    0.024    2.153    0.031    0.035
0.150
    AFF       (a2)   -0.012    0.014   -0.827    0.408   -0.015   -
0.065
    PAC       (a3)    0.171    0.043    3.947    0.000    0.149
0.640
    Home_D    (a4)   -0.042    0.040   -1.055    0.291   -0.042   -
0.125
  PAC ~
    Home_D    (b1)   -0.588    0.148   -3.963    0.000   -0.672   -
0.465
  ATT ~
    AFF       (b2)   -0.203    0.043   -4.765    0.000   -0.390   -
0.390

Intercepts:
```

	Estimate	Std.Err	Z-value	P(>|z|)	Std.lv	Std.all
MEASURE	1.150	0.059	19.597	0.000	1.150	1.725
AFF1	2.769	0.113	24.567	0.000	2.769	2.163
PAC1	4.053	0.108	37.427	0.000	4.053	3.057
PAC2	3.204	0.172	18.606	0.000	3.204	1.841
PAC3	2.504	0.150	16.694	0.000	2.504	1.668
PAC4	2.543	0.158	16.108	0.000	2.543	1.653
SusMobInd	0.587	0.021	28.507	0.000	0.587	2.514
ATT	0.000				0.000	0.000
AFF	0.000				0.000	0.000
PAC	0.000				0.000	0.000

Variances:

	Estimate	Std.Err	Z-value	P(>|z|)	Std.lv	Std.all
MEASURE	0.000				0.000	0.000
AFF1	0.000				0.000	0.000
PAC1	0.992	0.191	5.198	0.000	0.992	0.564
PAC2	2.778	0.196	14.198	0.000	2.778	0.917
PAC3	1.803	0.235	7.660	0.000	1.803	0.800
PAC4	1.810	0.221	8.202	0.000	1.810	0.765
SusMobInd	0.025	0.005	5.284	0.000	0.025	0.466
ATT	0.377	0.051	7.414	0.000	0.848	0.848
AFF	1.639	0.138	11.878	0.000	1.000	1.000
PAC	0.600	0.220	2.725	0.006	0.784	0.784

R-Square:

	Estimate
MEASURE	1.000
AFF1	1.000
PAC1	0.436
PAC2	0.083
PAC3	0.200
PAC4	0.235
SusMobInd	0.534
ATT	0.152
PAC	0.216

```
Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.100    0.032   -3.182    0.001   -0.100   -
0.298
    AFFie            -0.011    0.005   -2.051    0.040   -0.014   -
0.058
    AFFte            -0.023    0.014   -1.651    0.099   -0.029   -
0.124
    Home_Dte         -0.142    0.034   -4.245    0.000   -0.142   -
0.423

> fitMeasures(Mod3smi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.073 0.914 0.919
>
> #______________________STEP2____________#we add Values, U and C
>
> #Binomial dependent variable
> Mod4bin<-'ModBin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D+a5*U+a6*C
+ U=~Choice_Speed + Choice_Flexi + Choice_Reliable
+ C=~Choice_Cost + Choice_Pleasure + Choice_Green
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D+b2*U+b5*C
+ ATT~b3*AFF+b4*C
+ #Indirect effet
+ Home_Die:=b1*a3
+ Uie:=b2*a3
+ AFFie:=b3*a1
+ CieATT:=b4*a1
+ CiePAC:=b5*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)
+ Ute:=a5+(b2*a3)
+ AFFte:=a2+(b3*a1)
+ Cte:=a6+(b4*a1)+(b5*a3)'
> Mod4bin.fit<-sem(Mod4bin, data=dat, ordered=c("ModBin"))
> summary(Mod4bin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  84 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               98.424     112.596
  Degrees of freedom                                67          67
  P-value (Chi-square)                           0.007       0.000
  Scaling correction factor                                  1.110
  Shift parameter                                           23.962
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem
```

