

External drivers of choice:
Improving choice modelling and design by integrating
latent variables and optimally presenting explanatory
factors

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Thesis Abstract

In the choice modelling context, characteristics of alternatives, attributes, and attributes' levels have received great attention from researchers in the past decades. The main objective was to understand how much these variables had an influence on the decision-making process (Kahneman & Tversky, 1979, 1984; McFadden, 1986; Simon, 1956; Tversky & Kahneman, 1986). In recent years, however, several works focused their attention on external characteristics that are mainly connected to the decision maker: latent variables adoption, through hybrid choice models, has given the chance to throw lights on aspects not fully considered until then (Ben-Akiva & Boccara, 1995; Ben-Akiva, Walker, et al., 2002; Vredin Johansson, Heldt, & Johansson, 2006; Walker & Ben-Akiva, 2002; Walker, 2001). Following this research stream, this dissertation studies how intangible (i.e., not directly observable) individuals' characteristics influence the decision-making process.

The first article (Chapter 2) examines, in the context of public transportation, how the introduction of specific train sections based on travelers' habits and needs can increase the value of train subscriptions. It studies whether including the individuals' tendency towards out-group derogation influences travelers' preference for these specific train sections. It demonstrates, through the adoption of a hybrid choice model, that specific groups of individuals with a higher tendency towards out-group derogation indicate a strong preference for subscriptions that include specific train sections. In other words, it highlights how travelers' heterogeneity, represented in this case by the attitude to distance themselves from others with different characteristics, influences the choice process for a new train subscription.

The second article (Chapter 3) investigates, in the context of public transportation, the effect of not directly observable social norms on the subscription choice process beyond the characteristics of the subscription itself. First, it analyses travelers' preferences for subscriptions with different types of (constrained) access then it examines the effect of social norms on these preferences. It demonstrates that the presence of formal time constraints and professional social norms that affect their working time flexibility have a strong impact on travelers' subscription preferences.

Finally, the third article (Chapter 4) analyses, following the choice design approach adopted in the first two articles of this dissertation, the effect that different choice task layouts in the presentation phase have on the choice process. In the discrete choice experiment (DCE) framework, it examines whether a choice design with informative labels can influence their attribute importance scores compared to a choice design with non-informative labels and an attribute representing the original (and informative) labels. Adopting a choice-based conjoint (CBC) analysis with a Hierarchical Bayes (HB) estimation process, this article demonstrates that respondents ascribe a significant lower importance score to the attribute representing the labels when it has been placed among the other attributes in the choice task (compared to the case in which labels are used as attributes' titles).

With these three articles, this thesis contributes to the understanding of the effect that intangible respondents' traits have on their choices and highlights how important and sensitive the definition of alternatives' characteristics and their representation are in the choice design phase.

Keywords: discrete choice experiments, hybrid choice models, choice-based conjoint, hierarchical bayes estimation, latent variables, attribute importance

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Chapter 1: Introduction

In everyday life, each person must face choices, starting from the simplest ones (e.g., how to dress for a job interview or which restaurant to choose for a lunch break) that have a short-term effect up to the very complex ones that can affect his/her future (for example, the willingness to change his/her career path moving from employee to entrepreneur or the chance to purchase an apartment for his/her family). For each of these choices, people compare different options (alternatives) that can give them the desired result and make their final choice after a “rational” evaluation. With the theory of rational choices (Coleman, Coleman, & Farraro, 1992; Scott, 2000; Simon, 1956), it was thought that each person chose the best alternative based on its intrinsic characteristics. The best alternative was defined as the one that provided maximum utility (or minimum regret) among the alternatives available to the person at the moment of choice (Ramos, Daamen, & Hoogendoorn, 2014). Adopting the utility maximization assumption, individuals rationally evaluate the alternatives they have and choose the one that gives them the maximum benefit following the so-called expected utility theory (EUT) (Von Neumann & Morgenstern, 1947). Conversely, the minimization of regret assumes that people make their choice not only by evaluating the utility associated with their choice but also on the chance that not chosen alternative could outperform their choice (Chorus, Molin, Van Wee, Arentze, & Timmermans, 2006). By doing so, they intend to minimize the regret that could derive from their decision (de Moraes Ramos, Daamen, & Hoogendoorn, 2011).

Several techniques to study and analyze individuals’ choices have been developed by psychologists since the 1960s (Anderson, 1962; Luce & Tukey, 1964) but it is since the early 1970s that they received much more attention with their introduction into the marketing literature with the name of conjoint analysis (Green & Rao, 1971; Green & Srinivasan, 1978; Green, Wind, & Carmone, 1972). Conjoint analysis has taken a crucial role in predicting and understanding consumers’ choice behavior with the relative decision-making processes and its application and development increased quietly during the late 1970s and the 1980s (Kjaer, 2005). In the same period, another choice technique was developed: the so-called (discrete) choice experiments (Hanley, Wright, & Koop, 2002). This term was adopted for the first time by Louviere and Woodworth (1983). Among the choice techniques, the discrete choice experiment (DCE) is one of the simplest

and, therefore its biggest advantage is that requires a low cognitive effort concerning the task complexity and the difficulty of the experiment (Louviere, Hensher, & Swait, 2000). In general, respondents participating in a DCE make choice among a determined set of alternatives (two or more) respecting specifying criteria (Train, 1986):

- The number of alternatives that compose the set is limited;
- The alternatives adopted are reciprocally exclusive (to avoid dominant alternative);
- The set of alternatives is comprehensive (based on their characteristics, all possible alternatives are introduced).

The proposed alternatives in each choice are different from each other based on the characteristics presented to the respondents. These characteristics are called attributes of the alternatives. The assignment of distinct levels to these attributes through a systematic process called experimental design allows obtaining the desired level of variation across the alternatives. By introducing a certain dissimilarity among the levels of the alternatives' attributes in choice scenarios (i.e., choice tasks), it is possible to evaluate the impact that each attribute has on the choice process of the decision-maker; in other words, it can be possible to estimate the marginal rates of attributes' substitution (Louviere, et al., 2000). An exemplary choice task regarding respondents choosing their means of transport to reach their workplace is shown in Figure 1.

Figure 1 - Chapter 1 - Exemplary choice task

If these were the transportation modes you have, which of those would you choose?

	Mode 1	Mode 2
Means of transport	Car	Train
Travel time	30 minutes	45 minutes
Walking time to/from transportation	0 minutes	10 minutes
Parking fee	CHF 10.-	CHF 0.-
Price	CHF 15.-	CHF 5.-
Indicate your choice	<input type="radio"/>	<input type="radio"/>

Attribute Alternative Level

With the advent of behavioral economics (Camerer, Loewenstein, & Rabin, 2004; Kahneman, 2003; Mullainathan & Thaler, 2000; Wilkinson & Klaes, 2017), the theory of choices made entirely based on the alternatives' characteristics was no longer so supported and researchers began to evaluate whether there were other external factors (and not directly related to the alternatives) that somehow could influence the decision-making process. Specifically, behavioral economists did not accept the rationality purely limited to the economic factors and suggested a broader theoretical approach in which other factors, such as emotional, psychological, cognitive, and social factors, played an increasingly greater role in influencing the individuals' economic decisions (Kahneman, Knetsch, & Thaler, 1991; Kahneman & Ritov, 1994; Kahneman, Ritov, Schkade, Sherman, & Varian, 1999; Thaler, 1980, 1985).

Given the need to analyze an individual's choices and the uncertainty surrounding them, DCEs are based on the random utility theory that is coherent with neoclassical economics (Manski, 1977) and the economic theory of value (Lancaster, 1966). Adopting the random utility theory (Ben-Akiva & Lerman, 1985), researchers can obtain preferences for goods with complex characteristics from which specific models can be evaluated (Hall, Viney, Haas, & Louviere, 2004). These models, dealing with the uncertainty of an individual's choice, assign to each alternative a probability of being the individual's choice instead of the precise identification of the alternative that will be designated as the chosen option (Kjaer, 2005). Random utility models (RUM) have been introduced not to solve the individual's lack of rationality in the choice process, but to make up for the lack of information the researcher has about the characteristics of the alternatives and /or of the individual (Manski, 1977). In particular, these models suppose that both attributes of alternative and decision-maker characteristics influence the decision-making process conducting to the revealed choice.

Given the need to have models able to analyze and better understand individuals' choices based on their characteristics, several researchers have developed over time models capable of incorporating individuals' characteristics directly and not directly observable: by introducing this information as explanatory variables within the choice models, the predictive power of these models increased significantly and led to the birth of those that are today defined as "hybrid choice models" (Ben-Akiva, et al., 1999; Ben-Akiva, McFadden, et al., 2002; Ben-Akiva, Walker, et al., 2002; Bolduc & Alvarez-Daziano, 2010; McFadden, 1986; Walker & Ben-Akiva, 2002; Walker, 2001).

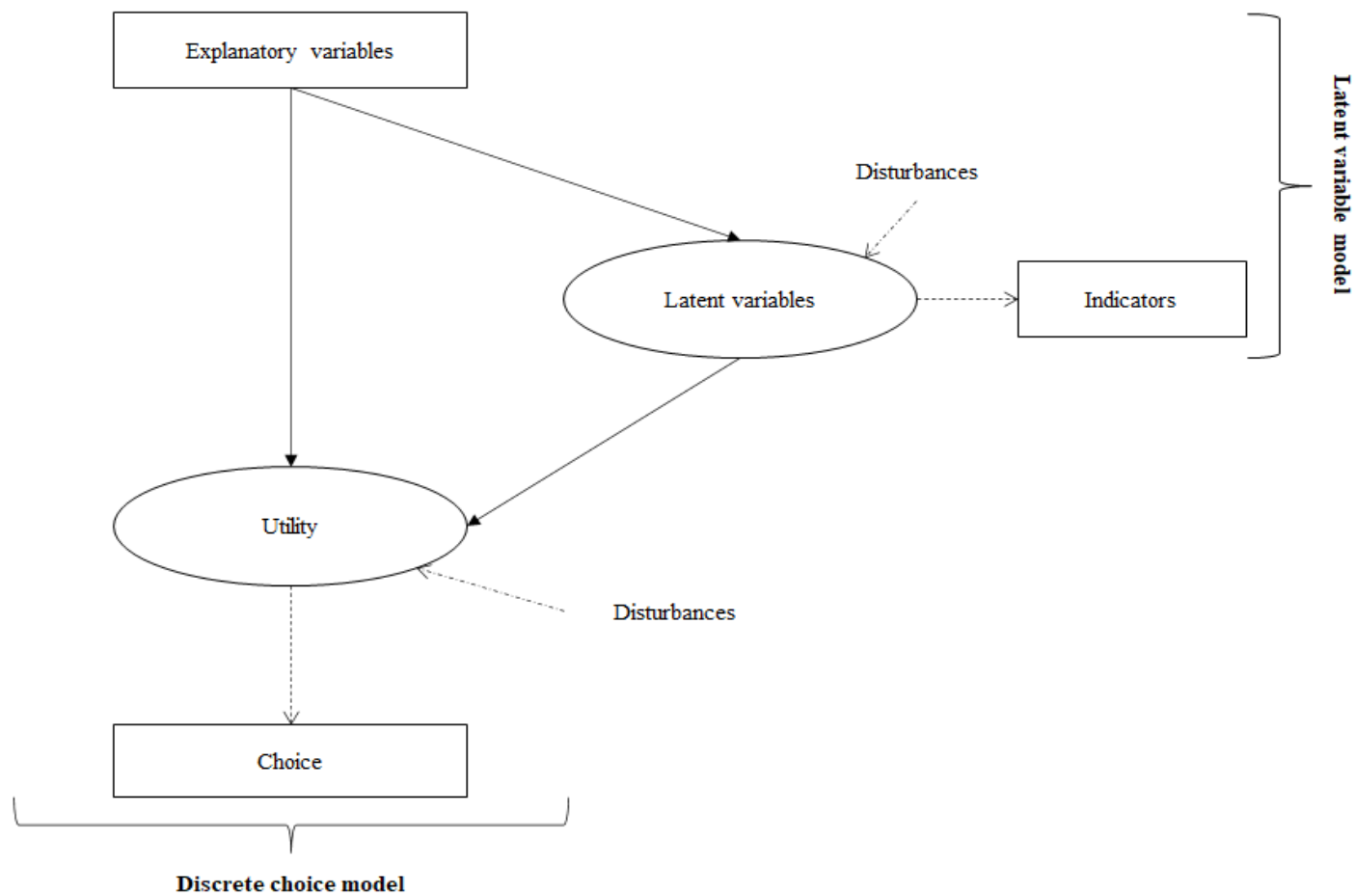
Unlike classic discrete choice models, in which respondents' choices (response variable) are analyzed according to the characteristics of the alternatives only, hybrid choice models introduce both directly observable information as explanatory variables (e.g., gender, social status, income) and not directly observable variables (latent constructs) such as attitudes and perceptions measured through appropriately validated measurement scales. By adopting these models, researchers have the great advantage of directly introducing all those irregularities and distinctive aspects of the decision maker, deriving from perceptions, attitudes, and adopted cognitive processes, among the

systematic and invariant characteristics of the random utility model (Ben-Akiva, Walker, et al., 2002). Moreover, these models have been enriched with the adoption of flexible disturbances to reduce the error terms associated with individual preference estimation.

The reference framework of the hybrid choice models presented in this dissertation can be summarized through the Integrated Choice and Latent Variable (ICLV) model (Figure 2 with reference to Walker and Ben-Akiva (2002)): this model extends the basic discrete choice model to enrich it with the behavioral characterizations of individuals and diminish its simplifying assumptions (Ben-Akiva, McFadden, et al., 2002). The extensions introduced in this type of model concern:

- The introduction of flexible disturbances to simulate an uncertainty structure that can affect several equations of the model;
- The definition of an explicit and well-structured model of not directly observable psychological factors (latent variables) such as perceptions and attitudes. In other words, it means integrating directly observable socio-economic characteristics with information regarding the population heterogeneity that is difficult to measure (e.g., psychological factors such as technology affinity, risk attitude, and self-control) within the discrete choice models. The final objective is to describe apparently irrational behaviors by adopting models that can explain a considerable part of the unobserved individuals' heterogeneity by integrating socio-economic and psychological data in the analysis of the choice process.

Figure 2 - Chapter 1 - Integrated Choice and Latent Variable (ICLV) Model



Given their flexibility, these models have had remarkable success in various fields of application. Several scientific applications have been conducted with interesting results and some of them are mentioned below for their scientific rigor and the innovation introduced in the related research fields.

Tourism

- Sarman, Scagnolari, and Maggi (2016) adopted an Integrated Choice and Latent Variable model to evaluate the effect that potential life-threatening events at the leisure travel destination of young tourists may have on the choice to undertake the trip itself. Their main findings concerned 1) the important variability in risk evaluation present in the sample (respondents with different characteristics evaluated the same hazards with different sensibilities), 2) the mitigation effect of trip length on the traveling aversion, 3) the direct effect that risk perception had on the decision to travel and perceived level of alert. Their results could not be generalized to the entire population given the structure of their sample, but their work contributed to the tourism literature introducing an innovative behavioral analysis of risk.
- Mäntymaa, Ovaskainen, Juutinen, and Tyrväinen (2018) designed a hybrid choice model with latent classes to analyze the preference heterogeneity of foreign and domestic visitors to the Ruka-Kuusamo forest area in Finland. The study aimed to highlight the good practices to enhance the quality of forested areas close to the tourist regions by involving private landowners and operators in the tourism sector in well-defined forest management activities on private land. The authors identified three groups of visitors based on their attitude towards the landscape and environmental benefits to which to provide a differentiated naturalistic offer increasing landscape quality and biodiversity. Given the specificity of the study, some findings may seem to be in part inconsistent (i.e., some environmental

improvements have been recognized as unpleasant or disadvantageous for visitors).

- Lindberg, Veisten, and Halse (2019) analyzed the attractiveness of natural areas for visitors in Norway to support wildlife interpretative centers. They developed a hybrid choice model integrating individuals' characteristics (i.e., attitudes and socio-demographic variables) and interpretative center features to fully understand visitors' preferences. Results suggested that interviewees pay more attention to avoiding negative effects on wild reindeer habitat than to achieving positive effects. Their findings strongly depend on the sample characteristics and the application context. The authors suggested replicating their study in different settings to increase the validity of their results.

Health economics

- Kløjgaard and Hess (2011) determined the effect that attitudes, beliefs, and perceptions of patients and health care practitioners have on the treatment choice in the context of low back pain by adopting a hybrid choice model. One of the main contributions to the literature on preferences in health economics is that peers' evaluations and opinions have a strong influence on patients' choices. This result indicates that future research has to carefully evaluate the effect that peers have on patients' preferences and the relative joint (e.g., patients with their parenthood) decision-making process.
- Santos, Roberts, Barreto, and Cairncross (2011) developed an Integrated Choice and Latent Variable model to estimate the cognitive process that affects sanitation adoption in Salvador (Brazil). By integrating the latent variables (such as attitudes and perceptions), the hybrid choice model provided a causal path among these variables and individuals' demographic and socio-economic characteristics. The authors found that respondents had a positive inclination toward sanitation in Salvador, and

this attitude had an impact on how they expressed their preferences for the different types of systems. They advised extending the study by introducing additional socioeconomic factors, such as the percentage of individuals that moved to another neighborhood (with a different sanitation system) in future research.

- Buckell, Hensher, and Hess (2021) adopted a hybrid choice model to determine the effect that smoking addiction, measured with a latent variable, had on US smokers' choices with a particular focus on nicotine levels. Results indicated that high level of addiction strongly increase the use of cigarettes, decrease the adoption of e-cigarettes and the number of quit attempts. The explicit introduction of a variable that measures nicotine addiction in the choice experiments allows to considerably improve the predictive capacity of the models with respect to the behavior of smokers.
- Arora, et al. (2022) introduced a 30-items scale in a hybrid choice model to evaluate the impact that motivation had on the job preferences of community health workers in Ethiopia. The authors found that health workers with a high level of intrinsic motivation were more inclined to jobs with a low number of training days (reducing the period of absence from work that could have an impact on their performance) and the possibilities to enhance the health results of patients. Future research could include additional latent constructs to enrich the underlying structure of the model and increase its validity and applicability in other countries with different cultural, health, and political systems.

Marketing

- Yangui, Font, and Gil (2013) inspected consumers' preferences towards extra virgin olive oil, in Spain, by developing an Integrated Choice and Latent variable model in which food-related personality traits, purchase habits, and lifestyle orientation were included. They identified that these variables are important drivers of food choice partially revealing the

uncertainty related to consumer's behavioral process. Introducing in future research more appropriate latent variable scales could enhance the estimation process and increase the accuracy of the results.

- Abdelradi and Abdu (2015) evaluated individuals' purchase intention of date palm (a largely produced fruit in Saudi Arabia) by introducing consumers' attitudes, social pressure, and perceived control of the supply chain into a hybrid choice model. Results pointed out that consumers preferred and expressed a higher willingness to pay for locally produced date palm. Moreover, personality traits had a relevant effect on the decision-making process. Introducing additional latent variables measuring the heterogeneity in consumers' preferences could improve the predictive ability of the model.
- Giansoldati, Rotaris, Scorrano, and Danielis (2020) estimated the impact of the electric car (EC) previous knowledge, based on the marketing strategies adopted by car manufacturers in Italy, on the purchasing decisions analyzing the individuals' preferences between electric and petrol cars. Results suggested a high price sensitivity of Italian respondents suggesting that small and low-priced electric vehicles could be suitable compared to expensive cars. These cheap vehicles could accommodate Italian users' needs and be conformed with the inadequate parking capacity of Italian cities. With the electric vehicle market growth, future research could combine stated and revealed preference data to reduce the hypothetical bias and increase the realism of the hypothetical scenarios.
- Kiss, Czine, Balogh, and Szakály (2022) combined chocolate-related characteristics, such as type of chocolate (dark, milk, or white), brand (private labels or manufacturer brands), health claim (sugar-free) and price, and a latent variable measuring consumers' brand loyalty in a hybrid choice model to determine consumers' preferences in chocolate bars. The authors observed that brand is an important attribute for Hungarian consumers in the choice process, and brand loyalty is higher for

manufacturer brands (compared to store brands). However, the largest part of the respondents declared to be not so loyal to chocolate brands easily replacing their favorite brand in case of price increment. Extending this research with the adoption of a larger and international sample could increase its validity.

Transportation

- Morikawa, Ben-Akiva, and McFadden (2002) developed a hybrid choice model based on data collected by the Hague Consulting Group in 1987 for the Netherlands Railways. They estimated a choice model with revealed and state preference data, perceptual data (for example, relaxation during the trip, reliability of the arrival time, the flexibility of choosing departure time), and latent attributes such as ride comfort and convenience. Results indicated that combining revealed and stated preference data in the model estimation could support the detection of specific biases linked to the stated preference data and better determine key variables coefficients. Moreover, including latent variables with their attributes significantly increase the predictivity of the discrete choice model.
- Dannewald, Paulssen, Temme, and Walker (2007) included abstract motivations such as flexibility, possession, passivity, and environmental protection into a binary logit model to evaluate German consumers' choices about travel modes they preferred. The authors identified that respondents' need of flexibility increased the probability to use the car for their traveling whereas environmental concerns motivated them to adopt public transport. They highlighted that respondents with high levels of hedonism (strictly connected with flexibility) and security associated higher importance on detaining the transportation mean. Future research could include additional latent variable scales to better evaluate the effect of attitudes and perceptions on the choice process.

- Kamargianni and Polydoropoulou (2013) designed a discrete choice experiment to analyze Cypriot teenagers' preferences about walking and cycling to their commuting destination. The hybrid choice experiment included attributes of the different modes (i.e., parents' car, bus, bicycle, and walk) and it evaluated the effect that the latent variable (i.e., willingness to walk or cycle) has on respondents' preferences. Results revealed that travel cost and time had a significant impact on teenagers' mode choice and that attitudes toward cycling and walking were quite important. Additionally, family is a decisive factor in forging adolescents' travel behavior. In future works, additional attitudes, such as ecological awareness and peers influence, could be introduced in the model to create more realistic econometric models.
- Jung and Yoo (2016) evaluated air passengers' flight choice behavior in Seoul Metropolitan Area (South Korea) by estimating an Integrated Choice and Latent variable model in which they included tangible attributes (e.g., airfare, flight time, frequency, access time, and access cost) and intangible information such as airport access convenience, airport facility service quality, and service satisfaction. In this work, results indicated that airport access convenience, unlike airport facility service quality and service satisfaction, had a significant impact on passengers' airport choice process. Future research could replicate the experiment in different countries including attitudes and perceptions that are strongly connected to passengers' habits.
- Ding, Chen, Duan, Lu, and Cui (2017) focused their work on investigating the influence that attitudes to cycling and walking had on Chinese commuters' choices. They estimated an Integrated Choice and Latent variable model in which these attitudes interacted with household characteristics (i.e., presence of children in the household, bicycle ownership, and car ownership) and with individual characteristics (i.e., age, gender, education, occupation, income, bus card, and driver license

ownership). The authors highlighted that respondents' attitudes towards walking and cycling had a positive impact on the nonmotorized travel mode choice. These results could be validated integrating built environment factors and additional attitudes into the model in future studies.

- Borriello, Scagnolari, and Rose (2019) proposed a novel approach to evaluate and introduce attitudes and perceptions measured via a Likert scale in a hybrid choice model: they adopted an Evaluative Space Grid for measuring attitudes and perceptions to overcome the issue of ambivalence and indifference that individuals can demonstrate. They collected data in Switzerland about mode choices for a commuting trip and estimated the impact that latent variables (i.e., practicality and convenience of using the private car for commuting purposes) had on commuting choices. Their findings underline that ambivalent individuals (i.e., subjects that evaluate commuting by private car comfortable and uncomfortable at the same time) had different preferences from indifferent subjects (i.e., respondents that evaluate commuting by private car as neither comfortable nor uncomfortable). These results could support policymakers in raising the public transport share for commuting purposes. In future research, collecting data in other cities with different transportation systems could be beneficial to strength the model and validate the results.
- Irawan, Belgiawan, Joewono, and Simanjuntak (2020) studied the impact that latent variables, such as forced bus use, bus service quality, and favorable conditions for bus use, had on bus passengers' preferences in Yogyakarta (Indonesia). Specifically, they estimated the influence these variables had on shifting passengers' preferences from motorcycle-based transport to bus service. This research demonstrated that the three latent variables introduced in the model had a strong influence on respondents' preferences for bus adoption. Among the three latent variables, the perceived bus quality had the highest impact on the respondents' choices.

Given that results highlighted that young passengers were the group most forced to adopt the bus system, future studies could focus on the habits and attitudes of this segment of the population to better understand their transport needs and make them more loyal to the bus adoption.

Environmental studies

- Groothuis, et al. (2021) used a hybrid choice model to evaluate the direct influence that scientific information had on respondents' choices about a stormwater management program. Specifically, they introduced the level of concern and understanding as latent variables and demonstrated that both variables had an impact on valuing a stormwater management plan. The authors found that the scientific information intensified individuals' uneasiness about stream water quality. This information without any supportive graphical representation increased individuals' level of concern and turned out in increased favor of the stormwater management plan. Integrating stated preference with revealed preference data in future studies could enhance the model estimation and provide detailed results in supporting future policy decisions.
- Salak, Lindberg, Kienast, and Hunziker (2021) conducted a study to evaluate citizens' preferences for different renewable energy systems across diverse landscape types in Switzerland. Their work estimated the influence that the landscape-technology fit, introduced as a latent variable, had on the choice process about renewable energy infrastructure adoption. Results showed that respondents' propensity for renewable energy infrastructure alternatives could be influenced by several factors such as experience with these types of infrastructure and how they impacted the landscapes. Moreover, the authors highlighted that the development of these alternatives in specific areas could lead to more social conflicts than in other areas. Future developments of this research could involve other samples from different countries to compare the results.

