Social Influence in the Context of Parking Choice: A Stated Preference Experiment

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Abstract

For many years, researchers, along with municipalities, have been trying to decrease growing congestions in the cities. Yet, despite employing sometimes drastic and inconvenient measures, drivers still choose to park in the centers of the cities. It has been brought to attention, that existing researches mainly focus on parking attributes and overlook other factors which may change the driver's behavior, such as the effect of social interactions. This study tried to find to what extent do parking attributes and social influence affect driver's choice of a parking spot. The conducted stated preference experiment, spread by the means of an online survey, within a month's time gathered the opinions of 603 respondents. The respondents were asked to evaluate eight attributes, out of which 4 regarded the parking attributes, and 4 social influence. The collected data was analyzed by the means of binary logit and latent class model. The results show, that parking attributes such as parking tariff or the walking distance play the most important role when choosing a parking spot, however, social influence also can be of importance. Individuals tend to be more responsive if the influence comes from people with whom they have closer ties. Otherwise, they tend to show indifference. This study is one of few which focuses on getting more insight into social influence in the context of parking. The gathered knowledge adds to the body of previous researches carried out in the recent years. Information gathered while creating this thesis can be later useful to the governmental bodies to improve the existing parking policies.

1. Introduction

1.1 Problem definition

The urbanization of our planet is a fast-forward moving process. People all over the world tend to move into densely populated areas rather than out of them. It is estimated that by 2050, 68% of the world's population will be living in the cities (United Nations, 2018). Such amount of people living in urban areas is a challenge to urban planners, policy makers and governments. Already now, cities must tackle a variety of issues with regard to the environment. One of them is the cities' congestion and parking problems. Congestion, caused by excess of cars on the streets, causes air pollution and greenhouse gas emission, which in turn leads to environmental and human health damage (Savan & Cohlmeyer, 2017). On top of congestion caused by people trying to reach their destination, there is one more element contributing to enormous traffic jams- parking cruising. Parking cruising in search for a vacant parking spot which fulfils the drivers' needs, has been estimated to add up to 50% of the total traffic jams (Chaniotakis & Pel, 2015). According to a report issued by the Organization for Economic Co-operation and Development (OECD) in 2014, the air pollution related to exhaustion fumes has caused damages to human health worth 850 million US dollars (Organization for Economic Co-operation and Development, 2014). Yet still, the overall number of cars and transport demand is increasing, therefore new policies have to be implemented in order to reduce the harmful impact of pollution on the environment as well as human health.

In the past, growing car and parking demand has been answered by investing in new and existing infrastructure. However, the practice has shown that this is not the solution and infrastructure's expansion only generates more traffic; moreover, it does not solve the environmental pollution problem (Maat, Wee, Stead & 2005). Various attempts to limit the number of cars on the streets seem to be backfiring: drivers, instead of adjusting and obeying the law, find ways to bypass it. For example, ever since the introduction of the license plate restriction in South American countries, the number of old polluting cars driving on the streets has significantly increased. The root cause is relatively simple: people, who could not use their primary car that day, used a second, older and therefore more polluting car (Cantillo & Ortúzar, 2014).

With failing car-reducing policies, the parking problems grow bigger. The number of cars entering and trying to park in the limited space of a city center is increasing. Therefore, governing bodies have been trying to cut this number down by influencing the drivers' behaviors in various ways, for example by enforcing a high charge (Mackett, 2012). However, despite their best legislative efforts, most of them seem to be working in a limited way. The history of failed policies has led politicians as well as scientists to look into the psychological side of the traffic behavior, hoping to find a working solution.