```
Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U =~
    Choice_Speed      1.000                               0.563
0.458
    Choice_Flexi      2.195    0.795    2.760    0.006    1.236
0.910
    Choice_Reliabl    1.298    0.391    3.315    0.001    0.731
0.563
  C =~
    Choice_Cost       1.000                               0.888
0.616
    Choice_Pleasur    0.674    0.235    2.871    0.004    0.598
0.417
    Choice_Green      1.382    0.403    3.428    0.001    1.227
0.906
  ATT =~
    MEASURE           1.000                               0.663
1.000
  AFF =~
    AFF1              1.000                               1.203
1.000
  PAC =~
    PAC1              1.000                               1.094
0.827
    PAC2              0.234    0.204    1.149    0.251    0.256
0.148
    PAC3              0.623    0.237    2.632    0.008    0.681
0.449
    PAC4              0.500    0.220    2.278    0.023    0.547
0.358

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModBin ~
    ATT       (a1)    0.111    0.124    0.894    0.371    0.073
0.070
    AFF       (a2)   -0.127    0.080   -1.583    0.113   -0.153   -
0.145
    PAC       (a3)    0.444    0.173    2.567    0.010    0.485
0.460
    Home_D    (a4)   -0.180    0.160   -1.125    0.260   -0.180   -
0.119
    U         (a5)   -0.682    0.214   -3.190    0.001   -0.384   -
0.364
    C         (a6)    0.585    0.162    3.605    0.000    0.519
0.492
  PAC ~
    Home_D    (b1)   -0.681    0.162   -4.216    0.000   -0.623   -
0.433
    U         (b2)   -0.517    0.248   -2.087    0.037   -0.266   -
0.266
    C         (b5)    0.383    0.166    2.306    0.021    0.311
0.311
  ATT ~
```

```
    AFF       (b3)   -0.246    0.058   -4.225    0.000   -0.446   -
0.446
    C         (b4)    0.146    0.084    1.746    0.081    0.195
0.195

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U ~~
    C                 0.017    0.052    0.320    0.749    0.033
0.033
    AFF               0.186    0.086    2.153    0.031    0.274
0.274
  C ~~
    AFF              -0.131    0.110   -1.187    0.235   -0.122   -
0.122

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Choice_Speed      3.840    0.154   24.918    0.000    3.840
3.121
    Choice_Flexi      3.776    0.174   21.660    0.000    3.776
2.779
    Choice_Reliabl    3.616    0.150   24.165    0.000    3.616
2.786
    Choice_Cost       3.512    0.170   20.654    0.000    3.512
2.437
    Choice_Pleasur    3.128    0.153   20.396    0.000    3.128
2.181
    Choice_Green      3.572    0.164   21.762    0.000    3.572
2.638
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.201
    PAC1              4.103    0.191   21.503    0.000    4.103
3.102
    PAC2              3.210    0.195   16.435    0.000    3.210
1.859
    PAC3              2.426    0.192   12.663    0.000    2.426
1.600
    PAC4              2.502    0.189   13.255    0.000    2.502
1.635
    ModBin            0.000                               0.000
0.000
    U                 0.000                               0.000
0.000
    C                 0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
```

```
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin|t1        -0.577    0.147   -3.924    0.000   -0.577   -
0.547

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Choice_Speed      1.196    0.202    5.908    0.000    1.196
0.790
    Choice_Flexi      0.317    0.390    0.814    0.415    0.317
0.172
    Choice_Reliabl    1.150    0.231    4.974    0.000    1.150
0.683
    Choice_Cost       1.288    0.270    4.774    0.000    1.288
0.620
    Choice_Pleasur    1.698    0.327    5.184    0.000    1.698
0.826
    Choice_Green      0.328    0.319    1.030    0.303    0.328
0.179
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.553    0.285    1.939    0.052    0.553
0.316
    PAC2              2.917    1.031    2.829    0.005    2.917
0.978
    PAC3              1.837    0.414    4.433    0.000    1.837
0.798
    PAC4              2.041    0.486    4.200    0.000    2.041
0.872
    ModBin            0.016                               0.016
0.015
    U                 0.317    0.160    1.978    0.048    1.000
1.000
    C                 0.788    0.362    2.179    0.029    1.000
1.000
    ATT               0.326    0.047    6.924    0.000    0.742
0.742
    AFF               1.448    0.303    4.776    0.000    1.000
1.000
    PAC               0.778    0.340    2.289    0.022    0.650
0.650