- Franceschinis, et al. (2022) investigated the role that social norm effects and personal norm activation had on the respondents' preferences about activities to be carried out to preserve the conservation of soil functions. They conducted the experiment in the Veneto region of Italy and in New South Wales (Australia), and the results provided evidence of the external validity of the latent variables adopted. With their research, they demonstrated that both personal and social norms had a positive impact on respondents' sensitivity and willingness to pay for soil conservation policies. Future studies could evaluate how customized procedures to assess respondents' normative assumptions about non-market goods supply could be introduced in survey research.
- Strazzera, Meleddu, and Atzori (2022) investigated the impact that the perception of economic benefits and the perception of environmental and health risks, introduced as latent variables in a hybrid choice model, had on the public acceptance of military facilities present in Sardinia (Italy). Results made evident that raising the opportunity of investing in tourism and agriculture activities for the territory and increasing the period of discontinuation of the military activities could boost the approval of a downsizing scenario of the military bases. From the methodological perspective, future studies could introduce the Monte Carlo estimation process to better evaluate the advantages of the two estimators adopted in this research.

Focusing on the transportation field, great methodological developments have been made over the last few decades (Ben-Akiva & Boccara, 1995; Ben-Akiva, et al., 1994; Ben-Akiva, et al., 1999; Ben-Akiva, McFadden, & Train, 2019; Ben-Akiva, McFadden, et al., 2002; Bierlaire, 2016; Bierlaire & Fétiarison, 2009; Bliemer & Rose, 2009; Hensher, Rose, & Greene, 2005; McFadden, 1986; Morikawa, et al., 2002; Rose & Bliemer, 2009; Walker & Ben-Akiva, 2002) and have given the possibility to study the propensities of choice of users who use different means of transportation by introducing

an increasing level of information and by adopting more and more complex models. In the context of research concerning public transport, many have highlighted the peculiarities that made users prefer one vehicle over another and compared it with private vehicles.

Deepening the studies carried out in the marketing and public transport fields, this thesis, consisting of three articles, examines how the effect of certain intangible individuals' characteristics can influence their choices and how the representation of alternatives can alter their choice process.

Article 1 (Chapter 2: Integrating travelers' heterogeneity in subscription choice processes through hybrid choice modelling: an application to the Swiss railway market) analyzes the effect of individuals' propensity to distance themselves from others with different characteristics (outgroup derogation) in the process of choosing a railway subscription, assuming that each train can be divided into categories of people and not into levels of service provided (that it has been constant throughout the train in this experiment).

Article 2 (Chapter 3: How social norms influence train subscription choice process in Switzerland: a hybrid choice model with different rush hour access alternatives) studies to what extent the presence of both directly and not directly observable social norms (i.e., behavioral habits accepted in specific groups) influence individuals' choice process about a railway subscription that allows access to the train during rush hours (i.e., peak traffic periods during the day).

Article 3 (Chapter 4: Informative vs. non-informative labels in discrete choice experiments with stated preferences: a quantitative analysis of attribute importance), focusing on a technical choice made during the design of experiments in the first two articles, explores the effect of a different alternatives' representation within a choice task on the importance that individuals associate with the attributes present in the aforementioned alternatives. Specifically, it investigates how much importance an attribute can acquire when it assumes the role of alternatives' labels with respect to the other attributes (comparing it to the importance that it has in the scenario in which no attribute has the role of alternatives' labels).

1.1. Integrating travelers' heterogeneity in subscription choice processes through hybrid choice modelling: an application to the Swiss railway market

Public transport companies often segment their offer based on the level of service they offer (i.e., first and second class). However, this type of segmentation does not take into account the increasingly diversified characteristics of travelers (Saameli, 2014) and it leads to a sub-optimal allocation of its customers (for example, certain sections of a train are crowded while others are almost empty) (Ungricht, 2010). In the specific case of the Swiss railway offer, the possible extension of the SBB (in German, Schweizerische BundesBahnen) product line, introducing a greater diversification of the services offered based on their customers' characteristics and needs, could increase their satisfaction and indirectly the profits of the company itself (Babakus, Bienstock, & Van Scotter, 2004; Steven, Dong, & Dresner, 2012; Williams & Naumann, 2011). Individuals with different characteristics and needs are induced to have social interactions (positive or not) with other individuals adopting public transport and this behavior could lead some of them to prefer (or not) certain categories of social groups. For some types of travelers, this type of social interaction, with other individuals with characteristics and needs different from their own, may be appreciated and, sometimes, desired, while, for other travelers, these interactions can be annoying and influence their travelling choices. Therefore, once they have identified the group of individuals – with characteristics and needs similar to their own – they feel part of, these travelers will have a tendency to distance themselves (i.e., out-group derogation) from groups of individuals with different characteristics and needs (Dasgupta, 2004).

In this chapter, we focus on this attitude and elaborate on the framework in which this experiment has been conducted. From the theory perspective, we follow the social identity theory (Tajfel & Turner, 1979) and the literature related to intergroup biases (Hewstone, Rubin, & Willis, 2002). In particular, individuals typically prefer the social group they appertain to and try to separate themselves from other groups with different characteristics, attitudes, and behaviors (Dasgupta, 2004; Hogg & Hains, 1996; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987; Turner, Oakes, Haslam, & McGarty, 2016; Vanhoomissen & Van Overwalle, 2010). For a specific person, the in-group specifies the

category that the individual belongs to as a member of, whereas the out-group identifies the group in which he/she does not recognize him or herself as a member (Hewstone, et al., 2002). The groups can be of different types (e.g., cultural, religious, sports groups) and, more generally, they could be identified as psychological groups given that they refer to psychological traits and are independent of external factors. Expectations, behavioral norms, and beliefs allow for a clear distinction between groups (Efferson, Lalive, & Fehr, 2008), and, based on how much people perceive the differences between these characteristics, these groups can be more or less dissimilar to each other (Jetten, Spears, & Manstead, 2001). Social identity theory describes the mechanisms developed by individuals to determine their belonging to a specific group. According to this theory, the definition of psychological groups to which an individual can be attracted is a process of self-classification. This process is based on the mere attraction that individuals have to group characteristics and not on the interactions they have with group members (Hogg & Turner, 1985). In other words, this process is thus based on the prototyping of the group and not on the characteristics of the single individuals present in the group (Hogg, Hardie, & Reynolds, 1995). A specific group prototype is a conceptual depiction of the average characteristics (e.g., normative and/or stereotypical) of the group members compared to the average characteristics of the individuals that do not belong to the specific group (Hogg, et al., 1995). Furthermore, the prototypical representation of these groups is based on the depersonalization of the members' traits by focusing on the definition of group standards rather than on the specific characteristics of the individual members (Hogg & Hardie, 1992; Hogg, et al., 1995; Turner, et al., 1987). External individuals will be attracted by the group members not because of their characteristics but because they represent the personification of that group, and the closer these members are to the prototype of the group the more they will be attractive to the outside (Hogg & Hains, 1996). The attraction of an individual to a group depends on the level of similarity between the attitudes of the group and the individual and the mental process for assessing this similarity depends on several factors (Davis, 1984). Thus, the degree of identification of an individual with a specific group influences the social attraction towards that group. Once the group to which individuals belong has been identified (i.e., the in-group), they

have the tendency to attribute more positive characteristics to it than other out-groups (Dasgupta, 2004). This behavior can be referred to as in-group favoritism (Lewis & Bates, 2010) and it can also be declined to the tendency of associating negative characteristics with groups to which one does not belong: this case has been defined as out-group derogation (Dasgupta, 2004). In general, this phenomenon can be defined as intergroup bias and be interpreted as the attitude to ascribe a better evaluation to an in-group than to an out-group (Hewstone, et al., 2002; Levin & Sidanius, 1999). Intergroup bias affects behaviors, decisions, and judgments and induces individuals to feel more connected with their in-group and to distance themselves from other out-groups (Dasgupta, 2004; Hogg & Hains, 1996; Turner, et al., 1987). Although out-group derogation can be interpreted as a declination of in-group favoritism, the literature has illustrated how these two tendencies differ as intergroup competition increases (Brewer, 1979; Brewer, Manzi, & Shaw, 2016; Jost, Glaser, Kruglanski, & Sulloway, 2003; McGregor, Haji, & Kang, 2008; Stangor & Thompson, 2002). Similarly, these tendencies also apply to travelers who can identify with different groups of travelers. In fact, each traveler belongs to a specific travel-related socio-psychological group which can be identified by the demographic and psychographic characteristics, and they can vary in the different socio-psychological groups present on the train. The mere presence of groups of travelers with different characteristics can have an impact on individuals' perceptions (especially related to travel comfort) and lead to a tendency to distance themselves from travelers who belong to the out-groups (Brewer, 1979) and to some forms of intergroup conflict (Tajfel & Turner, 1979).

Even though significant literature on railway traveler behavior is present (Löfgren, 2008), prior research has not examined the impact of train social mixing on travelers' choices, which is the focus of this research. Considering this tendency and the specific segmentation of the product line, in this chapter, we evaluate, through a discrete choice experiment, the impact of introducing dedicated sections into the train on the individuals' subscription choice process based on the travelers' characteristics and habits. The introduction within the experiment of certain train sections dedicated to specific groups of travelers allows them to self-identify into their respective social groups. The labels associated with the different train sections (e.g., business) act as markers of the social

groups present in them and allow travelers to infer the prototype characteristics of the individuals present in those sections. In order to minimize intergroup conflicts, travelers identify themselves with the train sections associated with the groups they are most socially attracted by adopting a self-categorization process. Furthermore, given the low propensity of travelers to have interpersonal interactions with other individuals on the train (Evans & Wener, 2007), they consider sitting distant from individuals belonging to out-groups more important than sitting close to members of their own in-group. In other words, travelers do not choose their train section based on whom they want to sit with (affirmative categorization) rather than whom they do not want to sit with (negational categorization). Negational categorization refers to out-group derogation whereas affirmative categorization refers to in-group favoritism (Zhong, Phillips, Leonardelli, & Galinsky, 2008). Therefore, the higher travelers' tendency towards out-group derogation, the higher their desire to distance themselves from individuals of the out-groups, and the higher their likelihood to prefer a subscription that includes access to dedicated train sections (Ajzen, 1985). Results indicate that specific groups of travelers with a higher tendency towards out-group derogation (e.g., young travelers with a high level of education) mainly prefer subscriptions that allow access to dedicated sections of the train where groups of travelers with similar characteristics and habits are present.

1.2. How social norms influence train subscription choice process in Switzerland: a hybrid choice model with different rush hour access alternatives

In an increasingly globalized world with a growing demand for individuals to travel for work and/or pleasure, general mobility increasingly faces problems related to infrastructure congestion. With a focus on public transport, train congestion is a common problem caused by individuals travelling more and more often during specific time slots, called “rush hours”, to reach their destinations (Bloch, 2011; Riedener, 2012; Valda, 2015; Vontobel & Guanziroli, 2008). This congestion of public transport creates management inconveniences and leads to a reduction in the quality offered. Over time, various solutions have been adopted (for example, mobility pricing, trip-based pricing, and tradable credit schemes) to solve this problem, but the desired results have not always been achieved

(Kaddoura, Kickhöfer, Neumann, & Tirachini, 2015; Olszewski & Xie, 2005; Vrtic, Schüssler, Axhausen, & Erath, 2011; Vrtic, Schüssler, Erath, & Axhausen, 2007; Wu, Yin, Lawphongpanich, & Yang, 2012; Yang & Wang, 2011). In Switzerland, where we collected our data and ran our experiments, previous literature shows that the adoption of different work solutions, such as flexible working hours and working from home, have had a positive effect on reducing the congestion problem but with limited results in terms of general mobility (Munch, 2014; Weichbrodt, et al., 2013; Zemp, 2014).

In light of the previous research carried out and the solutions already implemented, we adopt a new viewpoint by focusing on the effect of not directly observable factors that induce individuals to travel in certain time intervals going beyond the classic public transportation pricing schemes. Specifically, this article studies the effect that social norms (Cialdini, 2007; Cialdini & Trost, 1998) present in different environments have on the traveler's choice process. Unlike the definition of formal restrictions (Chang & Mahmassani, 1988; Jou, Kitamura, Weng, & Chen, 2008; Senbil & Kitamura, 2004, 2005), social norms represent a code of behavior recognized by a group of individuals that does not have an official written form (Smith, 2002). These rules are not usually part of a formal agreement and appear differently among groups of people present in different organizations (Andersson & Pearson, 1999; Feldman, 1984; Hartman, 1996). Failure to comply with these rules could lead to coercive measures that have an important impact on the individual's professional and/or private life (Ferdous, Pendyala, Bhat, & Konduri, 2011). For example, social norms affecting working time flexibility could lead people to leave their office no earlier than a specific time just because it is socially accepted by colleagues at the workplace even though it goes beyond the hours specified in their contract. In general, even if the adoption of flexible time management could be officially admitted at the travelers' destination, the presence of social norms could influence their freedom of travel by binding them to certain time intervals. This behavior reduces individuals' travelling flexibility, especially for those who are constrained to travel during rush hour intervals: these people could not modify their travelling behavior moving outside those intervals.

In this research, we argue that individuals cannot easily adjust their travel behavior according to different price schemes and alternatives as they are strongly influenced by not directly observable social norms present in their life. In order to study the effect of social norms on travelers' choices, this work extends the existing literature by introducing two different definitions of rush hour intervals and different forms of subscription access to these intervals. Operationally, this research analyzes travelers' preferences by developing a hybrid choice model that incorporates the effect of social norms as a latent variable within a multinomial logit model (MNL).

In general, results suggest that individuals favor travel cards that constrain their travelling during rush hours as minimum as possible. Specifically, commuters strongly indicate their preference for these travel cards given that they cannot easily deviate from their travelling habits and opting for different time intervals.

1.3. Informative vs. non-informative labels in discrete choice experiments with stated preferences: a quantitative analysis of attribute importance

During the last century, an increasing amount of research has been undertaken to analyze consumers' choice process adopting the study of preferences to provide useful information for the creation of products and services closer to consumers' needs. Among the different methodologies used to understand consumers' preferences, discrete choice experiments (DCEs) have become very popular and widely adopted in several research fields such as environmental research (Campbell, 2007; Fimereli & Mourato, 2013), medicine (Kruijshaar, et al., 2009), transportation (Devarasetty, Burris, & Shaw, 2012; Patil, Burris, & Shaw, 2011; Saleh & Farrell, 2005), health economics (Bansback, Brazier, Tsuchiya, & Anis, 2012; Viney, Savage, & Louviere, 2005), and marketing (Chrzan, 1994; Czellar, 2003; Dellaert, Donkers, & Van Soest, 2012). Specifically, these types of experiments fall into the category of attribute-based survey methods for evaluating the utility of characteristics (benefits) of specific products or services (Ryan, Gerard, & Amaya-Amaya, 2007). Specifically, DCEs evaluate individuals' preferences by analyzing their choices made as a function of the utility associated with the alternatives (Bliemer & Rose, 2009; Hensher, et al., 2005; Louviere, et al., 2000; Ryan, et al., 2007).

Operationally, respondents (decision makers) involved in these experiments are asked to indicate their preferred alternative among a series of alternatives presented and this task can be proposed several times changing alternatives' characteristics to favor trade-offs (Train, 2003). By way of example, the aforementioned alternatives can be substitutable products, medical treatments, or any other element that can be chosen by the decision maker while the latter can be identified as an individual, a family, or a company (Train, 2009). In the existing literature, there are several types of discrete choice models, and the main distinction can be made based on the preferences expressed and the type of alternatives' representation within the choice task. In reference to the type of preference expressed, DCEs could be categorized into revealed-preference (RP) and stated-preference (SP) experiments (Ben-Akiva, et al., 1994; Louviere, et al., 2000; Train, 2009). Using RP experiments, researchers collect data regarding individuals' choices on already existing alternatives (products or services) in the real-world situation whereas SP experiments are used to obtain data on hypothetical choice situations with alternatives that are not present on the market yet (Train, 2009). Both types of experiments have advantages and disadvantages and therefore researchers are increasingly adopting experiments that can combine the two types of data to overcome the limitations and benefit from both (Train, 2009). A further distinction about the type of DCEs can be made by focusing on the titles associated with the alternatives (i.e., alternatives' labels) presented in the choice tasks: labeled DCEs and unlabeled DCEs (Louviere, et al., 2000). In labeled experiments, labels are informative and provide relevant and characterizing information beyond the possible alternatives' order in the choice set (e.g., laptop, smartphone, tablet). In the case of unlabeled experiments, labels do not provide any information that can identify the alternatives to which they are associated other than the order in which they are presented in the choice set (e.g., alternative 1, alternative 2, etc.).

These two types of experiments have both pros and cons due to their specificities. Focusing on the advantages of labeled experiments with informative labels, they can propose a better approximation of real choice situations with a consequent better predictive validity (Blamey, Bennett, Louviere, Morrison, & Rolfe, 2000) and, including alternative-specific constants (ASCs) in the estimation function, they can infer respondents' prior

assumptions about alternatives that are not explicitly introduced in the model (Blamey, et al., 2000; Rolfe, Bennett, & Louviere, 2000). Concerning the disadvantages of labeled DCEs, informative labels may reduce respondents' ability to evaluate other attributes (i.e., attribute non-attendance) (Alemu, Mørkbak, Olsen, & Jensen, 2013; Hensher, Rose, & Greene, 2012; Scarpa, Zanolli, Bruschi, & Naspetti, 2013) inducing them to favor an alternative in the choice task based on the labels only (Bennett & Blamey, 2001). In addition, these labels could trigger feelings that are directly related to the peculiarities of the alternatives adopted in the choice tasks (Blamey, et al., 2000). Vice versa advantages and disadvantages of unlabeled experiments are the exact opposite of what has been mentioned above. For this and other reasons not listed in this thesis, these experiments are considered more adequate if the research question focuses on the trade-offs among attributes and their levels of the proposed alternatives (de Bekker-Grob, et al., 2010).

Given the advantages and disadvantages of the labeled and unlabeled DCEs, we combine the two techniques in this paper to take advantage of their strengths. In detail, we set up a labeled DCE with informative labels and investigate whether a different representation of the choice task layout (i.e., relocating informative labels among other attributes and adopting non-informative labels) could alter labels' influence in the choice process. Doing so, this work contributes to the existing literature concentrating on the importance associated with the different alternatives' attributes evaluated by adopting a choice-based conjoint (CBC) analysis with a Hierarchical Bayes (HB) estimation (Allenby, Rossi, & McCulloch, 2005; Johnson, 2000; Lenk, DeSarbo, Green, & Young, 1996; Orme, 2000; Sawtooth Software, 2009) diverging from prior research concentrated on the effect that experienced reading patterns have on the derived preferences (Sandorf, dit Sourd, & Mahieu, 2018) and on the influence that choice task layout has on the willingness-to-pay (WTP) evaluation (Fimereli & Mourato, 2013; Jin, Jiang, Liu, & Klampfl, 2017).

Results suggest that individuals ascribe significant lower importance to the attribute associated with the original labels dealing with choice tasks with our proposed structure (i.e., an attribute that contains the original informative labels and generic non-informative labels) compared to respondents that face choice tasks with classic labeled

layout (i.e., informative, and specific labels). In other words, manipulating the choice task layout affects the respondent's evaluation of the attribute chosen to represent the group of alternatives' labels and its importance diminishes when its position is among other attributes in the choice set (and not anymore on top of them).

The remainder of this dissertation has the following structure: Chapter 2 presents the first article, Chapter 3 is the second article, and Chapter 4 is the third article. Finally, Chapter 5 gathers some conclusions about the research presented in this thesis. Table 1 presents an overview of all three articles.

Table 1 - Chapter 1 - Overview over the articles of this dissertation

	Chapter 2 (Article 1*)	Chapter 3 (Article 2*)	Chapter 4 (Article 3)
DV	Railway subscription utility	Railway subscription utility	Smartphone attributes' importance scores
IV	Type of access to specific train sections	Type of access to rush hour intervals	Choice task layout
Theories	Travelling choice; social identity theory;	Travelling time decisions; rush hour avoidance; social norms	Choice experiment theory
Constraints	Train section specifications	Time intervals	Smartphone specifications
Conferences	2018 Global Marketing Conference in Tokyo	97 th Annual Meeting of Transportation Research Board	-
Journal	Submitted to Transportation Research Part F	Submitted to Transportation Research Part F	Submitted to Journal of Choice Modelling

* Previous versions of these articles have been included in the “Innovation Potential in Pricing and Product Line Design of SBB Based on the Increasing Heterogeneity of Customers: An Empirical Analysis of Train Section and Rush Hour Access” report published on the SBB Lab website of the University of St. Gallen. This project was co-financed by the SBB Research Fund.

Chapter 2: Integrating travelers' heterogeneity in subscription choice processes through hybrid choice modelling: an application to the Swiss railway market

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2.1. Abstract

Public transportation companies often classify their customers into only two classes (i.e., first and second class). Such a rough segmentation largely ignores travelers' specific characteristics, needs and habits and may thus leave significant heterogeneity within classes. In particular, individuals feel more comfortable and attracted to social groups that are perceived as similar to the self. Once part of a group, individuals have the tendency to evaluate their own social group (vs. others) more positively. As many social groups could be present on the train, a 2-class structure might not be optimal. An increasingly specific segmentation could reduce such issues and increase travelers' utility and overall satisfaction. In this article, we investigate if the introduction of dedicated sections based on travelers' specific habits and characteristics (vs. the traditional two-class structure) can provide value to travelers. Moreover, we argue that the key latent trait influencing travelers' preference for dedicated sections is individuals' tendency towards out-group derogation. We collected the choices of 506 Swiss-German travelers and analyzed their preferences for these sections adopting a hybrid choice model. Specifically, we integrate the tendency towards out-group derogation as a latent variable in a multinomial logit model (MNL). In summary, results indicate that the silence section is the most preferred dedicated section. Young travelers assign higher utility to travel cards with access to common and dedicated sections whereas commuters to travel cards with access to a common section only. In the end, specific segments of travelers with a higher tendency towards out-group derogation, such as young travelers with high educational levels, demonstrate a strong preference for alternatives with access to common and dedicated sections (compared to access to a common section only). In brief, this work demonstrates how travelers' heterogeneity, specifically the attitude to distance themselves from others, influences their subscription choices. Moreover, it highlights how important and profitable it can be for public transport companies to consider not directly observable characteristics in the formulation process of their travelling offerings.

Keywords: discrete choice experiments; hybrid choice models; out-group derogation

2.2. Introduction

Travelers who use the train for their travels have more and more different characteristics, and their needs have increased over time (Nguyen & Mariani, 2014). Offering targeted and differentiated services could be an opportunity for public transport companies to increase their revenues. At the time of the data collection (August 2016), the product line offered by the main Swiss railway company was primarily set up around core service offerings (i.e., travel cards). Introducing innovations, which aim at meeting the diverse needs of travelers, could diversify the variety of services offered by adapting the product line to customers' changes. Increasingly crowded trains (Ungricht, 2010) and at the same time the increasing heterogeneity of traveler characteristics (Saameli, 2014) call for more diversified offerings. At that time, special sections on the train were available to meet individual needs, such as silence, business, and family spaces.

Despite the fact that these sections provided supplementary values to specific categories of travelers, they did not have a separate price tag, and quantitative insights into passengers' satisfaction with these sections could be useful for future train redesign. We thus investigate whether it could be useful for the Swiss railway company to extend their product line by distinctly selling access to those sections on the train with specific prices. Presumably, travelers' demand to purchase the access to these specific sections can be associated with their desire to travel with other travelers with similar characteristics and a more distinct partition of different traveler groups can provide value to individuals that feel annoyed by other travelers' behaviors. Travelling by public transportation induces social encounters and they often happen with a heterogeneous multitude of persons. Especially in crowded trains, individuals have to physically travel very close together. Although this variety could provide additional value for some customers, it can constitute a disadvantage for others. These travelers may feel limited or irritated because others could behave differently on the train. Therefore, they could favor dedicated sections on the train where they can stay with travelers with similar characteristics and get away from others with different travel requirements.

In this paper, we seize this propensity by adopting the latent definition of out-group derogation and evaluate if it has an impact on travelers' preferences for dedicated

sections. Out-group derogation represents the individual's attitude to impute more negative traits to persons that do not belong to the own social group (Dasgupta, 2004). We measure and analyze individuals' choices for subscriptions with access to either common (i.e., a section where there are travelers with different types of needs) or common and dedicated (i.e., a section for individuals with specific travel needs) sections to verify this effect. Furthermore, we examine how demographics, special traveler characteristics, and the latent construct drive individuals' preferences during the choice process.

2.3. Data

2.3.1. Survey design

Nowadays, the study of traveler behavior is a complex task to be carried out and the selection of the products' characteristics could influence the consumer decision process. Work environment, infrastructure (i.e., number of trains, number of wagons per train, pick hour, amenities on the train), travel purpose, and even socio-demographic variables are attributes commonly considered. However, attitudes and perceptions can be also very crucial in the decision-making process. In this study, we include a latent variable because ignoring the effect of this type of variable can be one of the causes for being unable to accurately represent the real behavior of travelers.

Operationally, we adopt an online purpose-built survey lasting 20 minutes and recruit respondents with the help of the market research agency Intervista AG. The survey is structured as follows. First, we provide general instructions about the survey to respondents. Second, we ask a group of questions concerning their travelling preferences and habits following up a previously conducted segmentation study (SBB, 2013). Third, respondents must deal with the choice experiment. Fourth, they need to answer a set of questions referring to the latent variable. Lastly, they have to provide some details concerning their demographic traits. Details concerning the procedure of the choice experiment are provided in the following section.

Before the choice experiment, the notion of a travel card is introduced to allow the respondents to familiarize themselves with it. In the choice experiment, travel cards

provide a yearly access to Swiss public transportation with distinctive access options. We ask respondents to think that they may need to purchase a new travel card via the website. They will be confronted with 12 pages and each of them will have a different purchase case (i.e., choice task) from which the respondents will have to indicate their subscription preference. We also inform respondents that they have four options in each purchase situation. They can indicate their preference by either choosing one of the three proposed alternatives or moving to the following purchase scenario by clicking “None” if none of them is suitable. An illustrative choice task is shown in Figure 3. In the legend, attributes and their respective levels are again detailed to provide greater clarity during the evaluation of the choice task.

Figure 3 - Chapter 2 - Example of choice task (translated from German)

If these were the travel card options offered to you, would you buy any of those and if yes which one?