That is why, their attention has been brought to the phenomenon of social influence, an act of changing one's behavior or opinion under pressure of others. Until recently it was uncommon to apply it also in the travel context. Nowadays, with body of research expanding, studies contain more information about social influence phenomenon and its implications on travel decisions. For example, Sunitiyoso, Avineri and Chatterjee (2011) have reached a conclusion, that human interactions may lead to travel behavior change. Kim, Rasouli and Timmermans (2014) have stated, that people improve the state of their knowledge about existing choices through social interactions. A (travel) choice made by an individual may therefore be influenced by another's choice (Kim et al, 2014). Despite having this knowledge, it is still rare to find studies connecting social influence and parking choice. Most of the studies regarding parking choice behavior put main focus on an extensive study of the parking attributes, as it has always been assumed, that they play the most important role (Sunitiyoso, Avineri, & Chatterjee, 2011). However, the obtained results and their later implementation have proven to be insufficient and working in a limited way. This shows, that there may be more to the parking choice than just the facility's attributes.

The idea of connecting social influence and parking spot choice is fairly new. Therefore, its full implications are yet to be determined. Two studies which do include social influence in the context of parking are the studies of Laro (2018) and Iqbal (2018), who have determined, that a certain connection indeed exists. This thesis adds to their researches and gives more insight into the topic.

The improvement of the parking policies has become an important part of mobility management programs in the Netherlands (Van der Waerden, 2012). In case the social influence factors in the context of parking prove to matter, it will become a possibility to convince people to change their parking habits using social psychology. Such methods may deliver better results than obliging the drivers by law enforcement, as "tools are not enough to be successful, they have to be supported by right habits" (Flinchbaugh, 2015). With widespread technology, it is possible to use advertisements or signing to promote parking facilities further from the city centers. Using the (electronic) word-of-mouth, such as giving or writing positive reviews, can help with the process of reinforcing the habit of parking on the city's outskirt, eventually leading to the congestion decrease.

1.2 Research questions

As it is assumed, that social influence may play a role in the parking choice, the main research question is:

- RQ: "To what extent do social influence and parking attributes contribute to car driver's parking choice behavior?"

This research will include four social influence groups: family, friends, colleagues and others. It is one of the aims of this study to reach a conclusion about the group with the biggest influence, therefore the first sub-question:

- RQ1: “Whose influence is the strongest: from family members, friends, colleagues or others?”

A lot of studies regarding parking behavior put the focus on the parking attributes and omit other possibly influencing factors. It is possible, that this is one of the reasons why the existing parking models do not perform in a way that is satisfactory enough. This study, apart from parking attributes, focuses also on social influence and its implications. The way of the social influence factors inclusion is different from the research of Laro (2018) and Iqbal (2018), therefore there is hope of creating better performing models. Until now, most of the models used to predict human behavior are characterized by average predicting powers (Pituch & Stevens, 2016). That leads to the second sub-question:

- RQ2: “To what extent does the inclusion of social influence factors improve the predictive power of the models?”

By answering RQ2, it may become possible to determine the impact of social influence on the prediction powers of parking choice models. Furthermore, answering the RQ1 will determine the group with the biggest influence, what leads to answering the main RQ.

1.3 Research design

Research design includes a plan and procedure of the research which is to be carried out. The first step taken in order to find answers to the research question is conducting a literature research. It gives an overview of what has been already done, what the conclusions are and allows to base the current research on this knowledge. The literature review in case of this thesis will include collecting extensive information about social influence, choice behavior, decision-making process, parking attributes and parking models. Gathering this information will allow the design of the study: the process of setting up a choice experiment and creating a survey with it. Then, an online questionnaire will be spread out among the respondents. The collected data will then be analyzed with help of previously chosen statistical models. Based on the outcomes, conclusions will be drawn.