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModBin            1.000                               1.000
1.000

R-Square:
                   Estimate
    Choice_Speed      0.210
    Choice_Flexi      0.828
    Choice_Reliabl    0.317
    Choice_Cost       0.380
    Choice_Pleasur    0.174
```

```
    Choice_Green      0.821
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.684
    PAC2              0.022
    PAC3              0.202
    PAC4              0.128
    ModBin            0.985
    ATT               0.258
    PAC               0.350

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.302    0.121   -2.500    0.012   -0.302   -
0.199
    Uie              -0.230    0.127   -1.804    0.071   -0.129   -
0.123
    AFFie            -0.027    0.032   -0.845    0.398   -0.033   -
0.031
    CieATT            0.016    0.018    0.902    0.367    0.014
0.014
    CiePAC            0.170    0.085    1.999    0.046    0.151
0.143
    Home_Dte         -0.483    0.154   -3.131    0.002   -0.483   -
0.318
    Ute              -0.911    0.243   -3.753    0.000   -0.513   -
0.487
    AFFte            -0.154    0.069   -2.219    0.026   -0.185   -
0.176
    Cte               0.771    0.185    4.173    0.000    0.685
0.649

> fitMeasures(Mod4bin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.060 0.901 0.908
>
> #Trinomial dependent variable
> Mod4trin<-'ModTrin~a1*ATT+a2*AFF+a3*PAC+a4*Home_D+a5*U+a6*C
+ U=~Choice_Speed + Choice_Flexi + Choice_Reliable
+ C=~Choice_Cost + Choice_Pleasure + Choice_Green
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D+b2*U+b5*C
+ ATT~b3*AFF+b4*C
+ #Indirect effet
+ Home_Die:=b1*a3
+ Uie:=b2*a3
+ AFFie:=b3*a1
+ CieATT:=b4*a1
+ CiePAC:=b5*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)
+ Ute:=a5+(b2*a3)
+ AFFte:=a2+(b3*a1)
+ Cte:=a6+(b4*a1)+(b5*a3)'
> Mod4trin.fit<-sem(Mod4trin, data=dat, ordered=c("ModTrin"))
```

```
> summary(Mod4trin.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  69 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic               96.424     111.444
  Degrees of freedom                                67          67
  P-value (Chi-square)                           0.011       0.001
  Scaling correction factor                                  1.104
  Shift parameter                                           24.081
    for simple second-order correction (Mplus variant)

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U =~
    Choice_Speed      1.000                                0.680
0.552
    Choice_Flexi      1.393    0.509    2.735    0.006    0.947
0.697
    Choice_Reliabl    1.329    0.385    3.454    0.001    0.903
0.696
  C =~
    Choice_Cost       1.000                                0.795
0.552
    Choice_Pleasur    0.938    0.305    3.074    0.002    0.746
0.520
    Choice_Green      1.472    0.388    3.790    0.000    1.171
0.865
  ATT =~
    MEASURE           1.000                                0.663
1.000
  AFF =~
    AFF1              1.000                                1.194
1.000
  PAC =~
    PAC1              1.000                                0.991
0.754
    PAC2              0.406    0.259    1.570    0.116    0.402
0.232
    PAC3              0.670    0.258    2.595    0.009    0.664
0.437
    PAC4              0.636    0.245    2.595    0.009    0.630
0.409

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  ModTrin ~
    ATT       (a1)    0.028    0.138    0.201    0.841    0.018
0.017
```

```
    AFF         (a2)   -0.173    0.081   -2.142    0.032   -0.207   -
0.193
    PAC         (a3)    0.481    0.207    2.324    0.020    0.477
0.446
    Home_D      (a4)   -0.235    0.182   -1.291    0.197   -0.235   -
0.153
    U           (a5)   -0.027    0.149   -0.179    0.858   -0.018   -
0.017
    C           (a6)    0.690    0.194    3.549    0.000    0.549
0.513
  PAC ~
    Home_D      (b1)   -0.648    0.157   -4.119    0.000   -0.654   -
0.454
    U           (b2)   -0.365    0.189   -1.924    0.054   -0.250   -
0.250
    C           (b5)    0.423    0.188    2.251    0.024    0.340
0.340
  ATT ~
    AFF         (b3)   -0.254    0.061   -4.198    0.000   -0.458   -
0.458
    C           (b4)    0.157    0.095    1.650    0.099    0.189
0.189