Choose by clicking one of the buttons below:

	Travel Card Nr 1	Travel Card Nr 2	Travel Card Nr 3	None
Train Section Access	Common Section Only	Common Section + Dedicated Section (Business)	Common Section + Dedicated Section (Family)	I would not choose any of these.
Geographical Access	Area Big (Country)	Area Small (Zone)	Area Medium (Region, Canton)	
Rush Hour Access (7:00-8:00 and 17:00-18:00)	Yes (no time restrictions)	No (outside rush hour only)	No (outside rush hour only)	
Price	CHF 3'000.-	CHF 4'500.-	CHF 3'000.-	

LEGEND (Click on the attribute name to see the description)

- [Train Section Access](#)
- [Geographical Access](#)
- [Rush Hour Access \(7:00-8:00 and 17:00-18:00\)](#)
- [Price](#)

2.3.2. Choice Design

In order to maintain the high data quality without generating a complicated choice experiment, we use a stated preferences choice design divided into five blocks containing 12 choice tasks each. This type of choice design ensures a homogeneous distribution of attribute levels. At the beginning of the experiment, each respondent is randomly assigned to one of five blocks. Moreover, the sequence of the choice tasks is randomized in each block. Each task consists of three different travel cards and a non-choice option. Two of the three product alternatives have the same level for a specific attribute. In order to prevent that the decision-maker could make assumptions on omitted attributes connected to alternatives' labels (de Bekker-Grob, et al., 2010; Louviere, et al., 2000) and to

simultaneously keep the versatility of a labeled experiment, we adopt an approach that combines the features of the labeled and unlabeled methods. Alternatives have alternative-specific attributes, as a labeled experiment, but with generic labels, as an unlabeled experiment (i.e., alternative 1). Each alternative contains four attributes: “train section access”, “geographical access”, “travel during rush hour (7:00 – 8:00 and 17:00 – 18:00)”, and “price” (see Table 2 for details). These attributes and the relative levels have been defined in agreement with SBB representatives and with the previous studies conducted by the company (SBB, 2013; Weichbrodt, et al., 2013).

The “train section access” attribute defines the train sections which an individual can access using a specific travel card. Two levels have been defined for this attribute: “common section only” and “common + dedicated section”. “Common section only” indicates that the travel card provides access only to the common sections of the train. Any traveler with a valid subscription can access these sections. “Common section + dedicated section” defines access to the common sections and specific dedicated sections of the train. Unlike the common sections, these sections have distinct peculiar characteristics to meet the habits and needs of travelers. The substantial difference between the two access categories is linked to the types of travelers present in the different sections. Travel cards with “common section only” do not allow to access dedicated sections, whereas travel cards with “common section + dedicated section” give access to all the train sections specified in the subscription. Moreover, travel cards with the “common section + dedicated section” access have an additional attribute that defines the type of dedicated section to which the subscription owner has access. This attribute has four levels: “business”, “silence”, “family”, and “lifestyle”. For simplicity, we will refer to the “common + dedicated section” as simply “dedicated section” from now on throughout the paper.

The “geographical access” attribute characterizes the geographical dimension in which the travel card is valid. It has six levels: “area small (zone)” indicates that a travel card can be used in an area large as two zones; “area medium (region, canton)” determines access to an area as large as an entire region/canton; and “area big (country)” recognizes access to public transport throughout Switzerland.

The “travelling during rush hour (7:00 – 8:00 and 17:00 – 18:00)” attribute defines the rush hour intervals in which the subscription is valid and it has two levels: “no (outside rush hour only)” indicates a subscription that is not valid during the rush hour intervals and travelers cannot take the train with that travel card during rush hours; “yes (no time restrictions)” indicates that travelers who have this subscription can take the train without time restrictions.

The “price” attribute defines the expense that travelers must incur to purchase a specific travel card. It has four levels (“CHF 1’500.-”, “CHF 3’000.-”, “CHF 4’500.-”, and “CHF 6’000.-”), which covers the range of prices of existing railway products at the time of the data collection. In Table 2, attributes and attributes’ levels have been recapped.

Table 2 - Chapter 2 - Attributes and attributes’ levels

Attribute	# of levels	Description
Train section access	2	Common section only; common section + dedicated section (further referred to as “dedicated section” for simplicity reasons)
Train Section access (spec.)	4	Business; silence; lifestyle; family
Geographical access	3	Area small (zone); area medium (region, canton); area big (country)
Travelling during rush hour (7:00 – 8:00 and 17:00 – 18:00)	2	No (outside rush hour only); yes (no time restrictions)
Price	4	CHF 1’500.-; CHF 3’000.-; CHF 4’500.-; CHF 6’000.-

2.3.3. Attitudinal, Perceptual and Other Variables

Transportation choices are not only influenced by individuals’ intrinsic preferences but also by their social environment. Social influences have manifested in several domains of transportation choice. A substantial body of research has already investigated the relative strength of social influence compared with other factors driving travel choice (Ferdous, et al., 2011; Gaker, Zheng, & Walker, 2010; Sherwin, Chatterjee, & Jain, 2014; von Sivers, Templeton, Köster, Drury, & Philippides, 2014). Others have explored the role of social identity (Fielding, McDonald, & Louis, 2008; Lois, Moriano,

& Rondinella, 2015), social norms (Dieplinger & Fürst, 2014; Forward, 2009; Huth & Gelau, 2013; Paris & Broucke, 2008; Riggs, 2017; Schade & Schlag, 2003; Zhang, Schmöcker, Fujii, & Yang, 2015) and self-selection (Van Wee, 2009) when it comes to travelling.

Although there is a significant study of railway traveler behavior (Löfgren, 2008), none of this prior research, according to our knowledge, has investigated individuals' travelling choices influenced by the social mixing that occurs on the train, which is the focus of our investigation.

Conceptually, we adopt social identity theory (Tajfel & Turner, 1979) and research related to intergroup biases (Hewstone, et al., 2002). People generally favor the social group they belong to (i.e., the in-group) and try to distinguish themselves from other social groups (i.e., the out-groups) (Dasgupta, 2004; Hogg & Hains, 1996; Turner, et al., 1987; Turner, et al., 2016; Vanhoomissen & Van Overwalle, 2010). For a specific individual, the in-group refers to the group that the individual is a member of, and the out-group to the group he/she is not a member of (Hewstone, et al., 2002). This can be a cultural group, a religious group, or more generally, a so-called psychological group, which is based on psychological traits that are independent of external features. Groups often share beliefs, behavioral norms, and expectations, which can be clearly distinguished from other groups (Efferson, et al., 2008). The distinction between two different groups depends on the perceived dissimilarity between those groups on a specific comparison dimension (Jetten, et al., 2001).

Social identity theory explains how individuals identify their membership in a certain group. According to this theory, psychological group formation is a process of self-categorization. Self-categorization is an individual's attraction towards a group based merely on the group label and not on the interaction with individuals of the group (Hogg & Turner, 1985). This process is thus based on group prototypes and not on an individual basis (Hogg, et al., 1995). A prototype of a specific group is an abstract representation of average, stereotypical, or normative characteristics of group members in comparison with the average characteristics of non-group members (Hogg, et al., 1995). Group prototypes are formed through depersonalization, a process in which cognition, perception, and

behavior are defined by the standards of the group, i.e., the group norms, group stereotypes, and group prototypes instead of by personal standards (Hogg & Hardie, 1992; Hogg, et al., 1995; Turner, et al., 1987). Individuals of a certain group, usually the in-group, are then liked not because of their characteristics, but rather because they are the “embodiments of the group” and the more similar an individual is to the group prototype, the more it is liked (Hogg & Hains, 1996).

Davis (1984) shows that individuals’ attraction to a group increases with the level of similar attitudes between the group and the individual. How similar attitudes are perceived depends on a multitude of factors, such as external factors that include the evaluations of the group’s intelligence (Davis, 1984). Hence, how much a person can identify with a particular group directly influences social attraction. In fact, individuals have a general tendency to ascribe more positive characteristics to their in-groups than to their out-groups (Dasgupta, 2004). This phenomenon is called in-group favoritism and it is omnipresent in human societies (Lewis & Bates, 2010). On the other hand, out-group derogation describes the opposite perspective of the same phenomenon, i.e., that people have a tendency to ascribe negative characteristics more easily to their out-groups (Dasgupta, 2004). This phenomenon is also often called intergroup bias, which is defined as a more favorable evaluation of the in-group compared with the out-group (Hewstone, et al., 2002; Levin & Sidanius, 1999).

Intergroup biases influence judgments, decisions, and behaviors (Dasgupta, 2004). It leads to individuals feeling connected to their in-group and wanting to separate from their out-groups (Hogg & Hains, 1996; Turner, et al., 1987). Intergroup biases are positively influenced by intergroup competition since it renders the distinction between in- and out-group more salient (Brewer, 1979; Brewer, et al., 2016). Literature also evidenced that individuals differ in their tendency toward in-group favoritism and out-group derogation (Jost, et al., 2003; McGregor, et al., 2008; Stangor & Thompson, 2002). In a similar vein, travelers also belong to different travel-related groups. So, it can be argued that the in- and out-groups do matter to travelers on the train too.

Each traveler is a member of a specific travel-related socio-psychological group as defined by psychographic and demographic characteristics that may differ from the

socio-psychological groups of other travelers on the train. Travelers who do not belong to the same group (i.e., are considered as being part of the out-group), may be perceived as disturbing. In particular, they might interfere with a person's individually preferred way of travelling. This leads to a general tendency to separate oneself from the out-group (Brewer, 1979). In addition, the mere awareness of different groups being present on the train as signaled by different behaviors may lead to some form of intergroup conflict (Tajfel & Turner, 1979). Thus, mixing such different travelers together may cause dissatisfaction.

The creation of special sections on the train that are dedicated to a special group of travelers allows travelers to self-categorize into their respective social groups. The label given to the train section (i.e., business, lifestyle, family, or silence) functions as an indicator of the social group, allowing travelers to draw inferences about the prototype person in that section. Based on the self-categorization process, travelers should thus classify themselves into the section to which they feel most socially attracted to minimize intergroup conflicts. Moreover, train travelers are relatively unlikely to engage in active interpersonal interaction (Evans & Wener, 2007). They consider sitting with members of the in-group as being less important than sitting separately from out-group members. Hence, they choose a train section based on whom they do not want to sit with (negational categorization) rather than whom they want to sit with (affirmative categorization). Where affirmative categorization relates to in-group favoritism, negational categorization relates to out-group derogation (Zhong, et al., 2008). Consequently, the stronger the tendency towards out-group derogation, the stronger the desire to separate from the out-group, and the higher the likelihood to choose a travel card with dedicated section access (Ajzen, 1985).

In short, we propose a model to analyze the travelers' behavior in choosing a train subscription by integrating their tendency to distinguish themselves from different social groups on the train. In this work, we adopt a discrete choice model approach with the innovation of incorporating the tendency towards out-group derogation as a latent variable to take into account its effect on the choice process. Operationally, we first extend the scale to assess the tendency toward in-group favoritism originally developed by Lewis and

Bates (2010). This scale is composed of three items related to the capacity of identification with a group, the attitude toward associating themselves with internal members of a group, and the importance of marrying within the group items. We consider the first two items particularly relevant for this research and, based on them, we extend the scale to additional social groups. With this procedure, we can measure the concept in general and not on a single group dimension. Moreover, we introduce new context-specific items (i.e., travelers' needs and behaviors) to evaluate this attitude in the train situation. After several focus group sessions, we adjusted and validated all scale items. Finally, we conceptually

Figure 4 - Chapter 2 - Out-group derogation scale (translated from German)

	I strongly disagree. 1	2	3	4	5	6	I strongly agree. 7
When I am travelling alone on the train, I distance myself from people ...							
... who have a different type of work than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who have a different family status than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who are from a different social / economic class than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who are culturally different from me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When I am travelling alone, I separate from people ...							
... who have different personal characteristics than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who do not share my beliefs / values.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who have different interests than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who behave differently than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When I am travelling alone, I prefer not to be on the train with people ...							
... who have different travel needs than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who have different purposes of travelling than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who travel in different ways than me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
... who travel a distance different from mine.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

reversed the items to make them consistent with the definition of out-group derogation. The resulting scale has 12 items, as shown in Figure 4.

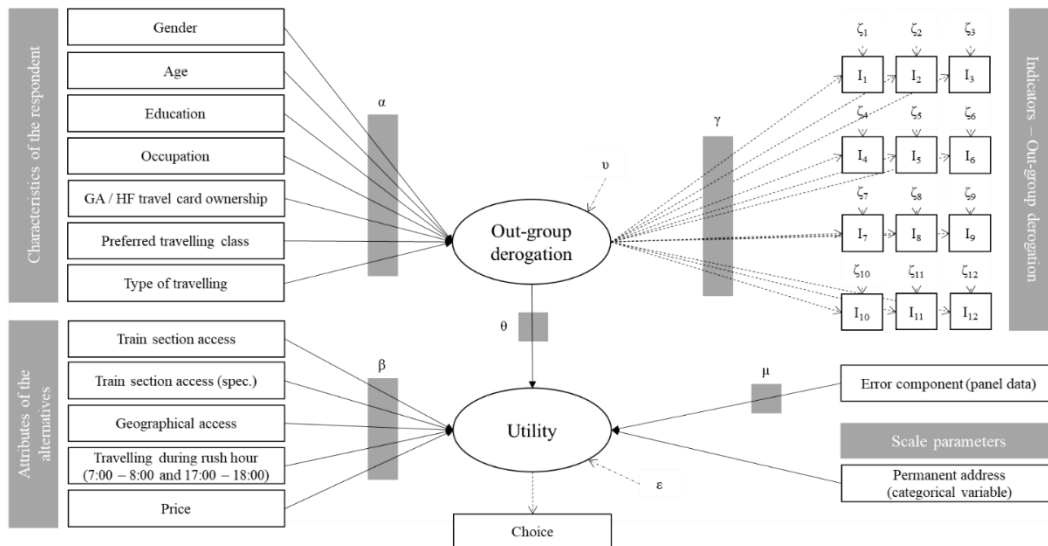
Before the estimation of the integrated choice and latent variable (ICLV) models, we conduct a factor analysis with the principal-factor method (Rencher & Christensen, 2012) adopting all the indicators available with the aim of verifying their consistency with the latent variable associated. From the analysis, we find that around 89% of the original data variability can be explained with one factor and the Cronbach's alpha of this scale is around 0.95. Furthermore, we analyze a set of variables collected in previous segmentation

studies to link our results with the existing findings (SBB, 2013). These variables include the travel card ownerships (GA and/or half-fare travelcard), the predominant travel class adopted (first class or second class) as well as the need for commuting (commuters vs. travelers).

2.4. Model Specification

In this section, we present the general ICLV model (Figure 5) implemented and the relative theoretical framework. Adopting an ICLV model, we develop a model that includes demographics, segmentation variables as well as a latent variable within a discrete choice modelling framework to estimate their effect on the choice process of a subscription. In other words, we estimate the probability of choosing specific train subscriptions among the proposed alternatives as a function of the previously mentioned variables. In particular, we implement traditional multinomial logit models (MNL), mixed logit models (ML), and an integrated choice and latent variable (ICLV) model to integrate respondents' preference heterogeneity and to keep in consideration the panel structure of the data (each respondent provides several responses).

Figure 5 - Chapter 2 - Full path diagram of ICLV model



Latent variables are considered unobservable factors that could influence the choice process. Given that these variables cannot be measured with a clear measuring scale, the typical approach to integrate their effect in the choice modelling framework is the MIMIC model (Bollen, 2016; Cantillo, Arellana, & Rolong, 2015). This model consists of two parts: a structural component and a measurement component. The structural component (equation 1) defines the relationship between the unobservable latent variables (η_n) and the observable individual and alternative characteristics (S_n). Moreover, the latent variables influence a set of attitudinal indicators (C_n) explained via measurement equations (2) and (3).

$$\eta_{lkn} = \sum_r \alpha_{lrk} S_{rkn} + v_{lkn} \quad (1)$$

where n relates to an individual, k to an alternative, l to a latent variable, and r to an explanatory variable. α and v_n are, respectively, parameters associated with measurable characteristics and error terms associated with each latent variable. Given the ordinal nature of the observed indicators, an ordinal logit model is usually adopted to describe the measurement component of the MIMIC model (Daly, Hess, Patruni, Potoglou, & Rohr, 2011). This model assumes that each discrete response j observed for each indicator p through a censoring mechanism is a function of the latent variables and an error term as reported in equations (2) and (3).

$$C_{pkn} = \begin{cases} 1 & \text{if } (-\infty) < C_{pkn}^* \leq \tau_{p1} \\ 2 & \text{if } \tau_{p1} < C_{pkn}^* \leq \tau_{p2} \\ \dots & \\ J & \text{if } \tau_{p(J-1)} < C_{pkn}^* \leq \infty \end{cases} \quad (2)$$

$$C_{pkn}^* = \sum_l \gamma_{lpk} \eta_{lkn} + \zeta_{pkn} \quad (3)$$

In equation (2), each discrete response ($C_{pkn} = j$) has been calculated adopting a set of thresholds (τ) that should be estimated. In equation (3), the vector of parameters (γ) has been assumed to be independent of the vector of error terms (ζ) and that the latter

follows a logistic distribution. The probability that C_{pkn} assumes a specific value (j) could be written including equation (3) into equation (2) and can be formulated as equation (4).

$$P\{C_{pkn} \in j | \boldsymbol{\eta}_n\} = F\left(\tau_{pj} - \sum_l \gamma_{lpk} \eta_{lkn}\right) - F\left(\tau_{p(j-1)} - \sum_l \gamma_{lpk} \eta_{lkn}\right) \quad (4)$$

where F is the cumulative distribution function.

Taking the utility function of the standard random utility model (RUM) as described in Walker and Ben-Akiva (2002) where the unobservable utility values are functions of the observable attributes \mathbf{X}_n and an error component Z_n , introduced to consider the panel structure of the dataset (5), we can directly include the latent model into it as shown in equation (6).

$$U_{kn} = \sum_j \beta_{jk} X_{jkn} + \mu_n Z_n + \varepsilon_{kn} \quad (5)$$

$$U_{kn} = \sum_j \beta_{jk} X_{jkn} + \sum_l \theta_{lk} \eta_{lkn} + \mu_n Z_n + \varepsilon_{kn} \quad (6)$$

where the vectors of parameters $\boldsymbol{\beta}$, $\boldsymbol{\theta}$, and $\boldsymbol{\mu}$ should be estimated. These utility functions are directly related to the preference indicators y , manifestations of these underlying utilities (Walker & Ben-Akiva, 2002). Following the RUM paradigm, individuals choose a specific alternative (y_k) among a set of possible alternatives present in a choice set (CS_n) if this alternative maximizes their utility as described in equation (7).

$$y_k = \begin{cases} 1 & \text{if } U_k \geq U_h, \forall h \in CS_n \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Using the maximum simulated likelihood, we can simultaneously estimate the joint probability of a specific choice taken by an individual and the attitudinal indicators associated with the latent variables (Train, 2009). It could be derived from equations (1), (4), (6), and (7) and written as a multi-dimensional integral (equation 8).

$$\begin{aligned} \bar{P}(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) = \\ \int_{\boldsymbol{\eta}} P(y_{kn} | \mathbf{X}_n, Z_n, \boldsymbol{\eta}_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\Sigma}_\varepsilon) f(\mathbf{C}_n | \boldsymbol{\eta}_n, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_\zeta) g(\boldsymbol{\eta}_n | \mathbf{S}_n, \boldsymbol{\alpha}, \boldsymbol{\Sigma}_v) d\boldsymbol{\eta}_n \end{aligned} \quad (8)$$

where $P(y_{kn} | \mathbf{X}_n, Z_n, \boldsymbol{\eta}_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\Sigma}_\varepsilon)$ represents the choice probability of choosing the alternative k , $f(\mathbf{C}_n | \boldsymbol{\eta}_n, \boldsymbol{\gamma}, \boldsymbol{\Sigma}_\zeta)$ is the density function associated with the indicators of the latent variable $\boldsymbol{\eta}_n$, and $g(\boldsymbol{\eta}_n | \mathbf{S}_n, \boldsymbol{\alpha}, \boldsymbol{\Sigma}_v)$ is the density function associated with the latent variables present in the model. To be able to estimate a Multinomial Logit Model, we assume that the vector of error terms of equation (5) are independent and identically distributed as a Gumbel whereas we consider the set of error terms of equation (1) independent and identically distributed as a Normal with mean zero and standard deviation to be estimated. Plugging information from equations (4) and (5) into equation (8), we can derive the conditional probability as equation (9).

$$\begin{aligned} \tilde{P}(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) = \\ \frac{\exp(\sum_j \beta_{jk} X_{jkn} + \sum_l \theta_{lk} \eta_{lkn} + \mu_n Z_n)}{\sum_{c \in S_n} \exp(\sum_h \beta_{jh} X_{jhq} + \sum_l \theta_{lh} \eta_{lhn} + \mu_n Z_n)} \times \prod_{p,k} \left[F\left(\tau_{pj} - \sum_l \gamma_{lpk} \eta_{lkn}\right) - F\left(\tau_{p(j-1)} - \sum_l \gamma_{lpk} \eta_{lkn}\right) \right] \end{aligned} \quad (9)$$

Given the nature of the multi-dimensional integral presented, we need to approximate it using the simulated probability (*SP*). We can compute it by averaging the conditional probability presented in equation (9) over D draws extracted for the error terms associated with the set of latent variables according to equation (1).

$$\begin{aligned} SP(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) = \\ \frac{1}{D} \sum_{d=1}^D \tilde{P}(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) \end{aligned} \quad (10)$$

We can adopt several types of draws to simulate random distributions, such as pseudo-random numbers, Halton sequences, and Modified Latin Hypercube Sampling draws (Hess, Train, & Polak, 2006). In this paper, we use 500 MLHS draws to estimate

the presented models and we do not use a higher number of draws for two reasons: the parameter estimates are quite stable, and the computational cost increases considerably. From Eq. (10), we can easily derive the simulated log-likelihood function (*SLL*) computing the logarithmic transformation of the simulated probability (*SP*) over the entire sample (*n*) collected (11). The maximization of the simulated log-likelihood function provides the estimated parameters presented in the previous equations.

$$SLL = \sum_n \ln SP(y_{kn}, c_n | X_n, S_n, Z_n, \beta, \theta, \mu, \alpha, \gamma, \tau, \Sigma_\epsilon, \Sigma_v, \Sigma_\zeta) \quad (11)$$

2.5. Results and Discussion

2.5.1. Sample Description

The sample consists only of individuals that plan to buy a Swiss public transport subscription or prolong their existing one within the next year and who would pay for their subscription autonomously. In August 2016, we collect the sample by stratifying it by age to represent the Swiss population and be conforming with the Swiss railway marketing research standards (Swiss Federal Statistical Office, 2014). Given that each respondent faced 12 choice tasks, the total number of observations is 6'072. Of the 506 respondents, more than fifty-three percent (53.56%) are females and more than sixty percent (61.46%) are 50 years old or younger. Almost the entire sample is Swiss (91.90%) with about seventy percent (69.96%) living in the areas of Central Plateau, North-west Switzerland, and Zurich. More than half of the sample (59.49%) have higher education studies such as universities, institutes of technology, technical college, and higher vocational schools, the prevalent occupation (65.81%) is employed, and more than fifty percent (52.97%) have a gross income between CHF 2'000 and 8'000. Concerning their travelling characteristics, more than eighty-six percent (86.96%) own a general abonnement (GA) or a half-fare travel card (HF), and more than half (53.36%) travel to and from their place of work and/or educational institution and almost half of them (48.62%) define themselves commuters.

2.5.2. Model Estimation and Results

Model estimates are shown in Table 3 and Table 4. We use three alternative-specific constants (i.e., common section access, dedicated section access, and none) and fix the one associated with “none” alternative to zero. Alternative 1 represents a travel card with access to the common section only whereas alternatives 2 and 3 refer to travel cards with access to the dedicated sections (that also includes access to the common section). Alternative 4 indicates the none option.

The attributes used in the models are:

- ASC_{Common} : alternative-specific constant associated with travel cards that allow access to a common section only;
- $ASC_{Dedicated}$: alternative-specific constant associated with travel cards that allow access to dedicated sections;
- Train section access specifications ($business_{Dedicated}$, $lifestyle_{Dedicated}$, $silence_{Dedicated}$): effect-coding variable (Hensher, et al., 2005) that specifies which dedicated section can be accessible with a “dedicated section” travel card (reference level: $family_{Dedicated}$);
- Geographical Access (area small (zone), area medium (region, canton)): effect coding variable (Hensher, et al., 2005) that indicates the geographical extension in which the subscription was valid (reference level: area big (country));
- Travelling during rush hour: binary variable that defines the subscription validity during the rush hour intervals;
- Price: categorical variable treated as continuous variable since the step is constant along the levels;
- Sigma: continuous variable that expresses the standard deviation of the error term introduced to consider the panel structure of the dataset;
- Scale parameters: categorical variable used to rescale the utility equations in the function of the respondent’s permanent address (reference level: Zurich) (Train, 2009);
- Gender (male): binary variable (reference level: female);

- Age (adults, best agers, seniors): categorical variable (reference level: young adults);
- Education (primary school, professional school, middle school): categorical variable (reference level: university);
- GA travel card ownership, HF travel card ownership: binary variables that indicate if respondents already own a general abonnement and/or a half-fare travelcard;
- Preferred travelling class (1st class): binary variable (reference level: 2nd class);
- Type of travelling (commuting): binary variable that indicates the need of commuting or not (reference level: non-commuting);
- Latent variable (out-group derogation): continuous variable included in the alternatives' specification formula of the ICLV model;
- Latent variable thresholds: estimated points of the ordered logit model developed in the measurement equation component of the included latent variable.

MNL1 and MNL2 models described in Table 3 can be considered as a specific application of a general random coefficient model and their goodness of fit can be compared using a likelihood ratio (LR) test. Given that MNL3, MNL4 and ICLV cannot be considered nested models of MNL1 and MNL2, their goodness-of-fit can be compared using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Analyzing the results of the four MNL models, we surprisingly find out that the ASC associated with the dedicated sections is significantly lower than the ASC associated with the common section only taking constant the effect of other attributes available in the experiment. This result could have occurred due to the specification of the dedicated sections: respondents could perceive the distinction in terms of services present in the different sections and not in terms of different travelers' subgroups.