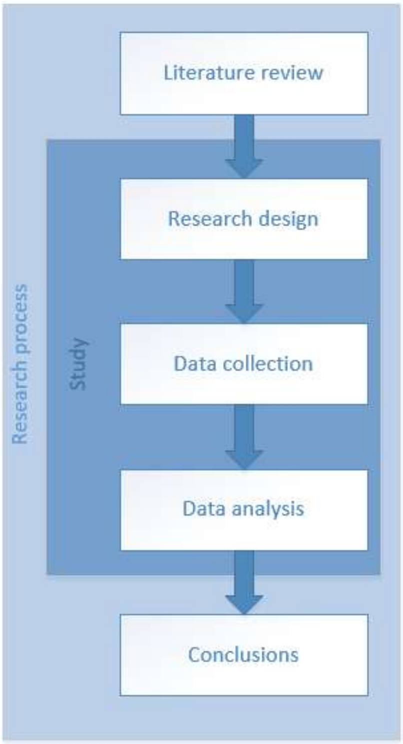


Fig. 1: Research design

1.4 Research methodology

A researcher, during the preparation must make many different decisions, the first one being the selection of the appropriate research approach type. Three main research approaches can be distinguished: qualitative, quantitative and mixed. Qualitative research aims to explore and understand the individuals and their behavior (Creswell, 2014): it tries to get insight into a person's feelings and emotions, seeing him/her as an individual entity (Johnson & Christensen, 2014). It follows, that the best research method of a qualitative research type are interviews, focus groups and observations, as they allow the subjects to express themselves and show their individuality. That is why, obtained data are in the form of words rather than numbers (Creswell, 2014). On the other side, there is quantitative research. It is mainly used to confirm theories through the numerical analysis of the collected data. The most popular methods of data collection are surveys, polls and questionnaires. This type of research is often used to explain visible trends, attitudes or opinions being visible in the society. The collected sample is used to profess opinions about the society as a whole, that is why it needs to be substantially large. Lastly, mixed research is a composition of both quantitative and qualitative research (Fowler, 2009). The type of research which will be conducted in this study is the quantitative research. As stated before, quantitative research is the best to capture and analyze a trend or phenomenon which can be observed in a society.

There exist two methods of empirical estimation of people's preferences: stated preference and revealed preference approach. Both allow the researcher to see how different people value different attributes and give insights into the hierarchy of certain attributes (Arentze & Mollin, 2013). Both methods are described below and compared afterwards.

The revealed preference (RP) data can be collected only when the actual choice has been made. This means, that researcher can observe an individual at the moment of choosing one alternative from the others available at that time. Revealed preference data have few obvious advantages. Firstly, they reflect on a real situation happening on the market. That means they show people's real choices, instead of placing them in a hypothetical situation, like it is in the case of stated preference (SP) data. That implies, that the choosers are bound by real constrains, such as, for example, income constraint. Those properties of RP data imply, that they are rather reliable: that with the experiment repetition, one is likely to obtain similar results. Moreover, they are characterized by face validity- the connection between what has been observed to be chosen and what has been indeed chosen. On the other hand, as the RP data reflect on the reality alone, there is no possibility of checking people's preferences in case of the new products or new companies. Moreover, RP data can be costly in terms of both time and money to collect (Hensher, Rose & Greene, 2005). On a more analytical side, the RP data by the nature of their collection are characterized by a strong correlation of variables of interest, what makes it difficult to distinguish trade-offs made by the respondents. It is also bound to measure attributes in the "objective/engineering units", what limits the number of data that can be collected to the ones objectively measurable, such as time and cost. With such a limitation, it becomes hard to measure secondary travel variables, such as, for example, available facilities (Kroes & Sheldon, 1988).

The SP collection method differs from the RP in many ways. It is easier to control, as it is the researcher that oversees the conditions, not the other way around. It is also more flexible, as it allows to deal with more variables simultaneously (Kroes & Sheldon, 1988). With the use of SP experiment a researcher can collect multiple number of observations from one choice set. This is often not the case in RP experiment, when usually one answer gives information about one choice that has been made (Hensher et al, 2005). But what is the most important feature of the SP is that it is not strictly limited to the existing alternatives. Quite the contrary, they place the respondent in a hypothetical situation, offering freedom to use it as a tool to test people's preferences regarding not-yet-existent products or brands (Hensher, et al, 2005). The SP data collection method is not bound by technological frontier and allows the researcher to explore outside of frontiers (Louviere, Hensher & Swait, 2000).