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U ~~
    C                 0.056    0.063    0.884    0.377    0.103
0.103
    AFF               0.237    0.102    2.325    0.020    0.292
0.292
  C ~~
    AFF              -0.117    0.101   -1.154    0.248   -0.123   -
0.123

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Choice_Speed      3.840    0.154   24.918    0.000    3.840
3.121
    Choice_Flexi      3.776    0.174   21.660    0.000    3.776
2.779
    Choice_Reliabl    3.616    0.150   24.165    0.000    3.616
2.786
    Choice_Cost       3.512    0.170   20.654    0.000    3.512
2.437
    Choice_Pleasur    3.128    0.153   20.396    0.000    3.128
2.181
    Choice_Green      3.572    0.164   21.762    0.000    3.572
2.638
    MEASURE           1.195    0.072   16.502    0.000    1.195
1.801
    AFF1              2.648    0.141   18.738    0.000    2.648
2.218
    PAC1              4.103    0.191   21.503    0.000    4.103
3.121
    PAC2              3.210    0.195   16.435    0.000    3.210
1.852
```

```
    PAC3              2.426    0.192   12.663    0.000    2.426
1.598
    PAC4              2.502    0.189   13.255    0.000    2.502
1.626
    ModTrin           0.000                               0.000
0.000
    U                 0.000                               0.000
0.000
    C                 0.000                               0.000
0.000
    ATT               0.000                               0.000
0.000
    AFF               0.000                               0.000
0.000
    PAC               0.000                               0.000
0.000

Thresholds:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin|t1       -0.615    0.146   -4.210    0.000   -0.615   -
0.575
    ModTrin|t2        0.875    0.146    5.982    0.000    0.875
0.818

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Choice_Speed      1.052    0.184    5.719    0.000    1.052
0.695
    Choice_Flexi      0.949    0.265    3.583    0.000    0.949
0.514
    Choice_Reliabl    0.869    0.253    3.434    0.001    0.869
0.516
    Choice_Cost       1.443    0.295    4.888    0.000    1.443
0.695
    Choice_Pleasur    1.499    0.266    5.633    0.000    1.499
0.729
    Choice_Green      0.463    0.246    1.883    0.060    0.463
0.252
    MEASURE           0.000                               0.000
0.000
    AFF1              0.000                               0.000
0.000
    PAC1              0.747    0.241    3.105    0.002    0.747
0.432
    PAC2              2.842    0.984    2.887    0.004    2.842
0.946
    PAC3              1.864    0.418    4.463    0.000    1.864
0.809
    PAC4              1.970    0.460    4.279    0.000    1.970
0.832
    ModTrin           0.245                               0.245
0.214
    U                 0.462    0.208    2.221    0.026    1.000
1.000
    C                 0.633    0.299    2.116    0.034    1.000
1.000
```

```
    ATT                0.323    0.047    6.851    0.000    0.734
0.734
    AFF                1.425    0.306    4.665    0.000    1.000
1.000
    PAC                0.621    0.282    2.200    0.028    0.633
0.633

Scales y*:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    ModTrin            1.000                               1.000
1.000

R-Square:
                   Estimate
    Choice_Speed      0.305
    Choice_Flexi      0.486
    Choice_Reliabl    0.484
    Choice_Cost       0.305
    Choice_Pleasur    0.271
    Choice_Green      0.748
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.568
    PAC2              0.054
    PAC3              0.191
    PAC4              0.168
    ModTrin           0.786
    ATT               0.266
    PAC               0.367