Concerning the dedicated sections, all models indicate that travelers evaluate both business and lifestyle as not so appealing compared to the family section whereas they consider the silence section much more attractive than the reference level. This result can be associated with the quite positive previous experience that travelers have with the silence section (already present in the trains) where the distinction between groups is much

more evident compared to the other three sections. The levels of geographical access have the expected magnitude: larger access areas provide higher utility. However, respondents do not perceive any difference between access to the medium area and the big area. Lastly, having access to the rush hour intervals provides higher value to respondents and this result can arise due to specific respondents' travelling routine that included these intervals.

The difference between MNL1 and MNL2 models is the introduction of the error component used to take into account the panel nature of the data. The error component draws are common between all observations of the same respondent to capture the panel structure and are normally distributed with zero mean and the same variance (i.e., sigma). Comparing the loglikelihood values of the two models using a Likelihood Ratio (LR) test, the goodness of fit of the MNL2 is significantly higher than MNL1 and it justifies the adoption of the error component ($LR = 1689.15$, $p < 0.05$). MNL3 model includes the permanent address variable as a rescaling factor of the three utility functions in order to take into account the size of the different subgroups present in the sample (Train, 2009). The lower values of AIC and BIC (vs. MNL2) support the introduction of the rescaling factor. Starting from MNL3, MNL4 introduces the previously mentioned demographics and segmentation variables in the three utility functions (i.e., the common section alternative and the two dedicated section alternatives). Male (vs. female) respondents express higher utility for access to dedicated sections than the common section only. Older respondents are less willing to choose dedicated sections than younger ones. Travelers with a primary school degree associate higher utility to travel cards with access to dedicated sections (compared to the common section only). The type of owned subscription (GA or HF subscription) and the preferred class (1st vs. 2nd class) do not play any role. Commuters (vs. travelers) indicate higher utility for travel cards with the common section only than the ones with dedicated section access. The LR test shows higher goodness of fit of MNL4 compared to MNL3 and it justifies its adoption ($LR = 100.43$, $p < 0.05$).

ICLV model includes the latent variable out-group derogation in each alternative (except for the none option) presented. In the ICLV formulation, demographics and

segmentation variables are not directly incorporated in the utility function (as for MNL4) because they are part of the latent variable specification and their effect would be manifested through it. In line with the MNL models, access to a larger area provides higher utility even if respondents do not perceive any difference between access to a medium area and a large area. Among the dedicated sections, the silence section is the only one that provides higher utility compared to the reference level (family section). BIC associated with the choice component of the ICLV model is lower than those obtained for the MNL models and the qualitative benefit in goodness-of-fit value indicates that the out-group derogation has a key explanatory role in the model. The parameters associated with the latent variable have a positive and significant effect on both alternatives (common section only and common + dedicated section). However, respondents with a higher tendency towards out-group derogation associate higher utility with alternatives with access to dedicated sections compared to alternatives with access to the common section only. Estimation results for the structural equation component of the ICLV model are presented in Table 4. The effect of age on the latent variable is in line with the expectations and estimates of the MNL models. Older respondents (compared to younger respondents), respondents with GA/HF subscriptions (compared to respondents without them), commuters (compared to travelers), and respondents with lower educational levels (i.e., primary school, professional school, and middle school) show a lower tendency towards out-group derogation and they are less likely to choose the proposed subscriptions. On the other hand, gender, and preferred class (1st vs. 2nd class) do not have any significant effect on the latent variable. Threshold estimates of the ordered logit model and measurement component estimates of the ICLV model are not presented in the chapter for length reasons, but they are all significant and with the expected signs.

2.6. Conclusion

This research investigates travelers' behavior when facing the decision to buy a new railway subscription in Switzerland. They have to choose their subscription based on the type of access they preferred: access to the common section only or access to common and dedicated sections. In order to evaluate if their choices are driven by unobservable

factors, we use a hybrid choice modelling approach including a latent variable, called out-group derogation, in the model. Model results unsurprisingly indicate that travelers prefer access to larger areas and during rush hours. They do not associate any additional value to the business and lifestyle of the dedicated sections compared to the family section whereas they do with the silence section. Looking at the interaction of the demographics and segmentation variables, the obtained results indicate that young travelers prefer dedicated sections and commuters associate higher values with alternatives with common section access (compared to common section + dedicated section access). Finally, the ICLV model shows that travelers with a higher tendency towards out-group derogation (i.e., young travelers with high educational levels) associate higher utility to alternatives with access to common and dedicated sections compared to the alternatives with access to the common section only.

Demonstrating how travelers' heterogeneity and specifically out-group derogation have an impact on their travelling behavior, this paper highlights how crucial it is the need for public transport companies to consider these characteristics in the future public transport design process. Moving from a two-classes distinction to a more granular offer could potentially increment the chance of satisfying that part of customers who do not choose a subscription based on the intrinsic characteristics of the same but according to the characteristics of the travelers present in that particular wagon.

Nevertheless, some limitations remain in the analysis conducted in this paper. Firstly, the sample includes Swiss German respondents only and it cannot be considered a representative sample of the entire Swiss population. Even though this limitation, the methodological approach presented in this work can be easily extended/replicated with a representative sample. Secondly, the choice design developed incorporates specific attributes and attributes' levels that could not be an exhaustive representation of possible offers present in the market. Finally, it can be also interesting to integrate into the choice design some alternatives already present in the actual offer combining stated preference and revealed preference data (Train, 2009). This would certainly provide a clearer picture of the actual respondents' behavior taking advantage of both datasets.

2.7. Appendix

Table 3 - Chapter 2 - Model estimates (part 1 - choice experiment)

Model	MNL1		MNL2		MNL3		MNL4		ICLV	
Number of observations	6072		6072		6072		6072		6072	
Number of respondents	506		506		506		506		506	
Number of parameters (choice component)	9		10		15		37		17	
LL (choice component)	-5336.419		-4491.844		-4474.903		-4424.688		-4449.300	
LL (ICLV models)									-11233.365	
AIC	10690.838		9003.688		8979.806		8923.376		8932.600	
BIC	10697.175		9010.728		8990.368		8949.430		8944.570	
	Estimate	t-test	Estimate	t-test	Estimate	t-test	Estimate	t-test	Estimate	t-test
ASC _{Common}	-0.179	-1.31	-0.201	-1.14	-0.247	-1.34	-0.617	-1.26	0.146	0.67
ASC _{Dedicated}	-0.586	-4.65	-0.709	-4.35	-0.769	-4.25	-1.050	-2.32	0.107	0.50
Business _{Dedicated}	0.084	1.46	0.066	1.02	0.067	0.97	0.071	1.03	0.060	0.86
Lifestyle _{Dedicated}	-0.033	-0.56	-0.050	-0.75	-0.043	-0.62	-0.042	-0.60	-0.042	-0.60
Silence _{Dedicated}	0.268	4.94	0.316	4.78	0.330	4.41	0.326	4.36	0.334	4.44
Area small (zone)	-0.936	-15.91	-1.110	-14.34	-1.170	-10.16	-1.160	-10.18	-1.170	-10.22
Area medium (region, canton)	-0.024	-0.58	-0.035	-0.68	-0.028	-0.53	-0.031	-0.60	-0.026	-0.49
Travelling during rush hour	0.985	11.46	1.110	10.98	1.180	8.49	1.170	8.53	1.180	8.56
Price	<-0.001	-18.91	<-0.001	-16.51	<-0.001	-10.91	-0.001	-10.99	<-0.001	-11.01
Sigma (EC panel data)			2.070	19.74	2.180	11.17	2.020	11.30	2.170	11.80
Out-group derogation _{Common}									0.232	2.52
Out-group derogation _{Dedicated}									0.534	4.68
Scale parameter, Lake Geneva region					2.580	5.09	2.430	5.16	2.810	5.04
Scale parameter, Central Plateau					0.890	8.29	0.907	8.43	0.888	8.50
Scale parameter, North-west Switzerland					0.846	8.33	0.847	8.44	0.854	8.51
Scale parameter, Eastern Switzerland					0.993	7.10	0.994	7.32	1.010	7.21
Scale parameter, Central Switzerland					1.190	7.51	1.220	7.76	1.200	7.73

Table 4 - Chapter 2 - Model estimates (part 2 – demog. and segmentation variables)

Model	MNL 4				ICLV*	
	Common Section		Dedicated Section		Estimate	t-test
	Estimate	t-test	Estimate	t-test		
Male	0.733	3.39	0.978	4.23	0.128	1.76
Adults	-0.376	-1.26	-0.739	-2.38	-0.881	-10.38
Best agers	-0.802	-2.26	-1.060	-2.89	-0.800	-7.05
Seniors	-0.571	-1.35	-1.470	-3.17	-0.827	-5.79
Primary school	2.220	4.42	3.020	3.77	-0.465	-3.32
Professional school	-0.524	-1.99	-0.278	-1.03	-0.197	-2.69
Middle school	-0.177	-0.49	-0.062	-0.17	-0.283	-2.87
GA travel card ownership	0.437	1.18	0.495	1.39	-0.642	-7.33
Half-fare travel card ownership	0.372	1.11	0.403	1.29	-0.893	-10.86
1 st class	-0.336	-0.92	0.455	1.20	0.046	0.48
Commuting	0.656	2.75	0.516	2.01	-0.216	-2.36

* Structural component estimates; LV: Out-group Derogation

**Chapter 3: How social norms influence train subscription choice process in
Switzerland: a hybrid choice model with different rush hour access alternatives**

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3.1. Abstract

Train congestion is a common issue in public transport. Travelers increasingly commute during rush hours to reach their commuting/travelling destinations. Mobility pricing, trip-based pricing, and tradable mobility credit schemes represent a typical approach to the problem, but their application has generated mixed results. In this research, we take a novel perspective and investigate the role of not directly observable social norms in driving travelling choices beyond pricing. We collected data from Switzerland, where the problem of rush hour congestion is quite relevant, and several studies have been conducted proposing different approaches to solve it. A sample of 504 Swiss-German travelers has been collected and their travel card preferences have been analyzed using a hybrid choice modelling approach. We first analyze travelers' preferences for travel cards with different types of access and then, we investigate how demographics, special traveler characteristics, and not directly observable factors influence travelers' preferences during the choice process. Results indicate that respondents prefer travel cards that allow them to travel with minimum constraints. This tendency is even higher for commuters (vs. travelers). In this specific case, the presence of formal time constraints (i.e., at their workplace) and professional social norms that affect their working time flexibility justify this result. In other words, commuters express a higher preference for a subscription that does not force them to commute outside rush hour intervals because they could not easily vary their habits away from these periods. Adults (26-49 years old) and best agers (50-64/50-63 years old) represent the most sensitive segment to possible travelling limitations. In summary, this work highlights how strongly external factors (i.e., formal time constraints and professional social norms) influence travelers' preferences regardless of how advantageous the proposed alternatives are. Therefore, commuters have to stick to their travelling routine and are insensitive to price-related incentives. Furthermore, this work shows how urgent it is for employers to change their mindset of organizing employees' working hours and places, moving from supervising them to trusting them, in order to minimize rush hour travels. A possible support initiative could be teleworking (working-from-home) even if it maintains the constraint of being available at specific

working hours or, even better, smart working where employees decide the place and the time to carry out their activities in agreement with their employers.

Keywords: discrete choice experiments; hybrid choice models; professional social norms

3.2. Introduction

The problem of highly crowded trains during rush hour intervals has become so relevant in the transportation field, in Switzerland as in the rest of the world, that it has been discussed in several newspaper articles (Bloch, 2011; Riedener, 2012; Valda, 2015; Vontobel & Guanziroli, 2008) and research papers (Ben-Elia & Ettema, 2011; Currie, 2010; Evans & Wener, 2007; Hale & Charles, 2009; Hirsch & Thompson, 2011; Kim, Kwon, Wu, & Sohn, 2014; Meissonnier & Richer, 2021; Tirachini, 2013; Zhang, Han, & Li, 2008). Several approaches to solve the rush hour problem have been proposed: mobility pricing (Olszewski & Xie, 2005; Vrtic, et al., 2011; Vrtic, et al., 2007), trip-based pricing (Kaddoura, et al., 2015), and tradable mobility credit schemes (Wu, et al., 2012; Yang & Wang, 2011). For instance, the Belgian railway company SNCB proposed a travel card to take the same train route two/three times a week for a reduced price (SNCB, 2016). In Switzerland, previous literature proved that a different approach, such as working from home or flexible working hours, could have a positive effect on the reduction of this problem but with limited success (Munch, 2014; Weichbrodt, et al., 2013; Zemp, 2014).

In this research, we take a novel perspective on the rush hour problem and investigate the role social norms play in influencing travelers' choices of travelling times, beyond pricing. Previous literature examined the effect of observable factors on commuting time choice such as the presence of formal restrictions at their commuting destination (Chang & Mahmassani, 1988; Jou, et al., 2008; Senbil & Kitamura, 2004, 2005). Different from that, we argue that individuals cannot sufficiently adjust their behavior as a reaction to alternative pricing as they are constrained by not directly observable social norms of their work or private environment. Social norms represent the behavioral code that is recognized in a group without the tangible presence of any official, formal, or written rules (Smith, 2002). In some cases, non-compliance with norms at the workplace can lead to harsher coercive measures than not adhering to the law (Ferdous, et al., 2011).

Moreover, investigating the effect of social norms on travelers' choices, this research operationally expanded existing literature by examining two different rush hour interval definitions (compared to the actual one) and different forms of rush hour access,

such as unlimited access, limited access in time and number of trips and no access. Different from prior research, this work did not explore the value of travel time reduction. Instead, it examined how being allowed (vs. not) to use the train during specific time intervals was valuable and its results could be used to draft incentivizing instruments to decrease train load during rush hours.

3.3. Data

3.3.1. Survey design

We developed an online three-section survey and enrolled 504 respondents in the German-speaking part of Switzerland with the assistance of a market research agency (Intervista AG). In the first section of the survey, we introduce a set of questions related to travel behavior and preferences to relate our results with a previously conducted segmentation study (SBB, 2013). In the second part, respondents face the choice experiment. Then, they have to fill in questions related to latent and socio-demographic variables. Further details about the procedure of the choice experiment are provided in the next paragraph. Before the choice experiment, the notion of a travel card is introduced to allow the respondents to familiarize themselves with it. In the choice experiment, travel cards provide yearly access to Swiss public transportation with distinctive access options. We invite respondents to imagine that they may need to buy online a new yearly subscription (or renew an existing one) and that they would confront with 12 pages and each of them will have a different purchase case (i.e., choice task) from which the respondents will have to indicate their subscription preference. We also inform respondents that they have four options in each choice scenario. They can express their preference by either choosing one of the three proposed alternatives or moving to the following purchase scenario by clicking “None” if none of them is suitable. An illustrative choice task is shown in Figure 6.

Figure 6 - Chapter 3 - Example of choice task (translated from German)

If these were the travel card options offered to you. Would you buy any of those and if yes which one?

Choose by clicking one of the buttons below:

	Travel Card Nr 1	Travel Card Nr 2	Travel Card Nr 3	None
Geographical Access	Area Medium (Region, Canton) + Route (> 10 km)	Area Small (Zone)	Area Medium (Region, Canton)	I would not choose any of these.
Comfort Level	1 st Class	2 nd Class	1 st Class	
Rush Hour Access	No Access during 6:00 – 9:00 and 16:00 – 19:00 (Wide)	Limited Access for 20 trips per year during 6:00 – 9:00 and 16:00 – 19:00 (Wide)	Unlimited Access	
Price	CHF 4'500.-	CHF 3'000.-	CHF 4'500.-	

LEGEND (Click on the attribute name to see the description)

- [Geographical Access](#)
- [Comfort Level](#)
- [Rush Hour Access](#)
- [Price](#)

3.3.2. Choice Design

We create the base for the choice experiment implementation using a qualitative analysis of SBB's current offerings and pricing structure. We focus our analysis on yearly subscriptions only and do not evaluate single tickets to diminish the complexity of the experiment. Operationally, we develop a stated preferences choice design and break it down into five blocks with twelve choice tasks per block. This type of choice design guarantees an equal partitioning of levels within each attribute. Respondents are randomly distributed among the blocks and each respondent faces choice tasks in random order. Each choice task includes three alternatives and a non-choice option. In order to avoid assumptions taken by decision-makers on omitted attributes linked with the alternatives' labels (de Bekker-Grob, et al., 2010; Louviere, et al., 2000) and to retain the flexibility of a labeled experiment at the same time, we implement an approach in between unlabeled and labeled choice design. We use generic labels (i.e., alternative 1) and alternative-specific attributes. Each alternative includes four main attributes: "geographical access", "comfort level", "rush hour (access)", and "price" (Table 5 for details). As with the study presented in Chapter 2: Integrating travelers' heterogeneity in subscription choice processes through hybrid choice modelling: an application to the Swiss railway market, attributes and their levels have outlined in agreement with SBB representatives and previous studies conducted by the company (SBB, 2013; Weichbrodt, et al., 2013).

The “geographical access” attribute characterizes the geographical dimension in which the travel card is valid. It has four levels: subscription with “area small (zone)” provides unlimited access in an area large as two zones; “area medium (region, canton)” grants access to an area as large as an entire canton/region; “area medium (region, canton) + route > 10 km” subscriptions give access both to an area as large as an entire canton/region and additionally to a precise route; travel card with “area big (country)” allows access to public transport throughout Switzerland.

The “comfort level” attribute describes the levels of service quality of train sections. It has two levels: subscription with the “first class” level provides access to train sections that provide high-quality services; “second class” travel cards grant access to train sections with essential services.

The “rush hour (access)” attribute describes the access options in the rush hour intervals. It has three levels: subscriptions with the “no access” level cannot be used during defined rush hour intervals; “limited access” subscriptions provide access for a limited number of trips during rush hour intervals; “unlimited access” indicates a subscription with access to public transport without time restrictions. Alternatives with “limited access” or “no access” levels have additional attributes to complete their access specification: “rush hour (time frame)” for both attribute levels and “rush hour (number of trips)” for “limited access” only.

The “rush hour (time frame)” attribute represents the time frames in which the travel card cannot be valid (“no access”) or valid for a limited number of trips only (“limited access”). It has two levels: “7:00 – 8:00 and 17:00 – 18:00 (narrow)” and “6:00 – 9:00 and 16:00 – 19:00 (wide)”. No restrictions are present outside these intervals. The narrow rush hour time frame indicates the actual congestion intervals during the day. The wide rush hour time frame extends the narrow rush hour time frame including one hour before and after the peak hour respectively since these hours are still widely used compared to the absolute off-peak hours (Bloch, 2011).

The “rush hour (number of trips)” attribute defines the number of trips allowed with a “limited access” travel card during the intervals specified in the previous attribute. It has two levels: “20 trips per year” and “30 trips per year”. After having reached the

limited number of trips, travelers cannot use their “limited access” subscription to access public transport during rush hour intervals.

The “price” attribute defines the expense that travelers must incur to purchase a specific travel card. It has four levels (“CHF 1’500.-”, “CHF 3’000.-”, “CHF 4’500.-”, and “CHF 6’000.-”), which covers the range of prices of existing railway products at the time of the data collection.

Table 5 - Chapter 3 - Attributes and attributes' levels

Attribute	# of levels	Description
Geographical access	4	Area small (zone); area medium (region, canton); area medium (region, canton) + route (> 10 km); area big (country)
Comfort level	2	First class; second class
Rush hour (access)	3	No access; limited access; unlimited access
Rush hour (time frame)	2	7:00 – 8:00 and 17:00 – 18:00 (narrow); 6:00 – 9:00 and 16:00 – 19:00 (wide)
Rush hour (number of trips)	2	20 trips per year; 30 trips per year
Price	4	CHF 1’500.-; CHF 3’000.-; CHF 4’500.-; CHF 6’000.-

3.3.3. Attitudinal, Perceptual and Other Variables

Beyond the above factors, commuters may have social norms at the workplace that affect their commuting time choices (Cialdini, Kallgren, & Reno, 1991; Cialdini, Reno, & Kallgren, 1990; Riggs, 2017; Zhang, et al., 2015). Even though flexible time could be officially admitted at the commuting destination, there might be unwritten rules (i.e., expectations in a team) that go beyond the formal agreement and inhibit individuals from freely travelling outside rush hour intervals. In fact, concerning the working environment, Morrison (1994) stated that “[many] jobs are socially constructed rather than objectively defined”. These rules comprise moral guidelines that have emerged in a group of people (i.e., team, department, or even the class in school) and could vary in different organizations (Andersson & Pearson, 1999; Feldman, 1984; Hartman, 1996). For example, if the whole group is at the workplace every day at the same time (i.e., between 07:45 and

16:45), this indicates that social norms affecting working time flexibility could be present. Reducing working time flexibility diminishes commuting flexibility although no contractual restrictions define these working times. Moreover, if somebody is mostly travelling during rush hour intervals and notes social norms affecting his/her working time flexibility, that person does not have the chance to move commuting times outside those intervals.

Given its relevance in the decision-making process, we, therefore, investigate the effect that professional social norms have on commuters' working time flexibility. We adopt a 6-item 7-point Likert scale (Figure 7) extending the scales proposed by Dambrun, Guimond, and Duarte (2002); Harris (2008); Spangenberg, Sprott, Grohmann, and Smith (2018). These scales analyze the effect of perceived social norms in different contexts, such as tolerance in academia, level of recycling behavior, and fraudulent return proclivity. We adapted the scale for the specific case of working time flexibility, adjusted and validated through several focus group sessions.

In order to connect our work with previous segmentation studies (SBB, 2013), we introduce demographics, segmentation, and commuting-time-related questions. These variables include age (divided into classes), occupation as well as the need for commuting (commuters vs. travelers). Moreover, only for respondents that identify themselves as commuters, we include additional questions concerning hard factors (i.e., formal professional and private restrictions) that constrain their travel time choices. Concerning these factors, we utilize two binary variables to measure whether respondents have formal time restrictions at their professional commuting destination (e.g., workplace, university, school, etc.) or in their private context (e.g., fixed training schedules sports clubs, picking up kids at school, etc.) that could influence their choices.

Figure 7 - Chapter 3 - Professional social norms on working time flexibility (direct and latent items)

	I do not agree at all 1	2	3	4	5	6	I completely agree 7
It is a social norm at my* that everybody always starts at the same time.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is a social norm at my* that everybody is always present at the same time.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is a social norm at my* that everybody always leaves at the same time.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
People at my*:							
	I do not agree at all 1	2	3	4	5	6	I completely agree 7
believe that it should be sanctioned if everybody is always present at the* during different times.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
do not approve, if not everybody is always present at the* during the same time.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
think that it is OK, if everybody is always present at the* during different times.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
expect that everybody is always present at the* during the same time.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

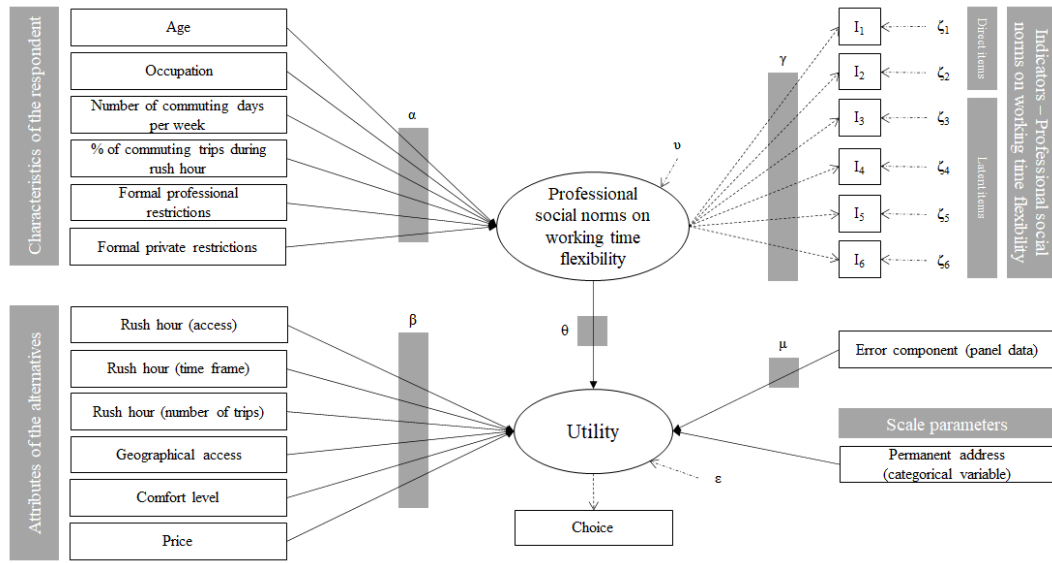
Before the estimation of the ICLV model, we perform a factor analysis with the principal-factor method (Rencher & Christensen, 2012) to verify the consistency of the previously illustrated indicators with the relative latent variable. From the analysis, we find out that only the third latent item has been misinterpreted and has an important level of uniqueness. Removing this item, almost the entire variability (99.01%) of the original data can be explained with one factor and the Cronbach's alpha of this scale is approximately 0.89.

3.4. Model Specification

In this paragraph, we present an introduction to the ICLV model (Figure 8) adopted and its theoretical background. Within a discrete choice modelling framework, we introduce several variables, such as demographics, segmentation variables, and a latent variable to evaluate their effect on the subscription choice process. Namely, we calculate the probability of opting for specific train subscriptions among those proposed taking into account the previously mentioned variables. We adopt traditional multinomial logit

models (MNL), mixed logit models (ML), and an integrated choice and latent variable (ICLV) model. In doing so, it is possible to integrate preference heterogeneity and include an error component associated with the panel structure of the data (i.e., each respondent faces several choice tasks during the experiment).