After comparing all the pros and cons of both methods, it has been decided to use the SP collection method. Using RP method in this case could prove to be difficult, as this method is limited to the data collection only after the choice has been made. There is also no guarantee, that obtained data would provide enough information about social influence factors to further proceed with the research. The SP data collection method proves to be more feasible, as it gives the researcher the control over experiment and freedom to design it. SP data are most often collected by the means of a survey and there are many ways of carrying them out: in person, through the phone, online, etc. In this research, online survey has been chosen, as a rather large sample is required to analyze the existing phenomenon, and this method is the best when a lot of data is required. It is also considered to be relatively fast and cheap in comparison with other methods (Johnson & Christensen, 2014).

1.5 The practical importance

This work is designed to find out if the drivers' decision regarding choosing a parking spot is based solely on parking attributes or if social influence also plays a role. In case it does, the obtained results can be used to influence the driver's parking behavior using their own social connections. It may become possible to improve parking policies and develop new parking strategies which may deliver better results than obliging drivers using the law. It is known, that people do not favor laws that infringe on or go against their personal beliefs or feelings. Instead of forcing an individual to change the parking habits, using social psychology may bring better long-term results, as it forms new, better parking habits out of person's free will.

1.6 Reading guide

Current chapter sketches the existing problem and offers a hypothetical solution to it. It also gives insight into research methodology and design. Chapter 2 includes a Literature Research, which focuses on topics related to this thesis: social influence, choice behavior and decision-making and parking attributes. It describes the underlying mechanisms of social influence, explains the decision-making process and gives an overview of the most parking attributes which are most often found to be important for the drivers. Chapter 3 focuses on the Research Approach and describes the process of creation of the experiment and survey, as well as the models which will be used to analyze the collected data. Chapter 4, Data Analysis, contains information about analysis of the data that have been collected. Chapter 5 contains the conclusions and recommendations for practice and future research.

2. Literature review

2.1 Decision-making and choice behaviour

Every day, individuals make a wide range of decisions. People, consciously or without realization, make choices only after several options have been considered and the relatively best one is chosen. That means that after considering all known options at the time of decision making, that particular option seemed to be the best one (Hastie & Dawes, 2010). An individual, while making a decision needs as many information as possible about the existing situation: criteria of the decisions, stakeholders involved, who may or will be affected by the decision and an alternative option (Saaty, 2008). This is why observing people making choices, for an outsider, may sometimes seem inexplicable- because a bystander will never possess all the information available to the decision-maker at the moment of making a decision. Therefore, it will never be possible to fully explain the outcome. Moreover, individuals make decisions based on their preferences, behind which there is always more in-depth reasoning. For example, preference of a car over a bus, can have many reasons, such as comfort, travel time, security or material status. On the other hand, the bus preference may have something to do with parking problems or trying to be environmental-friendly. Each person's decision is underlined by different reasoning, leading to a certain degree of variability. This is called the heterogeneity of the society- the differences between us, that make each person an individual. A person's behavior - which considers choosing a certain, most satisfactory, alternative based on their preference - is called utility-maximizing behavior (Hensher, Rose & Greene, 2015). This behavior takes place after all known alternatives have been evaluated. The theory assumes that the option with the highest utility will be chosen (Hess, 2004).

However, sometimes choosing the most preferable option is simply impossible. For example, bus-or-car choice may be also constrained by additional factors, such as lack of budget. Therefore, a person is forced to choose from all available alternatives which are within the imposed constraints (Hensher et al, 2015). The image below (Fig. 2) represents the individual's choice process step by step. In the beginning, one becomes aware of a need or an existing problem. Afterwards, there follows a time of information searching and processing during which a person learns about existing alternatives which can help to find a solution. After a satisfactory number of alternatives has been found, follows the time of comparison and evaluation of each alternative. When that is done, an individual starts to look into the trade-offs which he/she has to make. The alternative preference is formed based on one's reasoning, after taking into the account all the variables. It is then that one decides which options out of the ones that are known, may be the solution to the existing problem. Then, a belief is formed about a particular, subjectively best solution, followed by the preference of it. (Louviere, Hensher & Swait, 2000).