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die          -0.312    0.124   -2.511    0.012   -0.312   -
0.203
    Uie               -0.176    0.107   -1.642    0.101   -0.119   -
0.112
    AFFie             -0.007    0.035   -0.200    0.842   -0.008   -
0.008
    CieATT             0.004    0.021    0.207    0.836    0.003
0.003
    CiePAC             0.204    0.095    2.147    0.032    0.162
0.152
    Home_Dte          -0.547    0.159   -3.442    0.001   -0.547   -
0.355
    Ute               -0.202    0.143   -1.412    0.158   -0.137   -
0.128
    AFFte             -0.180    0.072   -2.508    0.012   -0.215   -
0.201
    Cte                0.898    0.220    4.086    0.000    0.714
0.668

> fitMeasures(Mod4trin.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.058 0.905 0.912
>
> #Continous dependent variable
```

```
> Mod4smi<-'SusMobInd~a1*ATT+a2*AFF+a3*PAC+a4*Home_D+a5*U+a6*C
+ U=~Choice_Speed + Choice_Flexi + Choice_Reliable
+ C=~Choice_Cost + Choice_Pleasure + Choice_Green
+ ATT=~MEASURE
+ AFF=~AFF1
+ PAC=~PAC1+PAC2+PAC3+PAC4
+ PAC~b1*Home_D+b2*U+b5*C
+ ATT~b3*AFF+b4*C
+ #Indirect effet
+ Home_Die:=b1*a3
+ Uie:=b2*a3
+ AFFie:=b3*a1
+ CieATT:=b4*a1
+ CiePAC:=b5*a3
+ #Total effect
+ Home_Dte:=a4+(b1*a3)
+ Ute:=a5+(b2*a3)
+ AFFte:=a2+(b3*a1)
+ Cte:=a6+(b4*a1)+(b5*a3)'
> Mod4smi.fit<-sem(Mod4smi, data=dat, estimator="MLM")
> summary(Mod4smi.fit, standardized = T, rsq=T)
lavaan (0.5-20) converged normally after  77 iterations

                                                  Used       Total
  Number of observations                           130         159

  Estimator                                         ML      Robust
  Minimum Function Test Statistic              158.200     154.842
  Degrees of freedom                                67          67
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.022
    for the Satorra-Bentler correction

Parameter Estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem

Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U =~
    Choice_Speed      1.000                               0.693
0.563
    Choice_Flexi      1.265    0.258    4.902    0.000    0.877
0.646
    Choice_Reliabl    1.526    0.303    5.040    0.000    1.058
0.815
  C =~
    Choice_Cost       1.000                               0.819
0.568
    Choice_Pleasur    0.931    0.190    4.912    0.000    0.763
0.529
    Choice_Green      1.464    0.276    5.306    0.000    1.199
0.879
  ATT =~
    MEASURE           1.000                               0.667
1.000
```

```
  AFF =~
    AFF1              1.000                                   1.280
1.000
  PAC =~
    PAC1              1.000                                   0.883
0.672
    PAC2              0.536    0.219    2.451    0.014    0.473
0.272
    PAC3              0.735    0.215    3.419    0.001    0.649
0.434
    PAC4              0.814    0.211    3.858    0.000    0.719
0.469

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  SusMobInd ~
    ATT       (a1)    0.003    0.023    0.136    0.892    0.002
0.009
    AFF       (a2)   -0.010    0.014   -0.678    0.498   -0.012   -
0.053
    PAC       (a3)    0.129    0.041    3.140    0.002    0.114
0.487
    Home_D    (a4)   -0.056    0.033   -1.678    0.093   -0.056   -
0.167
    U         (a5)   -0.049    0.031   -1.576    0.115   -0.034   -
0.146
    C         (a6)    0.100    0.030    3.301    0.001    0.082
0.351
  PAC ~
    Home_D    (b1)   -0.551    0.132   -4.178    0.000   -0.624   -
0.432
    U         (b2)   -0.305    0.157   -1.949    0.051   -0.240   -
0.240
    C         (b5)    0.408    0.145    2.811    0.005    0.379
0.379
  ATT ~
    AFF       (b3)   -0.183    0.044   -4.198    0.000   -0.351   -
0.351
    C         (b4)    0.210    0.079    2.638    0.008    0.257
0.257

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
  U ~~
    C                 0.085    0.063    1.335    0.182    0.149
0.149
    AFF               0.159    0.091    1.758    0.079    0.179
0.179
  C ~~
    AFF              -0.160    0.104   -1.540    0.124   -0.153   -
0.153