Figure 8 - Chapter 3 - Full path diagram of ICLV model



A latent variable is a not directly observable element that could have an impact on the choice process and the common method to introduce its effect in the choice modelling framework is the MIMIC model (Bollen, 2016; Cantillo, et al., 2015). It consists of two components: a structural model and a measurement model. The structural model (equation 12) describes the relation between a set of latent variables (η_n) and a set of individual and alternative characteristics (S_n). Furthermore, equations (2) and (3) describe the effect that latent variables have on a group of related attitudinal indicators (C_n). These equations represent the measurement part of the MIMIC model.

$$\eta_{lkn} = \sum_r \alpha_{lrk} S_{rkn} + v_{lkn} \quad (12)$$

where l refers to a latent variable, k to an alternative, n to an individual, and r to an explanatory variable. α represents the parameters associated with the directly observable characteristics whereas \mathbf{v}_n is the set of error terms associated with latent variables. These errors are considered independent and identically distributed (i.i.d.) as Normal with zero mean and standard deviation to be estimated. Given the non-continuous nature of the observed indicators adopted (i.e., 7-point Likert scale), ordinal logit models are usually used to describe the measurement component of the MIMIC model (Daly, et al., 2011). This model presumes that each observed discrete response j of an indicator p is a function of the related latent variables and an error term, through a censoring process, as indicated in equations (13) and (14).

$$C_{pkn} = \begin{cases} 1 & \text{if } (-\infty) < C_{pkn}^* \leq \tau_{p1} \\ 2 & \text{if } \tau_{p1} < C_{pkn}^* \leq \tau_{p2} \\ \dots & \\ J & \text{if } \tau_{p(J-1)} < C_{pkn}^* \leq \infty \end{cases} \quad (13)$$

$$C_{pkn}^* = \sum_l \gamma_{lpk} \eta_{lkn} + \zeta_{pkn} \quad (14)$$

We calculate the observed discrete response ($C_{pkn} = j$), as described in equation (13) adopting a set of thresholds (τ) that need to be estimated. Concerning equation (14), we assume that the vectors of error terms (ζ) and the vectors of parameters (γ) associated with latent variables are independent. Combining equations (13) and (14), we can formulate the probability that C_{pkn} assumes a specific value (j) as equation (15):

$$P\{C_{pkn} \in j | \eta_n\} = F\left(\tau_{pj} - \sum_l \gamma_{lpk} \eta_{lkn}\right) - F\left(\tau_{p(j-1)} - \sum_l \gamma_{lpk} \eta_{lkn}\right) \quad (15)$$

where F is the cumulative distribution function.

Concerning the utility function, we adopt a standard random utility model (RUM) as described in Walker and Ben-Akiva (2002). In this model, the utility value associated with an alternative k and an individual n is unobservable and is a function of observable attributes \mathbf{X}_n , an error component Z_n (to consider the panel structure of the dataset), and

an error term ε_{kn} as described in equation (16). We assume that the error terms (ε_n) are independent and identically distributed as a Gumbel whereas the error components Z are normally i.i.d..

$$U_{kn} = \sum_j \beta_{jk} X_{jkn} + \mu_n Z_n + \varepsilon_{kn} \quad (16)$$

In order to incorporate the latent model into the RUM model, we can rewrite equation (16) as equation (17) including the linear combination of latent variables (η_n):

$$U_{kn} = \sum_j \beta_{jk} X_{jkn} + \sum_l \theta_{lk} \eta_{lkn} + \mu_n Z_n + \varepsilon_{kn} \quad (17)$$

where the vectors of parameters β , θ , and μ should be estimated. These utility functions are not directly observable and, thus, they can only be estimated through their related preference indicators y (Walker & Ben-Akiva, 2002). Conform to the RUM model, an individual selects an alternative (y_k) among a set of existing alternatives (CS_n) only if this alternative can maximize his/her utility as illustrated in equation (18).

$$y_k = \begin{cases} 1 & \text{if } U_k \geq U_h, \forall h \in CS_n \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

Adopting the maximum simulated likelihood, we can estimate the joint probability of a specific choice that an individual has taken and the values of attitudinal indicators associated with latent variables simultaneously (Train, 2009). Combining equations (12), (15), (17), and (18), we can write the joint probability as a multi-dimensional integral (equation 19):

$$\begin{aligned} \bar{P}(y_{kn}, C_n | X_n, S_n, Z_n, \beta, \theta, \mu, \alpha, \gamma, \tau, \Sigma_\varepsilon, \Sigma_v, \Sigma_\zeta) = \\ \int_{\eta} P(y_{kn} | X_n, Z_n, \eta_n, \beta, \theta, \mu, \Sigma_\varepsilon) f(C_n | \eta_n, \gamma, \Sigma_\zeta) g(\eta_n | S_n, \alpha, \Sigma_v) d\eta_n \end{aligned} \quad (19)$$

where $P(y_{kn} | X_n, Z_n, \eta_n, \beta, \theta, \mu, \Sigma_\varepsilon)$ stands for the conditional probability of choosing the alternative k , $f(C_n | \eta_n, \gamma, \Sigma_\zeta)$ represents the density function of the indicators associated with the latent variable η_n , and $g(\eta_n | S_n, \alpha, \Sigma_v)$ is the density function of the latent variables

included in the model. After that, we can reformulate the conditional probability as equation (20) including equations (15) and (16) into equation (19).

$$\begin{aligned} \tilde{P}(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) = \\ \frac{\exp(\sum_j \beta_{jk} X_{jkn} + \sum_l \theta_{lk} \eta_{lkn} + \mu_n Z_n)}{\sum_{CS_n} \exp(\sum_h \beta_{jh} X_{jhq} + \sum_l \beta_{lh} \eta_{lhn} + \mu_n Z_n)} \times \prod_{p,k} \left[F\left(\tau_{pj} - \sum_l \gamma_{lpk} \eta_{lkn}\right) - F\left(\tau_{p(j-1)} - \sum_l \gamma_{lpk} \eta_{lkn}\right) \right] \end{aligned} \quad (20)$$

Given that we cannot directly solve the multi-dimensional integral presented in equation (19), we need to approximate it using the simulated probability (SP). We can calculate this probability as the average of the conditional probabilities presented in equation (20) over D draws extracted from the distribution associated with the error terms v_n (equation 12).

$$\begin{aligned} SP(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) = \\ \frac{1}{D} \sum_{d=1}^D \tilde{P}(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) \end{aligned} \quad (21)$$

To calculate the simulated probability, we can adopt different types of draws such as pseudo-random numbers, Halton sequences, and Modified Latin Hypercube Sampling draws (Hess, et al., 2006). In this work, we utilize 500 MLHS draws to estimate the presented model. We do not increase the number of draws given the remarkable increase in the computational costs and the stability of the estimates of parameters. Lastly, we can obtain the simulated log-likelihood function (SLL) by calculating the logarithmic transformation of the simulated probability (SP), presented in equation (21), over the entire sample (n) collected (22). Maximizing the simulated log-likelihood function, we can estimate the parameters presented in the previous equations.

$$SLL = \sum_n \ln SP(y_{kn}, \mathbf{C}_n | \mathbf{X}_n, \mathbf{S}_n, Z_n, \boldsymbol{\beta}, \boldsymbol{\theta}, \mu, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\Sigma}_\varepsilon, \boldsymbol{\Sigma}_v, \boldsymbol{\Sigma}_\zeta) \quad (22)$$

3.5. Results and Discussion

3.5.1. Sample Description

The sample is exclusively composed of individuals who have the intention to purchase a new public transport subscription in Switzerland (or prolong their existing one) within the next year and who are willing to pay for their subscription by themselves. The sample, collected in October 2016 with a purpose-built survey, is stratified by age to represent the Swiss population according to the Swiss railway marketing research standards (Swiss Federal Statistical Office, 2014). Given that each respondent faces 12 choice tasks, the total number of observations is 6'048. Of the 504 respondents, more than fifty-two percent (52.98%) are females and more than sixty-one percent (61.71%) are 50 years old or younger. Almost the entire sample is Swiss (93.25%) with more than seventy-two percent (72.22%) living in the areas of Zurich, Central Plateau, and North-west Switzerland. More than fifty-five percent (55.95%) have attended higher education studies such as universities, institutes of technology, technical college, and higher vocational schools, the prevalent occupation (65.87%) is employed, and more than fifty-six percent (56.15%) have a gross income between CHF 2'000 and 8'000. Concerning their travelling characteristics, more than eighty-nine percent (89.68%) own a general abonnement (GA) or a half-fare travel card (HF), more than sixty-five percent (65.07%) travel to and from their place of work and/or educational institution, and almost half of them (46.03%) define themselves as commuters. More than sixty-six percent (66.81%) of commuters take the train during the rush hour intervals (6:00 – 9:00, 16:00 – 19:00) for eighty percent and more of their commuting. More than seventy-three percent (73.71%) of the 232 commuters interviewed declare to have professional formal time constraints at their commuting destination whereas only thirty-three percent (33.19%) reveal to have private formal time constraints (e.g., fixed training schedules sports clubs, picking up kids at school, etc.).

3.5.2. Model Estimation

We present model estimates in Table 6 – Table 9. We adopt four alternative-specific constants (i.e., no access, limited access, unlimited access to the rush hour

intervals, and “none” option) and set up the one associated with the “none” alternative to zero. We have formalized the alternatives based on the levels of the “rush hour (access)” attribute. Alternative 1 represents a travel card that does not provide access during specified rush hour intervals; alternative 2 refers to a travel card that does give access to the defined rush hour intervals but only for a specific number of trips; alternative 3 ascribes to a travel card that grants access to public transport without time restrictions. Alternative 4 indicates the none option.

The attributes we adopt in the models are:

- $ASC_{No\ access}$: alternative-specific constant associated with travel cards with no access to the rush hour intervals;
- $ASC_{Limited\ access}$: alternative-specific constant associated with travel cards with no access to the rush hour intervals except for a specific number of trips;
- $ASC_{Unlimited\ access}$: alternative-specific constant associated with travel cards with complete access to the rush hour intervals;
- Rush hour (time frame): binary variable that defines the time extension of the rush hour intervals (reference level: 7:00 – 8:00 and 17:00 – 18:00 (narrow));
- Rush hour (number of trips): binary variable that indicates the number of trips allowed with a limited access subscription during defined rush hour intervals (reference level: 20 trips per year);
- Geographical Access (area small (zone), area medium (region, canton), area medium (region, canton) + route (> 10 km)): effect coding variable (Hensher, et al., 2005) that refers to the geographical range in which the travel card is valid (reference level: area big (country));
- Comfort level: binary variable that defines to which level of service quality the travel card provides access (reference level: 2nd class);
- Price: categorical variable considered as continuous given that the step is constant along the levels;
- Sigma: continuous variable representing the standard deviation of the error term included to consider the panel structure of the dataset;

- Scale parameters: categorical variable introduced to rescale the utility equations as a function of the respondent permanent address distribution (reference level: Zurich) as described by Train (2009);
- Age (adults, best agers, seniors): effect coding variable (reference level: young adults);
- Type of travelling (commuting): binary variable that denotes the need of commuting or not (reference level: non-commuting);
- Occupation (student, homemaker, pensioner / unemployed / other occupation): effect coding variable (reference level: employed including trainees and/or interns);
- Percentage of commuting trips during rush hour (50 – 80% of commuting trips during rush hour, 80 – 100% of commuting trips during rush hour): effect coding variable (reference: less than 50% of commuting trips during rush hour);
- Number of commuting days per week: continuous variable;
- Formal professional restrictions: binary variable that defines the presence of formal time restrictions at respondents' commuting destination (e.g., workplace, university, school, etc.);
- Formal private restrictions: binary variable that indicates the presence of formal time restrictions in respondents' private context (e.g., fixed training schedules sports clubs, picking up kids at school, etc.);
- Latent variable (professional social norms on working time flexibility): continuous variable introduced in the alternatives' formulation in the ICLV model;
- Latent variable thresholds: estimated points of the ordered logit model adopted for the measurement component of the ICLV model.

The model estimates that we present in Table 6 and Table 7 refer to the entire sample (504 respondents) whereas estimates in Table 8 and Table 9 concern only respondents that identified themselves as commuters (232 respondents). Considering MNL1 and MNL2 models as specific cases of a general random coefficient model, we can evaluate their difference in the goodness of fit by adopting a likelihood ratio (LR) test.

Given the introduction of scale parameters in MNL3 and MNL4, we cannot evaluate them as nested models of MNL1 and MNL2 using the LR test. To compare them, we utilize the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

Evaluating the alternative-specific constants in the models MNL1 – MNL4, we deduce how different levels of access to the rush hour intervals have a remarkable impact on the decision process: travel cards with unlimited access to the rush hour intervals provide the higher utility followed by limited access alternatives and, lastly, by alternatives with no access to those intervals. This result demonstrates that travelers need as much flexibility as possible in train adoption, probably due to their commitments with inflexible schedules. As described in paragraph 3.3.2. Choice Design, alternatives with limited access and no access to rush hour intervals have an additional attribute that specifies the extent of the intervals: narrow (7:00 – 8:00 and 17:00 – 18:00) and wide (6:00 – 9:00 and 16:00 – 19:00). Unsurprisingly, not having access to wider (vs. narrow) rush hour intervals has a negative impact on the utility of the specific alternative. This result may be due to two main factors: 1) the impossibility of using the travel card for a large amount of time (6 hours) regardless of its location in time, and 2) the need of travelers to reach more distant destinations within a certain time (usually connected to predefined schedules) or to reach those destinations quite in advance for external reasons unrelated to their intent. The same attribute has a similar effect – not as negative as in the “no access” alternative – in the case of travel cards with limited access to the rush hour intervals: we can relate the negative effect to the disutility of not having access to the rush hour intervals once the trips allowed with the travel card have been exhausted. Concerning the attribute related to the number of trips during rush hour intervals (in the case of travel cards with limited access), we find the expected sign: increasing the number of trips provides higher utility.

The levels of the geographical access attribute have the expected effect: access to larger areas brings higher utility. However, respondents do not recognize the value of having access to a 10-km point-to-point trip in addition to the access to a medium area (region, canton) compared to a large area (country). Lastly, travel cards with access to the first class (vs. second class) provide a significantly lower utility. We can justify this result considering travelers’ feelings about overcrowded first-class sections during rush hours.

If travelers do not find the expected level of comfort in the first class, it does not bring the additional utility it is meant to bring compared to the second class and thus they prefer it less. Compared to MNL1, we include an additional parameter in MNL2 (standard deviation of the error component distribution) to consider the panel structure of the dataset. We extract draws of the error component from a Normal distribution with zero mean and estimated variance and these draws are common among all the observations associated with the same respondent. The likelihood ratio (LR) test – we adopt to compare MNL1 and MNL2 – indicates that the increment in the goodness of fit is significantly different from zero and supports the introduction of the error component (LR = 1539.29, $p < 0.05$) in the model.

In MNL3, we incorporate the permanent address variable to rescale the four utility equations as a function of the different sizes of the sample subgroups (Train, 2009). The lower value of the AIC of this model (vs. MNL2) justifies the introduction of the rescaling factor. In MNL4, we further extend MNL3 by introducing the age and the type of travelling variables in the three utility equations. Young respondents are more willing to choose these new types of subscriptions (compared to the old ones). Respondents that identify themselves as commuters (vs. non-commuters) associate higher utility to travel cards with unlimited access (compared to no access and limited access) to the rush hour intervals. This result suggests an in-depth analysis to better understand the reasons that influence commuters' choices. The LR test indicates higher goodness of fit of MNL4 compared to MNL3 and it supports its adoption (LR = 104.66, $p < 0.05$).

Regarding the subsample of commuters, we estimate two models: 1) a multinomial logit model (MNL5) with demographic and segmentation variables included in the three utility equations and 2) an integrated choice and latent variable model (ICLV) with additional parameters to measure the impact of professional social norms on working time flexibility over the different type of access to the rush hour intervals. Unlike the results shown in MNL1 – MNL4, we find that the alternative-specific constants associated with the three types of access during rush hours are not significantly different from zero in MNL5. Results associated with other attributes are in line with the previous models: the

utility associated with the number of trips during rush hour intervals (in case of limited access) is still positive but slightly significant (compared to MNL1 – MNL4).

Commuters that declare to have (vs. do not have) formal professional restrictions at their commuting destination are less willing to choose travel cards with no access to rush hour intervals whereas the presence of formal private restrictions has a slightly significant positive effect on the utility of travel cards with unlimited access (Molloy, et al., 2021). Old commuters are less willing to choose travel cards with limited and no access to the rush hour intervals (compared to young respondents) whereas we do not observe this distinction in utility in the case of travel cards with unlimited access. Commuters whose main activity is housekeeping (i.e., homemaker) associate a higher utility to travel cards with unlimited access to rush hour intervals (compared to other occupation levels). The percentage of commuting trips during rush hour and the number of commuting days per week do not have a significant effect on the choice process.

In the ICLV model, we include the latent variable in the utility equation of each alternative except for the none option. Moreover, we do not directly introduce demographic and segmentation variables (except for the presence of formal private restrictions) in the utility function specification (as for MNL5) because we already incorporate them in the latent variable specification and their effect would be manifested through it. Partially in line with MNL5 results, we find that the alternative-specific constants associated with limited and unlimited access to the rush hour intervals are not significantly different from zero whereas no access alternative has a slightly significant negative constant. A large (vs. narrow) time frame provides lower utility in the case of travel cards with no access or limited access to the rush hour intervals. Increasing the number of trips during rush hour intervals has a slightly significant positive effect on the utility of alternatives with limited access to the rush hour intervals. Access to larger geographical areas provides higher utility (compared to smaller areas). Having access to the first class significantly decreases the alternative utility.

Commuters with private restrictions associate a slightly significant higher utility to travel cards with unlimited access to rush hour intervals (compared to respondents without private restrictions) (Molloy, et al., 2021). Although we notice that the BIC

associated with the choice model of the ICLV is higher than the one associated with the MNL5, the introduction of the latent variable leads to a qualitative gain in the interpretation of the phenomenon. In fact, we observe that commuters with high perceived pressure of professional social norms on working time flexibility associate significantly higher utility to travel cards with unlimited access and slightly significant higher utility to limited access (compared to respondents with lower perceived pressure). We present the estimates related to the structural component model of ICLV in Table 9. Commuters with (vs. without) formal professional restrictions perceive higher pressure of professional social norms on their working time flexibility albeit its effect is only slightly significant. Senior (compared to young) commuters perceive lower professional social norms on their working time flexibility and it can be due to their reduced working activity. We surprisingly find out that students perceive higher professional social norms on their working time flexibility (compared to employed respondents): a possible explanation could be found in a very inflexible course scheduling. Increasing the percentage of commuting trips during rush hour intervals and the number of commuting days per week do not amplify the perceived pressure of professional social norms on working time flexibility. Estimates of the ICLV measurement model and thresholds of the ordered logit model are not reported in the chapter for length purposes but they are significant and with expected signs.

3.6. Conclusion

The question of congested trains during rush hour intervals has become quite significant in the transportation field and several experiments have been conducted to investigate this phenomenon. This research investigates which features may drive travelers to prefer travel cards that restrict their travelling behavior during the above-mentioned intervals. Respondents have to indicate which subscriptions they favor based on the type of access to the rush hour intervals included in the travel cards: no access, limited access, or unlimited access to the rush hour intervals. In order to assess if their preferences were influenced by unobservable factors, we adopt a hybrid choice modelling approach and include the latent variable professional social norms on working time flexibility in the

model. Examining the results for the entire sample, respondents demonstrate a strong preference for travel cards with a certain level of travel flexibility: first, unlimited access to the rush hour intervals then limited access, and lastly no access. Consequently, some sort of access to the rush hour intervals seems to be crucial. Moving their trips out of the wide rush hour intervals would presumably hamper too much the fulfillment of their needs. Concerning travel cards with limited access to rush hour intervals, travelers rationally demonstrate their preference for a higher number of trips.

Concerning the effect of demographic and segmentation variables on three utility functions, results show that young travelers perceived a higher utility for all rush hour access alternatives whereas, for commuters, unlimited access options provide additional utility. The first result indicates a greater willingness to accept travel solutions with innovative characteristics compared to older respondents while the second result is quite intuitive and linked to their lower travelling flexibility compared to travelers. Our in-depth analysis carried out for the subsample of commuters only provides results that are partially in line with the analysis conducted on the entire sample.

Holding constant levels of other alternatives' attributes, commuters do not associate significantly different utility values with the three types of rush hour access. Both professional social norms and private social norms influence respondents' preferences directly (in the utility functions) and indirectly (via the latent variable specification). In particular, respondents that perceive the strong presence of professional social norms ascribe a higher utility to travel cards that allow them to somehow travel during rush hour intervals.

Although these results provide further information about the decision-making process, this work presents some limitations. Firstly, the sample consists of Swiss German respondents only and, for this reason, it is not representative of the entire Swiss population. Nevertheless, this methodological approach can be extended/replicated with a representative sample. Next in order, stated preference choice design includes attributes and attributes' levels that do not represent a comprehensive representation of the entire range of products present in the market. Future research may include different choice

designs and combine revealed preference with stated preference data (Train, 2009) providing a more precise picture of respondents' choice behavior.

Highlighting how social norms have an impact on travelling behavior and specifically for working people, this work implicitly suggests how important it is the need for employers to change their approach of organizing employees' working hours and places. Moving from an approach of supervising their employees to trust them (Kaushik & Guleria, 2020) and allowing flexible working solutions, such as work-from-home and / or in different working intervals, could potentially reduce the effect of professional social norms and related trips during rush hour intervals (Beck & Hensher, 2020). To further analyze aspects of work organization, future research could investigate the effect of social norms for different working occupations present in the sample including information about the different types of respondents' work, such as the type and the percentage of work and the sector of employment.

3.7. Appendix

Table 6 - Chapter 3 - Model estimates (part 1 - choice component)

Model	MNL 1		MNL 2		MNL 3		MNL 4	
Number of observations	6048		6048		6048		6048	
Number of respondents	504		504		504		504	
Number of parameters (choice component)	11		12		17		29	
LL (choice component)	-5329.349		-4559.705		-4554.334		-4502.002	
AIC	10680.698		9143.410		9142.668		9062.004	
BIC	10688.425		9151.839		9154.600		9082.374	
	Estimate	t-test	Estimate	t-test	Estimate	t-test	Estimate	t-test
ASC _{No access}	-0.603	-4.82	-0.669	-4.48	-0.625	-4.28	0.064	0.19
ASC _{Limited access}	-0.340	-2.82	-0.437	-3.00	-0.407	-2.94	0.543	1.63
ASC _{Unlimited access}	0.802	8.79	0.874	7.29	0.832	6.59	1.010	3.82
Rush hour (time frame) _{No access}	-0.567	-4.43	-0.596	-4.01	-0.567	-3.81	-0.580	-3.93
Rush hour (time frame) _{Limited access}	-0.214	-2.35	-0.255	-2.37	-0.246	-2.38	-0.261	-2.52
Rush hour (number of trips) _{Limited access}	0.265	3.09	0.276	2.65	0.272	2.74	0.276	2.75
Area small (zone)	-0.845	-12.03	-0.940	-11.25	-0.897	-9.59	-0.914	-9.38
Area medium (region, canton)	-0.148	-3.03	-0.214	-3.87	-0.203	-3.83	-0.211	-3.94
Area medium (region, canton) + route (> 10 km)	0.083	1.60	0.082	1.39	0.079	1.44	0.086	1.57
Comfort level	-0.322	-5.05	-0.374	-5.14	-0.365	-5.10	-0.370	-5.09
Price	<-0.001	-19.67	<-0.001	-18.90	<-0.001	-12.13	<-0.001	-12.07
Sigma (EC panel data)			1.940	19.50	1.840	13.08	1.800	12.81
Scale parameter, Lake Geneva region					1.460	3.47	1.370	3.05
Scale parameter, Swiss Plateau					1.060	10.41	1.080	10.47
Scale parameter, North-west Switzerland					1.110	10.33	1.090	9.88
Scale parameter, Eastern Switzerland					0.969	8.22	0.987	8.13
Scale parameter, Central Switzerland					1.190	8.10	1.170	8.18

Table 7 - Chapter 3 - Model estimates (part 2 - demog. and segmentation variables)

Model	MNL 4					
	No Access		Limited Access		Unlimited Access	
	Estimate	t-test	Estimate	t-test	Estimate	t-test
Adults	-0.639	-1.99	-0.726	-2.18	-0.246	-1.01
Best agers	-1.270	-3.22	-1.090	-2.88	-0.619	-2.20
Seniors	-0.925	-1.96	-1.580	-3.43	-1.260	-3.35
Commuting	0.108	0.44	-0.263	-1.07	0.548	2.87

Table 8 - Chapter 3 - Model estimates - commuters only (part 1 - choice component)

Model	MNL 5		ICLV	
Number of observations	2784		2784	
Number of respondents	232		232	
Number of parameters (choice component)	50		23	
LL (choice component)	-2119.257		-2154.840	
LL (ICLV model)			-4113.794	
AIC	4338.514		4355.680	
BIC	4356.788		4364.086	
	Estimate	t-test	Estimate	t-test
ASC _{No access}	1.200	0.96	-0.859	-1.70
ASC _{Limited access}	0.806	0.71	-0.778	-1.38
ASC _{Unlimited access}	-0.104	-0.13	0.160	0.40
Rush hour (time frame) _{No access}	-0.734	-3.74	-0.707	-3.70
Rush hour (time frame) _{Limited access}	-0.425	-2.91	-0.392	-2.73
Rush hour (number of trips) _{Limited access}	0.249	1.81	0.239	1.76
Area small (zone)	-0.819	-6.19	-0.801	-6.07
Area medium (region, canton)	-0.199	-2.78	-0.187	-2.66
Area medium (region, canton) + route (> 10 km)	0.056	0.82	0.039	0.55
Comfort level	-0.233	-2.86	-0.231	-2.90
Price	<-0.001	-7.79	<-0.001	-7.86
Sigma (EC panel data)	1.510	8.37	1.530	8.65
Professional social norms on working time flexibility _{No access}			0.282	1.53
Professional social norms on working time flexibility _{Limited access}			0.377	1.90
Professional social norms on working time flexibility _{Unlimited access}			0.254	2.14
Scale parameter, Lake Geneva region	0.951	5.78	0.912	5.81
Scale parameter, Swiss Plateau	1.410	7.10	1.450	7.10
Scale parameter, North-west Switzerland	1.180	6.50	1.140	6.83
Scale parameter, Eastern Switzerland	1.090	5.09	1.090	4.84
Scale parameter, Central Switzerland	1.340	6.72	1.300	6.61

Table 9 - Chapter 3 - Model estimates - commuters only (part 2 - demographic and segmentation variables)

Model	MNL 5						ICLV	
	No Access		Limited Access		Unlimited Access		Estimate	t-test
	Estimate	t-test	Estimate	t-test	Estimate	t-test		
Formal private restrictions _{No access}	-0.169	-0.49	-	-	-	-	0.094	0.28
Formal private restrictions _{Limited access}	-	-	-0.045	-0.13	-	-	0.022	0.06
Formal private restrictions _{Unlimited access}	-	-	-	-	0.431	1.84	0.462	1.78
Formal professional restrictions (*)	-0.839	-2.24	-0.230	-0.58	0.014	0.05	0.370	1.77
Adults (*)	-0.897	-2.21	-1.070	-2.39	-0.443	-1.71	0.255	0.60
Best agers (*)	-1.540	-2.81	-1.180	-2.25	-0.362	-1.08	0.106	0.25
Seniors (*)	-0.836	-0.61	-2.280	-1.67	-1.430	-1.38	-1.810	-1.98
Student (*)	-0.222	-0.40	-0.110	-0.22	0.126	0.43	0.898	2.26
Homemaker (*)	1.860	1.58	1.970	1.60	1.410	2.50	-0.203	-0.17
Pensioner / unemployed / other occupation (*)	0.893	1.10	0.891	1.03	0.428	0.68	0.736	1.86
50 – 80% of commuting trips during rush hour (*)	0.629	1.42	0.279	0.63	0.575	1.69	0.176	0.43
80 – 100% of commuting trips during rush hour (*)	-0.016	-0.04	-0.128	-0.34	0.276	1.08	0.252	1.04
Number of commuting days per week (*)	0.141	1.03	0.023	0.16	0.126	1.29	0.004	0.05

* Structural component estimates in ICLV

**Chapter 4: Informative vs. non-informative labels in discrete choice experiments
with stated preferences: a quantitative analysis of attribute importance**

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4.1. Abstract

In the last decades, discrete choice experiments (DCEs) have become a popular method to elicit preferences in several research fields such as health economics, marketing, and transportation. Based on the nature of preferences respondents express, DCEs could be divided into revealed preference (RP) and stated preference (SP) experiments. Moreover, these experiments can be classified as either unlabeled (i.e., generic, and non-informative labels) or labeled (i.e., specific, and informative labels) based on the type of titles attached to the alternatives used. Both labeled and unlabeled experiments have advantages and disadvantages but, more than others, respondents who face meaningful titles in labeled DCEs inferring information about missing (omitted) attributes leads to biased estimations. In this research, we take an innovative perspective and examine whether an experiment with specific alternatives (from the labeled experiment) having generic and non-informative labels (from the unlabeled experiment) and an attribute representing the original meaningful labels could reduce labels' impact on the choice process (compared to a classic labeled experiment). A sample of 401 participants has been collected via the online platform Amazon MTurk and their preferences about fictional smartphones were collected through a stated preference (SP) experiment. Analyzing respondents' choices in a choice-based conjoint (CBC) analysis framework with Hierarchical Bayes (HB) estimation, we investigate how the choice task layout influences attributes' importance during the choice process. Results indicate that respondents facing choice tasks with our novel layout (i.e., generic labels and the attribute with the original labels) associated significantly lower importance to the attribute representing the labels compared to choice tasks with specific and informative labels usually adopted in labeled choice experiments. In summary, this work demonstrated how choice task layout manipulation influences respondents' perception of the attribute used as a label and how its importance decreases when the attribute has been placed among the other attributes in the choice matrix. Furthermore, this work highlights how careful researchers have to be in choosing attributes, attributes' levels, and labels when they create choice experiments because their "choice" can indirectly influence respondents' choice process.

Keywords: choice-based conjoint; hierarchical bayes estimation; choice task layout

4.2. Introduction

In the recent past, the study of preferences acquired great relevance for the analysis of the decision-making process in supporting the intention to provide services and products closer to consumers' needs. Among the techniques used to elicit preferences, discrete choice experiments (DCEs) have become a popular method in several fields such as health economics (Bansback, et al., 2012; Viney, et al., 2005), marketing (Dellaert, et al., 2012), transportation (Devarasetty, et al., 2012; Patil, et al., 2011; Saleh & Farrell, 2005), medicine (Kruijshaar, et al., 2009) and environmental research (Campbell, 2007; Fimereli & Mourato, 2013). DCEs are part of the attribute-based survey methods for evaluating benefits (utility) (Ryan, et al., 2007). In these experiments, respondents (decision makers) face several tasks in which they have to indicate, each time, the preferred alternative among several alternatives that change along characteristics and/or attributes of interest (Ryan, et al., 2007). A decision maker could be any decision-making unit such as a person, a household, or a firm whereas alternatives could be competing products, health care treatments, or any other items over which choices could be made (Train, 2009). DCEs consider that decision makers' preferences can be unveiled through the study of their choices (Bliemer & Rose, 2009; Hensher, et al., 2005; Louviere, et al., 2000; Ryan, et al., 2007).

In the choice experiment literature, there are two types of DCEs based on the type of expressed preferences: revealed-preference (RP) and stated-preference (SP) experiments (Train, 2009). RP experiments collect data about the decision-maker's actual preferences regarding already existing alternatives in real-world circumstances. Their name is given by the fact that respondents reveal their preferences through the decisions they took in the real world. Conversely, SP experiments are used to gather data in experimental situations adopting surveys where respondents express (state) their preferences in hypothetical scenarios (Train, 2009). Data collected with RP experiments have the advantage to reflect choices related to existing products whereas SP data allow the estimation of choice models for products that have never been offered before or for new attributes of existing products. Both types of data present advantages and limitations.

Creating experiments that integrate both types of data (RP and SP) could reduce these limitations bringing the advantages of these two types of experiments (Train, 2009).

In addition to the type of preference expressed, DCEs can be classified into labeled (i.e., with informative labels) and unlabeled (i.e., with generic and non-informative labels) based on the titles attached to the alternatives used in the choice tasks (Louviere, et al., 2000). In labeled experiments, labels express meaningful information about the alternatives beyond their possible order (i.e., bus, train, and car) while labels adopted in unlabeled experiments provide only information about the order of the alternatives (i.e., alternative 1, alternative 2, etc.). Both labeled and unlabeled experiments have advantages and disadvantages. Adopting informative labels, labeled experiments better approximate actual choice situations reinforcing the predictive validity of DCEs (Blamey, et al., 2000) and they can additionally take into account any respondents' prior beliefs about alternatives including alternative-specific constants (ASCs) in the estimation function (Blamey, et al., 2000; Rolfe, et al., 2000). Differently, unlabeled experiments are considered more appropriate if the research focuses on the trade-offs among attributes and attributes' levels of products, procedures, or policies (de Bekker-Grob, et al., 2010). Focusing on the disadvantages, informative labels used in the labeled experiment may lower respondents' attention to the attributes (i.e., attribute non-attendance) (Alemu, et al., 2013; Hensher, et al., 2012; Scarpa, et al., 2013) and induce them to make their choices based on labels only (Bennett & Blamey, 2001). Moreover, these labels could arouse emotions that are not directly linked to specific characteristics of the alternatives (Blamey, et al., 2000).

Given the disadvantages of these two techniques, in this research, we take a different approach trying to combine them and profiting from their advantages. Specifically, we develop a choice experiment where alternatives have been created as labeled and examine whether a different choice task layout in the presentation phase (e.g., moving labels among other attributes) could influence labels' effect in the choice process.

Different from previous research focused on the effect that choice task layout has on the willingness-to-pay (WTP) estimates (Fimereli & Mourato, 2013; Jin, et al., 2017) or on the effect that learned reading patterns have on the elicited preferences (Sandorf, et

al., 2018), this research operationally expands existing literature focusing on the attributes' importance estimated using a choice-based conjoint (CBC) analysis with Hierarchical Bayes (HB) estimation (Allenby, et al., 2005; Johnson, 2000; Lenk, et al., 1996; Orme, 2000; Sawtooth Software, 2009).

4.3. Data

4.3.1. Survey design

In order to test the possible effect of different choice task layouts, we implemented an online survey about a possible purchase of a brand-new Android smartphone recruiting respondents using the Amazon MTurk platform. The survey has been divided into three sections and structured as follows. In the first section, respondents face a set of questions related to smartphone ownership and the prevalent uses of that device. In the second part, they deal with the choice experiment. Finally, they have to complete a section related to their demographic characteristics.

Before the choice experiment, we introduce the concepts of a smartphone (i.e., “a portable device that combines mobile telephone and computing functions into one unit”) (Wikipedia) and Android (i.e., “a [free and open-source] mobile operating system [...] designed primarily for touchscreen mobile devices”) (Wikipedia) in order to give respondents the ability to evaluate the alternatives presented in the choice tasks. We invite respondents to assume that they are about to buy a brand-new smartphone online and that, in the following nine pages, they would deal with nine different purchase cases (i.e., choice tasks) in which the website would present them with different combinations of smartphones to choose from. Moreover, we inform them that there are four alternatives in each choice situation: specifically, they could either select one of the three proposed smartphones or leave the page without choosing any of them by clicking “None”. The choice task layout that respondents face has been randomly assigned when they start the survey: respondents in the first group face choice tasks with informative labels whereas respondents in the second group deal with choice tasks where labels have been treated as levels of an attribute. Additional details of the choice experiment are presented in the next

section. Two exemplary choice tasks, one per choice task layout, are shown in Figure 9 and Figure 10.

Figure 9 - Chapter 4 - Labeled choice task

If these were the smartphones offered to you, would you buy any of those and if yes which one?

Choose by clicking one of the buttons below:

	LG	Huawei	Samsung	None
Processor (GHz)	1.5 GHz	2 GHz	2.5 GHz	I would not choose any of these.
Rear Camera (MP)	12 MP	5 MP	20 MP	
Internal Memory (GB)	16 GB	8 GB	32 GB	
Display Dimension (")	3.5"	6.9"	5.2"	
Price (USD)	USD 400.-	USD 600.-	USD 200.-	

Figure 10 - Chapter 4 - Unlabeled choice task

If these were the smartphones offered to you, would you buy any of those and if yes which one?

Choose by clicking one of the buttons below:

	Smartphone Nr 1	Smartphone Nr 2	Smartphone Nr 3	None
Brand	Samsung	LG	Huawei	I would not choose any of these.
Processor (GHz)	2.5 GHz	2.0 GHz	2.0 GHz	
Rear Camera (MP)	12 MP	5 MP	20 MP	
Internal Memory (GB)	32 GB	16 GB	16 GB	
Display Dimension (")	3.5"	5.2"	6.9"	
Price (USD)	USD 400.-	USD 600.-	USD 200.-	

4.3.2. Choice Design

To reduce the complexity of the experiment and avoid possible effects related to unobservable variables (e.g., brand loyalty) (Pinson & Brosdahl, 2014), we focus our experiment on Android smartphones and do not consider iOS smartphones. Operationally, we develop an EC-panel D-efficient (D error = 0.331487) stated preferences choice design with nine choice tasks using ChoiceMetrics Ngene 1.2.1 software (ChoiceMetrics, 2018).

Additional information about D-efficient choice design can be found in Kuhfeld, Tobias, and Garratt (1994), Bliemer and Rose (2009), and Rose and Bliemer (2009).

Subsequently, we formulate an additional version of this design manipulating the choice tasks' layout to have two different versions (in the presentation phase) of the same choice experiment: a labeled version (Figure 9) where brand names are presented as alternatives' labels and an unlabeled version (Figure 10) where brand names are presented as levels of the attribute "brand". In order to compare the two versions of the choice experiment, each individual randomly faces one of them only using the split sample approach (de Bekker-Grob, et al., 2010). Moreover, the order – but not the content – of choice tasks, attributes, and alternatives are completely randomized via an HTML/JavaScript manipulation to avoid possible order effects (Carlsson, Mørkbak, & Olsen, 2012; Chrzan, 1994). By observing the characteristics of the smartphones on the market at the time of the data collection (March 2018), we define the main alternatives' attributes and their levels covering a wide range of products.

Specifically, each alternative has six attributes: "brand", "display dimension", "internal memory", "rear camera", "processor", and "price". The "brand" attribute identifies the business organization that produces that smartphone and it has three levels: "Samsung", "LG" and "Huawei". We have chosen these three brands as they were the manufacturers with the highest sales volumes in the U.S. (Counterpoint Team, 2021; Musil, 2018). The "display dimension" attribute represents the display size of the smartphone. It has three levels: "3.5\"", "5.2\"", "6.9\"" and they respectively represent small-, medium- and big-size display. The "internal memory" attribute defines the capacity of the internal memory (ROM) and it has had three levels: "8 GB", "16 GB" and "32 GB". The "rear camera" attribute indicates the number of pixels in an image captured by the rear camera (the higher the number of pixels captured, the better the image quality will be) and it has three levels "5 MP", "12 MP" and "20 MP". The "processor" attribute identifies the clock speed of the main processor (the greater the speed, the greater the capacity to process tasks in a short time will be) and it had three levels "1.5 GHz", "2.0 GHz" and "2.5 GHz". The "price" attribute defines the monetary expense that individual

has to bear to purchase a specific smartphone and it has three levels “USD 200.-”, “USD 400.-” and “USD 600.-”.

Each choice task has four alternatives: the first three alternatives represent hypothetical smartphones they can find online whereas the fourth alternative indicated the none option (in case they would not choose any of them). In Table 10, attributes and attributes' levels have been summarized.

Table 10 - Chapter 4 - Attributes and attributes' levels

Attribute	# of levels	Description
Brand	3	Samsung; LG; Huawei
Display Dimension (")	3	3.5"; 5.2"; 6.9"
Internal Memory (GB)	3	8 GB; 16 GB; 32 GB
Rear Camera (MP)	3	5 MP; 12 MP; 20 MP
Processor (GHz)	3	1.5 GHz; 2.0 GHz; 2.5 GHz
Price	3	USD 200.-; USD 400.-; USD 600.-

4.4. Model Specification

Discrete choice experiments (DCEs) are a specific type of choice-based conjoint (CBC) experiments: specifically, they could be evaluated as choice-based conjoint surveys analyzed by adopting discrete choice methods (Ben-Akiva, et al., 2019). With the introduction of discrete choice approaches into the traditional conjoint analysis (Hensher & Louviere, 1983; Louviere & Woodworth, 1983; McFadden, 1986), choice-based conjoint (CBC) experiments became widely accepted and adopted in market research due to their capability to estimate the demand for consumer products (Cameron & DeShazo, 2013; Goett, McFadden, & Woo, 1988; Green, Krieger, & Wind, 2001; McFadden, 2014a, 2014b, 2017). Compared to other types of conjoint analysis (rating and raking), choice-based conjoint analysis is closer to real shopping, where respondents have to deal with several products with different characteristics, than rating or raking products (Natter & Feurstein, 2002). In these experiments, respondents select their preferred alternatives

(profiles) among groups of experimentally controlled sets of profiles (conjoint approach) and their choices are modeled using a multinomial logit as a function of the variables introduced in the experimental design (discrete choice approach) (Chrzan & Orme, 2000). Based on the respondents' choices, researchers can infer the relative importance of attributes and levels analyzing how respondents trade off among different alternatives. The utility of each alternative could be decomposed into the utilities of attributes and attributes' levels. Moreover, based on the ranges of attributes' levels and their utilities, relative importance values can be determined (Wellman & Vidican, 2008).

Due to the limited amount of information provided by CBC data compared to rating-based conjoint data, researchers were used to estimating CBC models at the aggregate respondent level only (Hein, Kurz, & Steiner, 2020). To improve the feasibility of these models, researchers introduced Hierarchical Bayes (HB) estimation procedures to estimate the heterogeneity of respondents at the individual level using CBC data (Allenby, Arora, & Ginter, 1995; Allenby & Ginter, 1995; Lenk, et al., 1996). This estimation method adopts an iterative process to approximate alternatives' and attributes' utilities for each subject based on their choices (Wellman & Vidican, 2008). Specifically, HB models are so-called "hierarchical" due to their two-level estimation process. At the higher level, respondents' utilities are distributed as a multivariate normal distribution (23):

$$\beta_i \sim N(\alpha, D) \quad (23)$$

where β_i represents a vector of utilities for the i -th respondent, α is a vector containing the means of utilities for the i -th respondent and D is a variance-covariance matrix of the utilities over respondents. At the lower level, the probabilities that i -th respondent chooses specific alternatives are distributed as multivariate logit models (Steenhard & Chou, 2004).

Adopting a user-written R (R Core Team, 2016) script, we integrate respondents' choices into the choice design and then create the CBC matrix in order to estimate the attributes' levels importance scores using the `rhierMnlRwMixture` function of the R package `bayesm` (Rossi, 2015). Per each group, we utilize a total of 600'000 MCMC iterations (Rossi, Allenby, & McCulloch, 2012) with a 30% burn-in phase to ensure the convergence of the Markov chain to the posterior distribution (Hein, et al., 2020).

Moreover, we retain draws only every 10-th draw for estimating individual-level parameters to reduce the possible correlation among adjacent draws.

4.5. Results and Discussion

4.5.1. Sample Description

The sample consists of 401 U.S. respondents recruited in March 2018 through the Amazon MTurk platform. Given the panel structure of the experiment where each respondent faces nine choice tasks, the total number of observations is 3'609. More than fifty-four percent (54.61%) of the sample are females and more than seventy-five percent (75.31%) are adults from 26 to 49 years old. Almost eighty percent (79.55%) are employed and, for more than half of the sample (59.35%), the monthly gross income is below 4'000 USD. Almost the entire sample (99.25%) declares to have at least one smartphone and the main operating system of their smartphone is Android (98.24%). Concerning their smartphone usage habits, they mostly declare to use it for listening to music (81.65%), shopping online (66.83%), taking pictures (56.78%), and playing games (54.27%).

Adopting the split sample approach (de Bekker-Grob, et al., 2010), two hundred and six (51.37%) respondents face the choice experiment with informative labels (Figure 9) where brand names are the alternatives' labels (Group 1) whereas one hundred ninety-five (48.63%) respondents deal with uninformative labels (Figure 10) where brand names are presented as levels of the attribute "brand" (Group 2).

4.5.2. Model Estimation

Using the parameters' estimation calculated by adopting a multinomial logit model, we can derive the relative importance scores associated with each of the six attributes. Moreover, these importance scores have been estimated for each attribute level using individual-level utilities and relying on the Hierarchical Bayes (HB) method (Lenk, et al., 1996). In doing so, we avoid any artificial bias introduced using importance scores calculated by adopting utilities at the aggregate level (Sawtooth Software, 2009; Wellman & Vidican, 2008; Zimmermann, et al., 2013) and exclude, by replicating the estimation

process by group, that preferences of a specific group affect utilities of the other one (Orme, 2019).

Given the type of data collected and the structure of the choice experiment, parameters have been effect-coded: the utilities of the levels of an attribute sum to zero within the attribute. In other words, negative utility associated with a level of the attribute decreases the total utility of the attribute whereas positive utility increases it. The total utility associated with an alternative is the sum of the utilities of its attributes with specific levels.

In Table 11 and Table 12, utility estimates have been summarized. Utilities shown in these tables provide relative information about the value of different levels for a specific attribute. As expected, respondents of both groups prefer a smartphone with the widest display, the biggest internal memory, the best rear camera, the fastest processor, and the lowest price. Concerning the brands, both groups prefer, in order of perceived utility, Samsung, LG, and Huawei.

In Table 13, t-test comparisons among the utility estimates of the attributes' levels have been provided. Respondents of group 2 (compared to group 1) associate a significantly lower utility with the Samsung brand whereas they associate a significantly higher utility (albeit negative) with the Huawei brand. No difference in utilities has been associated with the LG brand. The same analysis have been done on the remaining attributes and attributes' levels.

Based on the utility estimates calculated with the HB method, we calculate the importance scores (S) for each attribute (A) using the following formula (24):

$$S = \left(\frac{Range A_i}{\sum_{i=1}^n Range A_i} \right) \times 100 \quad (24)$$

where A_i identifies the i -th attribute; $Range A_i$ represents the difference between the higher utility value and the lower utility value associated with the levels of the i -th attribute; n is the number of attributes (Rosko, DeVita, McKenna, & Walker, 1985).

In Table 14 and Table 15, attribute importance scores (in percentage) have been described for both groups. Respondents of both groups associate the greatest importance to the brand attribute ($S_{brand;group_1} = 25.725$, $S_{brand;group_2} = 19.952$) and the lowest to

processor attribute ($S_{\text{processor;group}_1} = 10.119$, $S_{\text{processor;group}_2} = 11.990$). Other attributes have similar importance scores among the two groups. In order to unveil significant differences among attribute importance scores of the two groups, a series of non-parametric Mann-Whitney U (Bauer, 1972; Hollander, Wolfe, & Chicken, 2013) tests have been used (Table 16). Test results highlight that the importance scores of the brand ($W_{\text{brand}} = 24'925$; $p < 0.001$) and the processor ($W_{\text{processor}} = 14'455$; $p < 0.001$) attributes are significantly different in the two groups even though the greatest variation (in percentage) is associated with the brand attribute.

4.6. Conclusion

This research investigates the impact that informative labels associated with specific alternatives (compared to generic and non-informative labels) have on the respondents' evaluation in a discrete choice experiment. They must express their preference for a new smartphone based on its characteristics: brand, display dimension, internal memory, rear camera, processor, and price. To evaluate if their choices are influenced by the choice task layout (attributes' arrangement in the choice task), we create two versions of the same choice experiment (informative labels vs. non-informative labels) and adopt a choice-based conjoint (CBC) analysis with Hierarchical Bayes (HB) estimation method to evaluate importance difference scores they associate to alternatives' attributes. Results point out that respondents facing choice tasks with non-informative labels and an attribute representing the original meaningful labels impute a significantly lower importance to this attribute compared to respondents dealing with choice tasks with informative labels (used in labeled choice experiments).

Demonstrating how choice task layout and specifically the informativeness of alternatives' labels have an impact on attribute importance and consequently on the choice process, this paper emphasizes how sensitive the choice design process is. Choosing informative (or non-informative) labels could potentially and indirectly influence respondents' evaluations regardless of the researcher's preliminary intentions and this implies that the researcher must pay particular attention to the definition of attributes, attributes' levels, and labels during the choice design phase.

Nonetheless, this paper has some remaining limitations that can be solved with future research. Firstly, the fast-growing market of smartphones and their technological development can undermine the freshness of an experiment and the characteristics of the proposed fictional alternatives may be obsolete. Despite this limitation, the proposed approach can be replicated/extended with various products/services. In the second place, the sample consists of U.S. respondents only and it cannot be treated as a representative sample of the population of people interested in this specific product (i.e., Android smartphone). Replicating the experiment with respondents having different socio-demographic characteristics could provide additional information to validate the results and contribute to additional findings. Finally, it could be interesting to triangulate results coming from this type of experiment with innovative technologies, such as eye-tracking (Balcombe, Fraser, Williams, & McSorley, 2017; Brazil, Caulfield, & Bhat, 2017; Farooq, Cherchi, & Sobhani, 2018; Krucien, Ryan, & Hermens, 2017; Meißner & Decker, 2010; Uggeldahl, Jacobsen, Lundhede, & Olsen, 2016), that allow researchers to measure the time an individual spends focusing on a certain portion of the screen (in this case, the portion in which alternatives' labels are presented). The integration of these tools with this type of experiment would be beneficial for a better interpretation of the heuristics (e.g., attribute non-attendance) adopted by respondents in their choice process.

4.7. Appendix

Table 11 - Chapter 4 - Utility estimates from HB procedure - Group 1 (n = 206)

Attribute	HB utility		
	Estimate	Std err	t-test
Brand *			
Samsung	1.535	0.128	11.96
LG	0.004	0.142	0.03
Huawei	-1.396	0.119	-11.78
Display Dimension (")			
3.5"	-1.219	0.070	-17.45
5.2"	0.350	0.058	6.00
6.9"	0.868	0.071	12.31
Internal Memory (GB)			
8 GB	-1.121	0.046	-24.11
16 GB	-0.077	0.042	-1.85
32 GB	1.198	0.055	21.93
Rear Camera (MP)			
5 MP	-1.092	0.056	-19.33
12 MP	0.410	0.037	11.17
20 MP	0.681	0.067	10.24
Processor (GHz)			
1.5 GHz	-0.549	0.044	-12.40
2.0 GHz	0.325	0.037	8.77
2.5 GHz	0.225	0.055	4.12
Price			
USD 200.-	1.099	0.111	9.90
USD 400.-	-0.203	0.051	-3.96
USD 600.-	-0.869	0.091	-9.87

* Sum of HB utilities differs from 0 due the effect of the none alternative.

Table 12 - Chapter 4 - Utility estimates from HB procedure - Group 2 (n = 195)

Attribute	HB utility		
	Estimate	Std err	t-test
Brand *			
Samsung	0.861	0.109	7.91
LG	-0.128	0.092	-1.39
Huawei	-0.955	0.095	-10.00
Display Dimension (")			
3.5"	-1.167	0.066	-17.70
5.2"	0.379	0.056	6.72
6.9"	0.788	0.082	9.56
Internal Memory (GB)			
8 GB	-1.093	0.066	-16.67
16 GB	0.031	0.036	0.84
32 GB	1.062	0.058	18.46
Rear Camera (MP)			
5 MP	-0.851	0.065	-13.15
12 MP	0.321	0.041	7.77
20 MP	0.530	0.082	6.50
Processor (GHz)			
1.5 GHz	-0.709	0.053	-13.41
2.0 GHz	0.152	0.039	3.86
2.5 GHz	0.557	0.043	13.10
Price			
USD 200.-	0.705	0.110	6.40
USD 400.-	0.114	0.040	2.85
USD 600.-	-0.819	0.094	-8.70

* Sum of HB utilities differs from 0 due the effect of the none alternative.