Intercepts:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
```

```
   Choice_Speed      3.792    0.108   34.955    0.000    3.792
3.078
   Choice_Flexi      3.785    0.120   31.638    0.000    3.785
2.786
   Choice_Reliabl    3.608    0.114   31.571    0.000    3.608
2.780
   Choice_Cost       3.469    0.127   27.322    0.000    3.469
2.406
   Choice_Pleasur    3.031    0.127   23.891    0.000    3.031
2.103
   Choice_Green      3.454    0.120   28.738    0.000    3.454
2.530
   MEASURE           1.150    0.059   19.597    0.000    1.150
1.725
   AFF1              2.769    0.113   24.567    0.000    2.769
2.163
   PAC1              4.036    0.109   36.974    0.000    4.036
3.069
   PAC2              3.185    0.170   18.765    0.000    3.185
1.832
   PAC3              2.482    0.148   16.749    0.000    2.482
1.660
   PAC4              2.518    0.158   15.973    0.000    2.518
1.643
   SusMobInd         0.579    0.020   28.458    0.000    0.579
2.486
   U                 0.000                               0.000
0.000
   C                 0.000                               0.000
0.000
   ATT               0.000                               0.000
0.000
   AFF               0.000                               0.000
0.000
   PAC               0.000                               0.000
0.000

Variances:
                  Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
   Choice_Speed      1.038    0.180    5.758    0.000    1.038
0.683
   Choice_Flexi      1.077    0.210    5.121    0.000    1.077
0.583
   Choice_Reliabl    0.565    0.222    2.544    0.011    0.565
0.336
   Choice_Cost       1.409    0.194    7.280    0.000    1.409
0.678
   Choice_Pleasur    1.494    0.157    9.494    0.000    1.494
0.720
   Choice_Green      0.425    0.220    1.932    0.053    0.425
0.228
   MEASURE           0.000                               0.000
0.000
   AFF1              0.000                               0.000
0.000
   PAC1              0.949    0.193    4.930    0.000    0.949
0.549
```

```
    PAC2              2.797    0.195   14.346    0.000    2.797
0.926
    PAC3              1.816    0.236    7.699    0.000    1.816
0.812
    PAC4              1.831    0.219    8.353    0.000    1.831
0.780
    SusMobInd         0.020    0.004    5.586    0.000    0.020
0.371
    U                 0.481    0.152    3.161    0.002    1.000
1.000
    C                 0.671    0.223    3.002    0.003    1.000
1.000
    ATT               0.348    0.044    7.898    0.000    0.783
0.783
    AFF               1.639    0.138   11.878    0.000    1.000
1.000
    PAC               0.499    0.200    2.493    0.013    0.639
0.639

R-Square:
                   Estimate
    Choice_Speed      0.317
    Choice_Flexi      0.417
    Choice_Reliabl    0.664
    Choice_Cost       0.322
    Choice_Pleasur    0.280
    Choice_Green      0.772
    MEASURE           1.000
    AFF1              1.000
    PAC1              0.451
    PAC2              0.074
    PAC3              0.188
    PAC4              0.220
    SusMobInd         0.629
    ATT               0.217
    PAC               0.361

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv
Std.all
    Home_Die         -0.071    0.026   -2.741    0.006   -0.071   -
0.211
    Uie              -0.039    0.023   -1.693    0.090   -0.027   -
0.117
    AFFie            -0.001    0.004   -0.136    0.892   -0.001   -
0.003
    CieATT            0.001    0.005    0.136    0.892    0.001
0.002
    CiePAC            0.053    0.021    2.529    0.011    0.043
0.185
    Home_Dte         -0.127    0.026   -4.865    0.000   -0.127   -
0.378
    Ute              -0.088    0.033   -2.665    0.008   -0.061   -
0.263
    AFFte            -0.010    0.015   -0.707    0.480   -0.013   -
0.057
    Cte               0.153    0.030    5.046    0.000    0.125
0.538
```

```
> fitMeasures(Mod4smi.fit, c("rmsea", "cfi", "ifi"))
rmsea   cfi   ifi
0.102 0.780 0.792
```