Table 13 - Chapter 4 - T-test comparisons of utility estimates - Group 1 & 2

Attribute	Group 1		Group 2		Comparison
	Estimate	Std err	Estimate	Std err	t-test
Brand					
Samsung	1.535	0.128	0.861	0.109	4.01
LG	0.004	0.142	-0.128	0.092	0.78
Huawei	-1.396	0.119	-0.955	0.095	-2.90
Display Dimension (")					
3.5"	-1.219	0.070	-1.167	0.066	-0.54
5.2"	0.350	0.058	0.379	0.056	-0.35
6.9"	0.868	0.071	0.788	0.082	0.74
Internal Memory (GB)					
8 GB	-1.121	0.046	-1.093	0.066	-0.35
16 GB	-0.077	0.042	0.031	0.036	-1.95
32 GB	1.198	0.055	1.062	0.058	1.72
Rear Camera (MP)					
5 MP	-1.092	0.056	-0.851	0.065	-2.80
12 MP	0.410	0.037	0.321	0.041	1.61
20 MP	0.681	0.067	0.530	0.082	1.44
Processor (GHz)					
1.5 GHz	-0.549	0.044	-0.709	0.053	2.32
2.0 GHz	0.325	0.037	0.152	0.039	3.19
2.5 GHz	0.225	0.055	0.557	0.043	-4.80
Price					
USD 200.-	1.099	0.111	0.705	0.110	2.52
USD 400.-	-0.203	0.051	0.114	0.040	-4.88
USD 600.-	-0.869	0.091	-0.819	0.094	-0.59

Table 14 - Chapter 4 - Attribute importance scores - Group 1 (n = 206)

Attribute	Importance score		
	Estimate	Std err	t-test
Brand	25.725	1.106	23.25
Display Dimension (")	16.371	0.628	26.07
Internal Memory (GB)	15.700	0.510	30.77
Rear Camera (MP)	14.269	0.450	31.69
Processor (GHz)	10.119	0.606	16.69
Price	17.816	0.755	23.60

Table 15 - Chapter 4 - Attribute importance scores - Group 2 (n = 195)

Attribute	Importance score		
	Estimate	Std err	t-test
Brand	19.952	0.986	20.23
Display Dimension (")	18.573	0.820	22.66
Internal Memory (GB)	16.624	0.611	27.19
Rear Camera (MP)	15.472	0.533	29.01
Processor (GHz)	11.990	0.416	28.81
Price	17.389	0.775	22.44

Table 16 - Chapter 4 - Wilcoxon-Mann-Whitney tests of attribute importance scores - Group 1 & 2

Attribute	Group 1		Group 2		Comparison	
	Estimate	Std err	Estimate	Std err	W	p-value
Brand	25.725	1.106	19.952	0.986	24'925	<0.001
Display Dimension (")	16.371	0.628	18.573	0.820	18'448	0.158
Internal Memory (GB)	15.700	0.510	16.624	0.611	18'911	0.312
Rear Camera (MP)	14.269	0.450	15.472	0.533	18'516	0.176
Processor (GHz)	10.119	0.606	11.990	0.416	14'455	<0.001
Price	17.816	0.755	17.389	0.775	20'607	0.653

Chapter 5: Conclusion

This dissertation, consisting of three articles, examined how intangible characteristics influence consumers' choices and how alternatives' representation affects choice processes.

Chapter 2 deals with analyzing the behavior of travelers when they are faced with the choice of having to take out a new railway subscription in Switzerland. In the case in question, respondents can choose their subscription based on the type of access to the train sections they prefer: access to the common sections only or access to the common and dedicated sections. These areas differ in the heterogeneity of the people who frequent them and the services dedicated to them. The choices they make may be influenced both by directly observable factors such as the characteristics of the subscription (e.g., price and geographic validity) and the travelers' socio-demographic information and by factors that are not directly observable. In order to verify whether these latter factors have an impact on the choices, we have adopted a hybrid choice modelling approach by including a latent variable (i.e., a factor that cannot be directly observed) called out-group derogation. Adopting a specific 12-item Likert scale, this variable measures the propensity of individuals to distance themselves from others who have characteristics different from theirs (Dasgupta, 2004; Hogg & Hains, 1996; Turner, et al., 1987; Turner, et al., 2016; Vanhoomissen & Van Overwalle, 2010). Results of models that refer only to the subscriptions' characteristics indicate that individuals prefer to have access to larger geographical areas and during the so-called rush hour intervals. Furthermore, respondents do not ascribe a significant additional value to subscriptions that give them access to the business and lifestyle dedicated sections (compared to the family dedicated section) whereas they indicate a significant preference for access to the silence dedicated section. In the models in which the demographics and segmentation variables are included, results indicate that younger individuals associate higher utility values with subscriptions that give them access to the dedicated sections while the so-called commuters prefer subscriptions with access to the common section only (compared to common section + dedicated section access). In conclusion, the ICLV model that integrates the out-group derogation variable indicates that travelers with a higher tendency towards out-group derogation (i.e., highly educated young people) prefer subscriptions that allow them to

access common and dedicated sections compared to alternatives that limit their access to a common section only.

Chapter 3 deals with exploring which characteristics can influence travelers in choosing railway travel cards that reduce their mobility during rush hours intervals (Ben-Elia & Ettema, 2011; Currie, 2010; Evans & Wener, 2007; Hale & Charles, 2009; Hirsch & Thompson, 2011; Kim, et al., 2014; Meissonnier & Richer, 2021; Tirachini, 2013; Zhang, et al., 2008). Specifically, each respondent expresses their preference for a subscription based on the degree of access to rush hours intervals: no access, limited access, or unlimited access to these intervals. The choices made by the respondents may be the result of the influence of both directly observable information such as subscriptions' (e.g., type of access to rush hours intervals and time extension of these intervals) and travelers' (e.g., status employment, education, marital status) characteristics and not directly observable factors. In order to study the effect of these factors, we have used a hybrid choice modelling approach and introduced a latent variable representing the social norms that could be present in the place of work/study and have an effect on their time flexibility. Using a specific-designed 6-item Likert scale, extending previous research carried out in other fields (Dambrun, et al., 2002; Harris, 2008; Spangenberg, et al., 2018), this variable assesses the effect of the social norms perceived in the aforementioned context. The results indicate that individuals have a strong preference for subscriptions that do not limit their time flexibility: subscriptions with unlimited access to the rush hour intervals are the favorite followed by subscriptions with some sort of limitation and finally subscriptions with no access during these intervals. Regarding the width of the rush hour intervals, individuals express a clear reduction in the utility for those subscriptions that require the shifting of their trips outside the wide rush hours. Also, for those subscriptions with a limited number of trips during rush hour intervals, respondents indicated a significant preference for those with a higher number of them. In the models in which the demographic and segmentation variables are included, results show that younger individuals associate an almost indistinct preference to the proposed alternatives (both with full access to rush hour intervals and no access to them) whereas commuters indicated a strong preference for alternatives with unrestricted access to the rush hour intervals. The

first result indicates a greater propensity to accept flexible solutions by younger users (compared to older ones) while the second result is linked to lower flexibility of this category of users compared to non-commuters. Conducting a detailed analysis of the subsample of commuters, the models' estimates are somewhat aligned with those provided by the analysis conducted on the entire sample. In fact, commuters do not ascribe substantially dissimilar utility values to the three defined rush hour access modes. Social norms (professional and private) prove to have a direct and indirect influence on the preferences of these respondents. Specifically, the ICLV model indicates that users, whom most perceive the effect of social norms on working/studying time flexibility, associate greater utility with subscriptions that give them the possibility to somehow commute during rush hour intervals.

Finally, Chapter 4 deals with analyzing the impact that the representation of the choice matrix (choice matrix layout) of a discrete choice experiment has on the respondents' decision-making process. Specifically, this research investigates the effect of adopting informative labels (typical of labeled choice experiments) associated with specific alternatives compared to generic and non-informative labels (used in unlabeled choice experiments) (Bennett & Blamey, 2001; Bliemer & Rose, 2009; de Bekker-Grob, et al., 2010; Louviere, et al., 2000; Rolfe, et al., 2000; Rose & Bliemer, 2009). Each respondent expresses their preference for a new smartphone based on certain characteristics such as brand, display size, internal memory, rear camera, processor, and price. Individuals' choices can be influenced by how the alternatives' attributes are presented within the choice task and specifically by how much one attribute (in this research, the brand) is highlighted compared to the others (Alemu, et al., 2013; Blamey, et al., 2000; de Bekker-Grob, et al., 2010; Hensher, et al., 2012; Scarpa, et al., 2013). In order to study the effect of the attributes' disposition within the choice task (choice task layout) on the individuals' perception of alternatives, we have provided two versions of the same choice experiment to the respondents varying the type of the alternatives' labels: informative and specific labels vs. non-informative and generic labels (with the adoption of an attribute containing the information of the specific label). The data from this experiment have been analyzed using a choice-based conjoint (CBC) analysis with the

Hierarchical Bayes (HB) estimation method to estimate the difference in importance scores that individuals associate with the attributes of the alternatives (Allenby, et al., 2005; Johnson, 2000; Lenk, et al., 1996; Orme, 2000, 2019; Sawtooth Software, 2009; Wellman & Vidican, 2008; Zimmermann, et al., 2013). The results indicate that individuals who have seen the choice task layout with the non-informative and generic labels (adopted in the unlabeled choice experiments) associate less importance with the attribute in question than those who have seen the choice task layout with the informative and specific labels (used in labeled choice experiments).

5.1. Theoretical implications

The findings of this dissertation expand the existing literature concerning the study of individuals' choice behavior by introducing new factors that influence their choices. In this thesis, the factors can be identified both in latent variables (suitably introduced through ICLV models) and in specific representations of the choice tasks that users face during the experiments. In addition to the general contribution to the literature on choice behavior, each of these chapters distinctively contributes to different segments of literature.

The results of Chapter 2 extend the literature on railway traveler behavior (Löfgren, 2008) by demonstrating that the social mixing that occurs on the train has an impact on individuals' travelling choices. In particular, these results suggest that the process of choosing a railway subscription can be influenced by subscription characteristics but above all by individual attitudes such as the out-group derogation (Dasgupta, 2004).

In Chapter 3, this thesis expands the literature on commuting time choice (Chang & Mahmassani, 1988; Jou, et al., 2008; Senbil & Kitamura, 2004, 2005) and rush hour avoidance (Ben-Elia & Ettema, 2011; Meissonnier & Richer, 2021; Munch, 2014). Specifically, it demonstrates that travelers cannot freely adjust their behavior according to the price patterns of the railway subscriptions since they are strongly influenced by not directly observable social norms (Cialdini, 2007; Cialdini & Trost, 1998; Eisenberg,

Neumark-Sztainer, Story, & Perry, 2005; Hammer, Saksvik, Nytro, Torvatn, & Bayazit, 2004; Riggs, 2017; Zhang, et al., 2015) present in their work/study environment.

Finally, Chapter 4 mainly contributes to the choice design literature (Bliemer & Rose, 2009; Huber & Zwerina, 1996; Rose & Bliemer, 2009) combining labeled and unlabeled choice experiments profiting from their advantages (Blamey, et al., 2000; de Bekker-Grob, et al., 2010; Jin, et al., 2017; Kruijshaar, et al., 2009). Results indicate that individuals dealing with choice designs with non-informative labels (unlabeled choice design) and an attribute characterizing the original meaningful labels associate significantly lower importance with this attribute than to the labeled choice designs.

5.2. Managerial implications

In the everyday decision-making processes, individuals are strongly influenced by both external factors such as their surroundings, and internal factors such as their attitudes and perceptions. Among the external factors, firms play a particularly significant role since with their decisions they can induce consumers' choices. The findings of this dissertation give support to companies that have to make these decisions.

Chapter 2 emphasizes how important travelers' out-group derogation is in their decision-making process about new public transport subscriptions and how careful companies in this field must be when it comes to redefining the characteristics of future public transportation. It shows that, by moving from a division of the trains into two classes to a more detailed offer, the probability of purchasing a railway subscription increases for that part of consumers who do not pay attention exclusively to the subscription's intrinsic characteristics but also to the other travelers' characteristics present in that specific wagon.

Chapter 3 demonstrates the effect of social norms in workplaces on travelling behavior and relative choice processes. It implicitly recommends a paradigm shift in the work organization to companies encouraging flexible working solutions such as work-from-home and/or in different time intervals. By doing so, the effect of social norms that have an impact on the travelling behavior of their employees could potentially be reduced, and consequently, overcrowded trains during rush hours could decrease in the long run.

Finally, this dissertation proves that the informativeness of alternatives' labels in choice tasks can alter attributes' importance and consequently influence the choice process. In fact, Chapter 4 demonstrates how much attention researchers must pay during the choice design process: informative labels (compared to non-informative ones) could potentially and indirectly alter respondents' decisions and therefore they must be chosen with great caution to avoid biased results.

5.3. Limitations and future research

The main limitations of Chapter 2 are related to the structure of the sample and the definition of the developed choice design. The collected sample is mainly composed of respondents residing in the German part of Switzerland and cannot be treated as a representative sample of the entire Swiss population. Despite this limitation, the methodological framework adopted in this work can be efficiently reproduced with a representative sample of the reference population in future research. Concerning the definition of the adopted choice design, it includes attributes and relative levels that could not be a comprehensive description of the entire product assortment present in this specific market. Future research could also combine the structure of the alternatives proposed in this article (i.e., stated preference data) with products already present in the actual market (i.e., revealed preference data). By doing so, it could be possible to have a choice experiment that benefits from the advantages of the two types of data providing more realistic choice tasks to respondents and a better representation of the decision-making process adopted.

As for Chapter 2, Chapter 3 is also affected by two main limitations: the sample composition and the restricted number of examined limited-access alternatives to rush hour. The socio-demographic characteristics of the respondents well represent the Swiss German subpopulation therefore the results of this work cannot be extended to the entire Swiss population. Future research could extend the sample by including the other Swiss subpopulations in the data collection. Concerning the second limitation, the complexity of the developed model and the need to limit the survey length reduced the investigation scenarios. Future research could extend the definition of limited-access alternatives in

terms of rush hour intervals and the number of allowed trips during these intervals. Moreover, as mentioned above for Chapter 2, future research could introduce existing subscriptions with proposed alternatives combining revealed preference with stated preference data to increase the model predictivity.

The main limitations of Chapter 4 are the peculiarities of the chosen product and the specificity of the adopted sample. The first limitation refers to the technological development of smartphones and how much the characteristics introduced within the experiment may be obsolete given the speed with which the related market grows and evolves. Future research may focus on other products with characteristics that do not vary so quickly and widely over time (e.g., choice of a new laptop for home working, choice of a new apartment, etc.). The second limitation is given by the adopted sample: specifically, the data were collected with U.S. respondents via an online platform therefore this sample cannot be considered representative of the reference population (i.e., respondents with different origins interested in purchasing a new Android smartphone). Therefore, further experiments that rely on samples with respondents having diverse socio-demographic peculiarities may be a successful approach to corroborate these results and enrich them with new findings. In conclusion, future research could evaluate the interaction of data collected with this type of experiment and with innovative technologies for a more valuable evaluation of the respondents' mental mechanisms (e.g., attribute non-attendance) used during the choice process. Specifically, it may be beneficial to evaluate individuals' choices by integrating the measure of time an individual devotes to a specific portion of text (i.e., alternatives' labels) by adopting eye-tracking technologies (Balcombe, et al., 2017; Brazil, et al., 2017; Farooq, et al., 2018; Krucien, et al., 2017; Meißner & Decker, 2010; Uggeldahl, et al., 2016).

References

- Abdelradi, F., & Abdu, K. (2015). Evaluation of consumers' lifestyles and willingness to pay for dates: A hybrid choice model approach. In: European Association of Agricultural Economists.
- Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action control* (pp. 11-39): Springer.
- Alemu, M. H., Mørkbak, M. R., Olsen, S. B., & Jensen, C. L. (2013). Attending to the reasons for attribute non-attendance in choice experiments. *Environmental and resource economics*, 54, 333-359.
- Allenby, G. M., Arora, N., & Ginter, J. L. (1995). Incorporating prior knowledge into the analysis of conjoint studies. *Journal of Marketing Research*, 32, 152-162.
- Allenby, G. M., & Ginter, J. L. (1995). Using extremes to design products and segment markets. *Journal of Marketing Research*, 32, 392-403.
- Allenby, G. M., Rossi, P. E., & McCulloch, R. E. (2005). Hierarchical bayes models: A practitioners guide. *Social Science Research Network, Rochester, NY*.
- Anderson, N. H. (1962). Application of an Additive Model to Impression Formation. *Science*, 138, 817-818.
- Andersson, L. M., & Pearson, C. M. (1999). Tit for tat? The spiraling effect of incivility in the workplace. *Academy of management review*, 24, 452-471.
- Arora, N., dit Sourd, R. C., Hanson, K., Woldesenbet, D., Seifu, A., & Quaife, M. (2022). Linking health worker motivation with their stated job preferences: A hybrid choice analysis in Ethiopia. *Social Science & Medicine*, 307, 115151.
- Babakus, E., Bienstock, C. C., & Van Scotter, J. R. (2004). Linking perceived quality and customer satisfaction to store traffic and revenue growth. *Decision Sciences*, 35, 713-737.
- Balcombe, K., Fraser, I., Williams, L., & McSorley, E. (2017). Examining the relationship between visual attention and stated preferences: A discrete choice experiment using eye-tracking. *Journal of Economic Behavior & Organization*, 144, 238-257.
- Bansback, N., Brazier, J., Tsuchiya, A., & Anis, A. (2012). Using a discrete choice experiment to estimate health state utility values. *Journal of health economics*, 31, 306-318.

- Bauer, D. F. (1972). Constructing confidence sets using rank statistics. *Journal of the American Statistical Association*, 67, 687-690.
- Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia—The early days of easing restrictions. *Transport Policy*, 99, 95-119.
- Ben-Akiva, M., & Boccara, B. (1995). Discrete choice models with latent choice sets. *International Journal of Research in Marketing*, 12, 9-24.
- Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., & Rao, V. (1994). Combining revealed and stated preferences data. *Marketing Letters*, 5, 335-349.
- Ben-Akiva, M., & Lerman, S. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9): MIT press.
- Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Börsch-Supan, A., Delquié, P., Larichev, O., & Morikawa, T. (1999). Extended framework for modeling choice behavior. *Marketing Letters*, 10, 187-203.
- Ben-Akiva, M., McFadden, D., & Train, K. (2019). *Foundations of stated preference elicitation: Consumer behavior and choice-based conjoint analysis*: Now.
- Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., & Bunch, D. S. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters*, 13, 163-175.
- Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., & Polydoropoulou, A. (2002). Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, 431-470.
- Ben-Elia, E., & Ettema, D. (2011). Rewarding rush-hour avoidance: A study of commuters' travel behavior. *Transportation Research Part A: Policy and Practice*, 45, 567-582.
- Bennett, J., & Blamey, R. (2001). *The choice modelling approach to environmental valuation*: Edward Elgar Publishing.
- Bierlaire, M. (2016). PythonBiogeme: a short introduction. In.
- Bierlaire, M., & Fretschler, M. (2009). Estimation of discrete choice models: extending BIOGEME. In *Swiss Transport Research Conference (STRC)*.

- Blamey, R. K., Bennett, J. W., Louviere, J. J., Morrison, M., & Rolfe, J. (2000). A test of policy labels in environmental choice modelling studies. *Ecological Economics*, 32, 269-286.
- Bliemer, M. C., & Rose, J. M. (2009). *Designing stated choice experiments: state of the art*. Emerald.
- Bloch, U. (2011). Wo es wirklich eng ist. In *Neue Züricher Zeitung*.
- Bolduc, D., & Alvarez-Daziano, R. (2010). On estimation of hybrid choice models. In *Choice Modelling: The State-of-the-Art and the State-of-Practice: Proceedings from the Inaugural International Choice Modelling Conference*. Emerald Group Publishing (pp. 259).
- Bollen, K. A. (2016). A New Incremental Fit Index for General Structural Equation Models. *Sociological Methods & Research*, 17, 303-316.
- Borriello, A., Scagnolari, S., & Rose, J. M. (2019). Reducing the randomness of latent variables using the evaluative space grid: Implementation in a hybrid choice model. *Transportation research part F: traffic psychology and behaviour*, 62, 192-211.
- Brazil, W., Caulfield, B., & Bhat, C. R. (2017). The potential role of eye tracking in stated preference survey design and piloting.
- Brewer, M. B. (1979). In-group bias in the minimal intergroup situation: A cognitive-motivational analysis. *Psychological bulletin*, 86, 307.
- Brewer, M. B., Manzi, J. M., & Shaw, J. S. (2016). In-Group Identification as a Function of Depersonalization, Distinctiveness, and Status. *Psychological Science*, 4, 88-92.
- Buckell, J., Hensher, D. A., & Hess, S. (2021). Kicking the habit is hard: A hybrid choice model investigation into the role of addiction in smoking behavior. *Health Economics*, 30, 3-19.
- Camerer, C. F., Loewenstein, G., & Rabin, M. (2004). *Advances in behavioral economics*: Princeton university press.
- Cameron, T. A., & DeShazo, J. (2013). Demand for health risk reductions. *Journal of Environmental Economics and Management*, 65, 87-109.
- Campbell, D. (2007). Willingness to pay for rural landscape improvements: Combining mixed logit and random-effects models. *Journal of agricultural economics*, 58, 467-483.

- Cantillo, V., Arellana, J., & Rolong, M. (2015). Modelling pedestrian crossing behaviour in urban roads: A latent variable approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32, 56-67.
- Carlsson, F., Mørkbak, M. R., & Olsen, S. B. (2012). The first time is the hardest: A test of ordering effects in choice experiments. *Journal of Choice Modelling*, 5, 19-37.
- Chang, G.-L., & Mahmassani, H. S. (1988). Travel time prediction and departure time adjustment behavior dynamics in a congested traffic system. *Transportation Research Part B: Methodological*, 22, 217-232.
- ChoiceMetrics. (2018). Ngene 1.2 User Manual & Reference Guide. In. Australia.
- Chorus, C. G., Molin, E. J., Van Wee, B., Arentze, T. A., & Timmermans, H. J. (2006). Responses to transit information among car-drivers: regret-based models and simulations. *Transportation Planning and Technology*, 29, 249-271.
- Chrzan, K. (1994). Three kinds of order effects in choice-based conjoint analysis. *Marketing Letters*, 5, 165-172.
- Chrzan, K., & Orme, B. (2000). An overview and comparison of design strategies for choice-based conjoint analysis. *Sawtooth software research paper series*, 98382, 360.
- Cialdini, R. B. (2007). Descriptive Social Norms as Underappreciated Sources of Social Control. *Psychometrika*, 72, 263-268.
- Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A Focus Theory of Normative Conduct: A Theoretical Refinement and Reevaluation of the Role of Norms in Human Behavior. *Advances in Experimental Social Psychology*, 24, 201-234.
- Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, 58, 1015-1026.
- Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity and compliance.
- Coleman, J. S., Coleman, J. S., & Farraro, T. J. (1992). Rational choice theory: Advocacy and critique.
- Counterpoint Team. (2021). US Smartphone Market Share: By Quarter. In (Vol. 2021).
- Currie, G. (2010). Quick and effective solution to rail overcrowding: free early bird ticket experience in Melbourne, Australia. *Transportation research record*, 2146, 35-42.

- Czellar, S. (2003). Consumer attitude toward brand extensions: an integrative model and research propositions. *International Journal of Research in Marketing*, 20, 97-115.
- Daly, A., Hess, S., Patruni, B., Potoglou, D., & Rohr, C. (2011). Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. *Transportation*, 39, 267-297.
- Dambrun, M., Guimond, S., & Duarte, S. (2002). The impact of hierarchy-enhancing vs. attenuating academic major on stereotyping: The mediating role of perceived social norm. *Current Research in Social Psychology*, 7, 114-136.
- Dannebald, T., Paulssen, M., Temme, D., & Walker, J. (2007). Hybrid choice models estimation using canned SEM software. In *Flexible marketing in an unpredictable world. Proceedings of the 36th EMAC conference*.
- Dasgupta, N. (2004). Implicit ingroup favoritism, outgroup favoritism, and their behavioral manifestations. *Social Justice Research*, 17, 143-169.
- Davis, J. M. (1984). Attraction to a Group as a Function of Attitude Similarity and Geographic Distance. *Social Behavior and Personality: an international journal*, 12, 1-5.
- de Bekker-Grob, E. W., Hol, L., Donkers, B., van Dam, L., Habbema, J. D., van Leerdam, M. E., Kuipers, E. J., Essink-Bot, M. L., & Steyerberg, E. W. (2010). Labeled versus unlabeled discrete choice experiments in health economics: an application to colorectal cancer screening. *Value Health*, 13, 315-323.
- de Moraes Ramos, G., Daamen, W., & Hoogendoorn, S. (2011). Expected utility theory, prospect theory, and regret theory compared for prediction of route choice behavior. *Transportation Research Record*, 2230, 19-28.
- Dellaert, B. G., Donkers, B., & Van Soest, A. (2012). Complexity effects in choice experiment-based models. *Journal of Marketing Research*, 49, 424-434.
- Devarasetty, P. C., Burris, M., & Shaw, W. D. (2012). The value of travel time and reliability-evidence from a stated preference survey and actual usage. *Transportation Research Part A: Policy and Practice*, 46, 1227-1240.
- Dieplinger, M., & Fürst, E. (2014). The acceptability of road pricing: Evidence from two studies in Vienna and four other European cities. *Transport Policy*, 36, 10-18.

- Ding, C., Chen, Y., Duan, J., Lu, Y., & Cui, J. (2017). Exploring the influence of attitudes to walking and cycling on commute mode choice using a hybrid choice model. *Journal of advanced transportation*, 2017.
- Efferson, C., Lalive, R., & Fehr, E. (2008). The coevolution of cultural groups and ingroup favoritism. *Science*, 321, 1844-1849.
- Eisenberg, M. E., Neumark-Sztainer, D., Story, M., & Perry, C. (2005). The role of social norms and friends' influences on unhealthy weight-control behaviors among adolescent girls. *Social Science & Medicine*, 60, 1165-1173.
- Evans, G. W., & Wener, R. E. (2007). Crowding and personal space invasion on the train: Please don't make me sit in the middle. *Journal of Environmental Psychology*, 27, 90-94.
- Farooq, B., Cherchi, E., & Sobhani, A. (2018). Virtual immersive reality for stated preference travel behavior experiments: A case study of autonomous vehicles on urban roads. *Transportation research record*, 2672, 35-45.
- Feldman, D. C. (1984). The Development and Enforcement of Group Norms. *The Academy of Management Review*, 9, 47-53.
- Ferdous, N., Pendyala, R. M., Bhat, C. R., & Konduri, K. C. (2011). Modeling the Influence of Family, Social Context, and Spatial Proximity on Use of Nonmotorized Transport Mode. *Transportation Research Record: Journal of the Transportation Research Board*, 2230, 111-120.
- Fielding, K. S., McDonald, R., & Louis, W. R. (2008). Theory of planned behaviour, identity and intentions to engage in environmental activism. *Journal of Environmental Psychology*, 28, 318-326.
- Fimereli, E., & Mourato, S. (2013). Assessing the effect of energy technology labels on preferences. *Journal of Environmental Economics and Policy*, 2, 245-265.
- Forward, S. E. (2009). The theory of planned behaviour: The role of descriptive norms and past behaviour in the prediction of drivers' intentions to violate. *Transportation Research Part F: traffic psychology and behaviour*, 12, 198-207.
- Franceschinis, C., Liebe, U., Thiene, M., Meyerhoff, J., Field, D., & McBratney, A. (2022). The effect of social and personal norms on stated preferences for multiple soil functions: evidence from Australia and Italy. *Australian Journal of Agricultural and Resource Economics*, 66, 335-362.

- Gaker, D., Zheng, Y., & Walker, J. (2010). Experimental Economics in Transportation. *Transportation Research Record: Journal of the Transportation Research Board*, 2156, 47-55.
- Giansoldati, M., Rotaris, L., Scorrano, M., & Danielis, R. (2020). Does electric car knowledge influence car choice? Evidence from a hybrid choice model. *Research in Transportation Economics*, 80, 100826.
- Goett, A. A., McFadden, D. L., & Woo, C.-K. (1988). Estimating household value of electrical service reliability with market research data. *The Energy Journal*, 9.
- Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty years of conjoint analysis: Reflections and prospects. *Interfaces*, 31, S56-S73.
- Green, P. E., & Rao, V. R. (1971). Conjoint measurement-for quantifying judgmental data. *Journal of Marketing research*, 8, 355-363.
- Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: issues and outlook. *Journal of consumer research*, 5, 103-123.
- Green, P. E., Wind, Y., & Carmone, F. J. (1972). Subjective evaluation models and conjoint measurement. *Behavioral Science*, 17, 288-299.
- Groothuis, P. A., Mohr, T. M., Whitehead, J. C., Cockerill, K., Anderson, W. P., & Gu, C. (2021). Measuring the direct and indirect effect of scientific information on valuing storm water management programs with a hybrid choice model. *Water Resources Research*, 57, e2020WR027552.
- Hale, C., & Charles, P. (2009). Managing peak demand for passenger rail: A literature review.
- Hall, J., Viney, R., Haas, M., & Louviere, J. (2004). Using stated preference discrete choice modeling to evaluate health care programs. *Journal of Business Research*, 57, 1026-1032.
- Hammer, T. H., Saksvik, P. O., Nytro, K., Torvatn, H., & Bayazit, M. (2004). Expanding the psychosocial work environment: workplace norms and work-family conflict as correlates of stress and health. *J Occup Health Psychol*, 9, 83-97.
- Hanley, N., Wright, R. E., & Koop, G. (2002). Modelling recreation demand using choice experiments: climbing in Scotland. *Environmental and resource economics*, 22, 449-466.

- Harris, L. (2008). Fraudulent Return Proclivity: An Empirical Analysis. *Journal of Retailing*, 84, 461-476.
- Hartman, E. (1996). *Organizational Ethics*. Oxford, England: Oxford University Press.
- Hein, M., Kurz, P., & Steiner, W. J. (2020). Analyzing the capabilities of the HB logit model for choice-based conjoint analysis: a simulation study. *Journal of Business Economics*, 90, 1-36.
- Hensher, D. A., & Louviere, J. J. (1983). Identifying individual preferences for international air fares: an application of functional measurement theory. *Journal of transport economics and policy*, 225-245.
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: a primer*: Cambridge University Press.
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2012). Inferring attribute non-attendance from stated choice data: implications for willingness to pay estimates and a warning for stated choice experiment design. *Transportation*, 39, 235-245.
- Hess, S., Train, K. E., & Polak, J. W. (2006). On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. *Transportation Research Part B: Methodological*, 40, 147-163.
- Hewstone, M., Rubin, M., & Willis, H. (2002). Intergroup bias. *Annu Rev Psychol*, 53, 575-604.
- Hirsch, L., & Thompson, K. (2011). I can sit but I'd rather stand: Commuter's experience of crowdedness and fellow passenger behaviour in carriages on Australian metropolitan trains.
- Hogg, M. A., & Hains, S. C. (1996). Intergroup relations and group solidarity: Effects of group identification and social beliefs on depersonalized attraction. *Journal of Personality and Social Psychology*, 70, 295-309.
- Hogg, M. A., & Hardie, E. A. (1992). Prototypicality, conformity and depersonalized attraction: A self-categorization analysis of group cohesiveness. *British Journal of Social Psychology*, 31, 41-56.
- Hogg, M. A., Hardie, E. A., & Reynolds, K. J. (1995). Prototypical similarity, self-categorization, and depersonalized attraction: A perspective on group cohesiveness. *European Journal of Social Psychology*, 25, 159-177.

- Hogg, M. A., & Turner, J. C. (1985). Interpersonal attraction, social identification and psychological group formation. *European Journal of Social Psychology*, 15, 51-66.
- Hollander, M., Wolfe, D. A., & Chicken, E. (2013). *Nonparametric statistical methods* (Vol. 751): John Wiley & Sons.
- Huber, J., & Zwerina, K. (1996). The Importance of Utility Balance in Efficient Choice Designs. *Journal of Marketing Research*, 33, 307-317.
- Huth, V., & Gelau, C. (2013). Predicting the acceptance of advanced rider assistance systems. *Accid Anal Prev*, 50, 51-58.
- Irawan, M. Z., Belgiawan, P. F., Joewono, T. B., & Simanjuntak, N. I. (2020). Do motorcycle-based ride-hailing apps threaten bus ridership? A hybrid choice modeling approach with latent variables. *Public Transport*, 12, 207-231.
- Jetten, J., Spears, R., & Manstead, A. S. R. (2001). Similarity as a source of differentiation: the role of group identification. *European Journal of Social Psychology*, 31, 621-640.
- Jin, W., Jiang, H., Liu, Y., & Klampfl, E. (2017). Do labeled versus unlabeled treatments of alternatives' names influence stated choice outputs? Results from a mode choice study. *PloS one*, 12, e0178826.
- Johnson, R. M. (2000). Understanding HB: an intuitive approach. In: Sawtooth Software Inc., Sequim, WA.
- Jost, J. T., Glaser, J., Kruglanski, A. W., & Sulloway, F. J. (2003). Political conservatism as motivated social cognition. *Psychological Bulletin*, 129, 339-375.
- Jou, R.-C., Kitamura, R., Weng, M.-C., & Chen, C.-C. (2008). Dynamic commuter departure time choice under uncertainty. *Transportation Research Part A: Policy and Practice*, 42, 774-783.
- Jung, S.-Y., & Yoo, K.-E. (2016). A study on passengers' airport choice behavior using hybrid choice model: A case study of Seoul metropolitan area, South Korea. *Journal of Air Transport Management*, 57, 70-79.
- Kaddoura, I., Kickhöfer, B., Neumann, A., & Tirachini, A. (2015). Agent-based optimisation of public transport supply and pricing: impacts of activity scheduling decisions and simulation randomness. *Transportation*, 42, 1039-1061.
- Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American economic review*, 93, 1449-1475.

- Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives*, 5, 193-206.
- Kahneman, D., & Ritov, I. (1994). Determinants of stated willingness to pay for public goods: A study in the headline method. *J Risk Uncertain*, 9, 5-37.
- Kahneman, D., Ritov, I., Schkade, D., Sherman, S. J., & Varian, H. R. (1999). Economic preferences or attitude expressions?: an analysis of dollar responses to public issues. In *Elicitation of preferences* (pp. 203-242): Springer.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the econometric society*, 263-291.
- Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, 39, 341-350.
- Kamargianni, M., & Polydoropoulou, A. (2013). Hybrid choice model to investigate effects of teenagers' attitudes toward walking and cycling on mode choice behavior. *Transportation research record*, 2382, 151-161.
- Kaushik, M., & Guleria, N. (2020). The impact of pandemic COVID-19 in workplace. *European Journal of Business and Management*, 12, 1-10.
- Kim, H., Kwon, S., Wu, S. K., & Sohn, K. (2014). Why do passengers choose a specific car of a metro train during the morning peak hours? *Transportation Research Part A: Policy and Practice*, 61, 249-258.
- Kiss, M., Czine, P., Balogh, P., & Szakály, Z. (2022). The connection between manufacturer and private label brands and brand loyalty in chocolate bar buying decisions—A hybrid choice approach. *Appetite*, 177, 106145.
- Kjaer, T. (2005). *A review of the discrete choice experiment-with emphasis on its application in health care*: Syddansk Universitet Denmark.
- Kløjgaard, M. E., & Hess, S. (2011). Understanding the role of practitioners' and patients' perceptions in treatment choices in the face of limited clinical evidence: A Hybrid Choice Model approach. *Social Science & Medicine*, 114, 138-150.
- Krucien, N., Ryan, M., & Hermens, F. (2017). Visual attention in multi-attributes choices: What can eye-tracking tell us? *Journal of Economic Behavior & Organization*, 135, 251-267.
- Kruijschaar, M. E., Essink-Bot, M. L., Donkers, B., Looman, C. W., Siersema, P. D., & Steyerberg, E. W. (2009). A labelled discrete choice experiment adds realism to the

- choices presented: preferences for surveillance tests for Barrett esophagus. *BMC Med Res Methodol*, 9, 31.
- Kuhfeld, W. F., Tobias, R. D., & Garratt, M. (1994). Efficient experimental design with marketing research applications. *Journal of Marketing Research*, 31, 545-557.
- Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy*, 74, 132-157.
- Lenk, P. J., DeSarbo, W. S., Green, P. E., & Young, M. R. (1996). Hierarchical Bayes conjoint analysis: recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science*, 15, 173-191.
- Levin, S., & Sidanius, J. (1999). Social Dominance and Social Identity in the United States and Israel: Ingroup Favoritism or Outgroup Derogation? *Political Psychology*, 20, 99-126.
- Lewis, G. J., & Bates, T. C. (2010). Genetic evidence for multiple biological mechanisms underlying in-group favoritism. *Psychol Sci*, 21, 1623-1628.
- Lindberg, K., Veisten, K., & Halse, A. H. (2019). Analyzing the deeper motivations for nature-based tourism facility demand: a hybrid choice model of preferences for a reindeer visitor center. *Scandinavian Journal of Hospitality and Tourism*, 19, 157-174.
- Löfgren, O. (2008). Motion and emotion: Learning to be a railway traveller. *Mobilities*, 3, 331-351.
- Lois, D., Moriano, J. A., & Rondinella, G. (2015). Cycle commuting intention: A model based on theory of planned behaviour and social identity. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32, 101-113.
- Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: analysis and applications*: Cambridge University Press.
- Louviere, J. J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: an approach based on aggregate data. *Journal of marketing research*, 20, 350-367.
- Luce, R. D., & Tukey, J. W. (1964). Simultaneous conjoint measurement: A new type of fundamental measurement. *Journal of mathematical psychology*, 1, 1-27.
- Manski, C. F. (1977). The structure of random utility models. *Theory and decision*, 8, 229-254.

- Mäntymaa, E., Ovaskainen, V., Juutinen, A., & Tyrväinen, L. (2018). Integrating nature-based tourism and forestry in private lands under heterogeneous visitor preferences for forest attributes. *Journal of Environmental Planning and Management*, 61, 724-746.
- McFadden, D. (1986). The choice theory approach to market research. *Marketing science*, 5, 275-297.
- McFadden, D. (2014a). An economist's perspective on environmental damages. In *paper at The Eighth Annual Advanced Conference on Litigating Natural Resource Damages, Law Seminars International*.
- McFadden, D. (2014b). The new science of pleasure: consumer choice behavior and the measurement of well-being. In *Handbook of choice modelling*: Edward Elgar Publishing.
- McFadden, D. (2017). Stated preference methods and their applicability to environmental use and non-use valuations. In *Contingent Valuation of Environmental Goods*: Edward Elgar Publishing.
- McGregor, I., Haji, R., & Kang, S.-J. (2008). Can ingroup affirmation relieve outgroup derogation? *Journal of Experimental Social Psychology*, 44, 1395-1401.
- Meißner, M., & Decker, R. (2010). Eye-tracking information processing in choice-based conjoint analysis. *International Journal of Market Research*, 52, 593-612.
- Meissonnier, J., & Richer, C. (2021). Rush hour. Why despite flexible working workers resist change ? *Applied Mobilities*, 1-13.
- Molloy, J., Schatzmann, T., Schoeman, B., Tchervenkova, C., Hintermann, B., & Axhausen, K. W. (2021). Observed impacts of the Covid-19 first wave on travel behaviour in Switzerland based on a large GPS panel. *Transport Policy*, 104, 43-51.
- Morikawa, T., Ben-Akiva, M., & McFadden, D. (2002). Discrete choice models incorporating revealed preferences and psychometric data. *Econometric Models in Marketing*, 16, 29-55.
- Morrison, E. W. (1994). Role definitions and organizational citizenship behavior: The importance of the employee's perspective. *Academy of management journal*, 37, 1543-1567.
- Mullainathan, S., & Thaler, R. H. (2000). Behavioral economics. In: National Bureau of Economic Research Cambridge, Mass., USA.

- Munch, E. (2014). Could harmonised working times spell an end to the rush hour? *Métropolitiques. eu*, 5.
- Musil, S. (2018). Huawei knocks off Apple to become No. 2 phone seller. In (Vol. 2021). c|net.com.
- Natter, M., & Feurstein, M. (2002). Real world performance of choice-based conjoint models. *European Journal of Operational Research*, 137, 448-458.
- Nguyen, D.-Q., & Mariani, D. (2014). Swiss population getting larger, older, more diverse. In *Digging into data*.
- Olszewski, P., & Xie, L. (2005). Modelling the effects of road pricing on traffic in Singapore. *Transportation Research Part A: Policy and Practice*, 39, 755-772.
- Orme, B. (2000). Hierarchical Bayes: Why All the Attention? In: Sawtooth Software Inc., Sequim, WA.
- Orme, B. (2019). *Getting Started with Conjoint Analysis : Strategies for Product Design and Pricing Research* (Fourth Edition ed.): Madison, Wis. : Research Publishers LLC.
- Paris, H., & Broucke, S. V. d. (2008). Measuring cognitive determinants of speeding: An application of the theory of planned behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11, 168-180.
- Patil, S., Burris, M., & Shaw, W. D. (2011). Travel using managed lanes: An application of a stated choice model for Houston, Texas. *Transport Policy*, 18, 595-603.
- Pinson, C., & Brodahl, D. J. (2014). The Church of Mac: Exploratory examination on the loyalty of Apple customers. *Journal of Management and Marketing Research*, 14, 1.
- R Core Team. (2016). R: A language and environment for statistical computing. In. Vienna, Austria: R Foundation for Statistical Computing.
- Ramos, G. M., Daamen, W., & Hoogendoorn, S. (2014). A state-of-the-art review: developments in utility theory, prospect theory and regret theory to investigate travellers' behaviour in situations involving travel time uncertainty. *Transport Reviews*, 34, 46-67.
- Rencher, A. C., & Christensen, W. F. (2012). Chapter 10, Multivariate regression–Section 10.1, Introduction. *Methods of Multivariate Analysis, Wiley Series in Probability and Statistics*, 709, 19.
- Riedener, J. (2012). Überfüllte Züge während Stosszeiten. In *20 Minuten*.

- Riggs, W. (2017). Painting the fence: Social norms as economic incentives to non-automotive travel behavior. *Travel Behaviour and Society*, 7, 26-33.
- Rolfe, J., Bennett, J., & Louviere, J. (2000). Choice modelling and its potential application to tropical rainforest preservation. *Ecological Economics*, 35, 289-302.
- Rose, J. M., & Bliemer, M. C. J. (2009). Constructing Efficient Stated Choice Experimental Designs. *Transport Reviews*, 29, 587-617.
- Rosko, M. D., DeVita, M., McKenna, W. F., & Walker, L. R. (1985). Strategic marketing applications of conjoint analysis: an HMO perspective. *J Health Care Mark*, 5, 27-38.
- Rossi, P. E. (2015). bayesm: Bayesian Inference for Marketing/Micro-Econometrics. In (R package version 3.0-2 ed.).
- Rossi, P. E., Allenby, G. M., & McCulloch, R. E. (2012). *Bayesian statistics and marketing*: John Wiley & Sons.
- Ryan, M., Gerard, K., & Amaya-Amaya, M. (2007). *Using discrete choice experiments to value health and health care* (Vol. 11): Springer Science & Business Media.
- Saameli, N. (2014). Handy-Lärm nervt die Pendler. In *20 Minuten*.
- Salak, B., Lindberg, K., Kienast, F., & Hunziker, M. (2021). How landscape-technology fit affects public evaluations of renewable energy infrastructure scenarios. A hybrid choice model. *Renewable and Sustainable Energy Reviews*, 143, 110896.
- Saleh, W., & Farrell, S. (2005). Implications of congestion charging for departure time choice: Work and non-work schedule flexibility. *Transportation Research Part A: Policy and Practice*, 39, 773-791.
- Sandorf, E. D., dit Sourd, R. C., & Mahieu, P.-A. (2018). The effect of attribute-alternative matrix displays on preferences and processing strategies. *Journal of Choice Modelling*, 29, 113-132.
- Santos, A. C., Roberts, J. A., Barreto, M. L., & Cairncross, S. (2011). Demand for sanitation in Salvador, Brazil: a hybrid choice approach. *Soc Sci Med*, 72, 1325-1332.
- Sarman, I., Scagnolari, S., & Maggi, R. (2016). Acceptance of life-threatening hazards among young tourists: a stated choice experiment. *Journal of Travel Research*, 55, 979-992.
- Sawtooth Software. (2009). The CBC/HB System for Hierarchical Bayes Estimation. In: Sawtooth Software Inc., Sequim, WA.

- SBB. (2013). Segmentierungsalgorithmus. In.
- Scarpa, R., Zanolli, R., Bruschi, V., & Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics*, 95, 165-180.
- Schade, J., & Schlag, B. (2003). Acceptability of urban transport pricing strategies. *Transportation Research Part F: Traffic Psychology and Behaviour*, 6, 45-61.
- Scott, J. (2000). Rational choice theory. *Understanding contemporary society: Theories of the present*, 129, 671-685.
- Senbil, M., & Kitamura, R. (2004). Reference points in commuter departure time choice: a prospect theoretic test of alternative decision frames. In *Intelligent Transportation Systems* (Vol. 8, pp. 19-31): Taylor & Francis.
- Senbil, M., & Kitamura, R. (2005). Heterogeneity in commuter departure time decision: A prospect theoretic approach. In *Applied Research in Uncertainty Modeling and Analysis* (pp. 369-398): Springer.
- Sherwin, H., Chatterjee, K., & Jain, J. (2014). An exploration of the importance of social influence in the decision to start bicycling in England. *Transportation Research Part A: Policy and Practice*, 68, 32-45.
- Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63, 129-138.
- Smith, B. M. (2002). Time norms in the workplace: their exclusionary effect and potential for change. *Colum. J. Gender & L.*, 11, 271.
- SNCB. (2016). Belgian Rail. In (Vol. 2016).
- Spangenberg, E. R., Sprott, D. E., Grohmann, B., & Smith, R. J. (2018). Mass-Communicated Prediction Requests: Practical Application and a Cognitive Dissonance Explanation for Self-Prophecy. *Journal of Marketing*, 67, 47-62.
- Stangor, C., & Thompson, E. P. (2002). Needs for cognitive economy and self-enhancement as unique predictors of intergroup attitudes. *European Journal of Social Psychology*, 32, 563-575.
- Steenhard, D., & Chou, N. (2004). Using SAS-IML to Perform Hierarchical Bayes Estimation for Discrete Choice Modeling. In.
- Steven, A. B., Dong, Y., & Dresner, M. (2012). Linkages between customer service, customer satisfaction and performance in the airline industry: Investigation of non-

- linearities and moderating effects. *Transportation Research Part E: Logistics and Transportation Review*, 48, 743-754.
- Strazzera, E., Meleddu, D., & Atzori, R. (2022). A hybrid choice modelling approach to estimate the trade-off between perceived environmental risks and economic benefits. *Ecological Economics*, 196, 107400.
- Swiss Federal Statistical Office. (2014). Population and Households Statistics (STATPOP). In.
- Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. *The social psychology of intergroup relations*, 33, 74.
- Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of economic behavior & organization*, 1, 39-60.
- Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science*, 4, 199-214.
- Tirachini, A. (2013). Estimation of travel time and the benefits of upgrading the fare payment technology in urban bus services. *Transportation Research Part C: Emerging Technologies*, 30, 239-256.
- Train, K. (1986). *Qualitative choice analysis: Theory, econometrics, and an application to automobile demand* (Vol. 10): MIT press.
- Train, K. (2003). *Discrete choice methods with simulation*: Cambridge university press.
- Train, K. E. (2009). *Discrete choice methods with simulation*: Cambridge university press.
- Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*: Basil Blackwell.
- Turner, J. C., Oakes, P. J., Haslam, S. A., & McGarty, C. (2016). Self and Collective: Cognition and Social Context. *Personality and Social Psychology Bulletin*, 20, 454-463.
- Tversky, A., & Kahneman, D. (1986). Rational Choice and the Framing of Decisions. *The Journal of Business*, 59, S251-S278.
- Uggeldahl, K., Jacobsen, C., Lundhede, T. H., & Olsen, S. B. (2016). Choice certainty in discrete choice experiments: Will eye tracking provide useful measures? *Journal of Choice Modelling*, 20, 35-48.
- Ungricht, T. (2010). Überfüllte SBB-Züge - Die Erfindung des Steh-Pendlers. In *Blick*.
- Valda, A. (2015). «Mögliche Trendwende» bei überlasteten Zügen. In *Tagesanzeiger*.

- Van Wee, B. (2009). Self-selection: a key to a better understanding of location choices, travel behaviour and transport externalities? *Transport Reviews*, 29, 279-292.
- Vanhooymissen, T., & Van Overwalle, F. (2010). Me or not me as source of ingroup favoritism and outgroup derogation: A connectionist perspective. *Social cognition*, 28, 84-109.
- Viney, R., Savage, E., & Louviere, J. (2005). Empirical investigation of experimental design properties of discrete choice experiments in health care. *Health Econ*, 14, 349-362.
- Von Neumann, J., & Morgenstern, O. (1947). Theory of games and economic behavior, 2nd rev.
- von Sivers, I., Templeton, A., Köster, G., Drury, J., & Philippides, A. (2014). Humans do not always act selfishly: Social identity and helping in emergency evacuation simulation. *Transportation Research Procedia*, 2, 585-593.
- Vontobel, W., & Guanziroli, S. (2008). Überfüllte Züge machen Reisende sauer. In *Blick*.
- Vredin Johansson, M., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice*, 40, 507-525.
- Vrtic, M., Schüssler, N., Axhausen, K. W., & Erath, A. (2011). Mobility Pricing: Zahlungsbereitschaft und Verhaltensreaktionen. *Heureka 11 "Optimierung in Verkehr und Transport 2011 in Stuttgart"*.
- Vrtic, M., Schüssler, N., Erath, A., & Axhausen, K. W. (2007). Route, mode and departure time choice behaviour in the presence of mobility pricing. *Arbeitsbericht Verkehrs- und Raumplanung*, 446, 1-25.
- Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, 43, 303-343.
- Walker, J. L. (2001). *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*. Massachusetts Institute of Technology.
- Weichbrodt, J., Sprenger, M., Steffen, M., Tanner, A., Meissner, J. O., & Schulze, H. (2013). WorkAnywhere. In: SBB AG and Swisscom (Switzerland) Ltd.
- Wellman, G. S., & Vidican, C. (2008). Pilot study of a hierarchical Bayes method for utility estimation in a choice-based conjoint analysis of prescription benefit plans including medication therapy management services. *Res Social Adm Pharm*, 4, 218-230.
- Wikipedia, c. Android (operating system). In: Wikipedia, The Free Encyclopedia.

- Wikipedia, c. Smartphone. In: Wikipedia, The Free Encyclopedia.
- Wilkinson, N., & Klaes, M. (2017). *An introduction to behavioral economics*: Macmillan International Higher Education.
- Williams, P., & Naumann, E. (2011). Customer satisfaction and business performance: a firm-level analysis. *Journal of services marketing*.
- Wu, D., Yin, Y., Lawphongpanich, S., & Yang, H. (2012). Design of more equitable congestion pricing and tradable credit schemes for multimodal transportation networks. *Transportation Research Part B: Methodological*, 46, 1273-1287.
- Yang, H., & Wang, X. (2011). Managing network mobility with tradable credits. *Transportation Research Part B: Methodological*, 45, 580-594.
- Yangui, A., Font, M. C., & Gil, J. M. (2013). The effect of food related personality traits and lifestyle orientation on consumer's behaviour related to extra virgin olive oil: estimation of an extended hybrid choice model. In *2013 Fourth International Conference, September 22-25, 2013, Hammamet, Tunisia*: African Association of Agricultural Economists (AAAE).
- Zemp, T. (2014). SBB-Mitarbeiter verstopfen Pendlerzüge. In *Tagesanzeiger*.
- Zhang, D., Schmöcker, J.-D., Fujii, S., & Yang, X. (2015). Social norms and public transport usage: empirical study from Shanghai. *Transportation*, 43, 869-888.
- Zhang, Q., Han, B., & Li, D. (2008). Modeling and simulation of passenger alighting and boarding movement in Beijing metro stations. *Transportation Research Part C: Emerging Technologies*, 16, 635-649.
- Zhong, C. B., Phillips, K. W., Leonardelli, G. J., & Galinsky, A. D. (2008). Negational categorization and intergroup behavior. *Pers Soc Psychol Bull*, 34, 793-806.
- Zimmermann, T. M., Clouth, J., Elosge, M., Heurich, M., Schneider, E., Wilhelm, S., & Wolfrath, A. (2013). Patient preferences for outcomes of depression treatment in Germany: a choice-based conjoint analysis study. *J Affect Disord*, 148, 210-219.