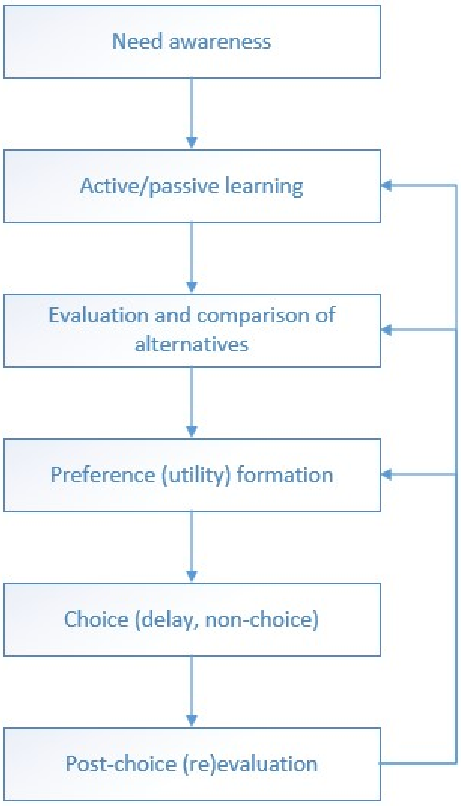


Fig. 2: Individual's choice process (Louviere, Hensher & Swait, 2000)

Griffioen-Young, Janssen, van Amelsfoort & Langefeld (2004) in their research have dived into the topic of psychology of parking. In their attempt to understand seemingly irrational behavior of people, they have divided individual's behavior into reasoned and automatic. They have postulated, that reasoned behavior, contrary to automated behavior, is determined by the parking and trip characteristics, environmental characteristics and one's attitude towards it. Environmental characteristics account for, for example, the weather or the traffic volume, whereas the trip characteristics define the destination, time of the trip and length of the parking time. Griffioen-Young et al (2004) have hypothesized that the importance of those factors changes depending on the given situation. For example, while going for a business meeting, in which the punctuality is important, one will most likely choose for a parking which is located closest to the destination and will not mind the possible high prices. On the other hand, when going for shopping, the long walking distance may not be of hindrance as one is most likely not in a hurry and plans on spending hours on foot. Moreover, as an individual going shopping is paying him/herself, the price for parking will most likely play an important role (Griffioen-Young et al, 2004). This theory has found a confirmation in an experiment conducted by Anderson, Das and Tyrell (2006) in which the researchers checked the route preferences of tourists coming to Rhode Island during summer. A theory was created, that tourists, on the contrary to commuters, value different attributes. For example, a commuter, whose goal is to be at work on time, will choose the parking closest to the destination and is willing to queue up in long traffic if it happens on the shortest route. For a tourist, navigating through a traffic jam can significantly decrease the satisfaction of the journey. Anderson et al (2006) hypothesized, that taking a longer route, avoiding traffic while at the same time admiring the city's scenery may be a much better choice. Based on the results of the stated preference experiment, they drew the conclusions that tourists do indeed prioritize attributes differently. Their preference is to avoid the traffic jams, as it does indeed decrease their satisfaction. Instead of driving through the city and parking there, they prefer to pay less and get to the destinations faster. They also do not mind paying more for the trip if the road would go through a place with pleasurable scenery.

2.2 Social influence

Social influence is a psychological process of changing one's opinion, behavior or attitude when exposed to interactions with others. It is considered by some to be one of the most important topics in social psychology or, even more, to be synonymous with it (Fischer & Vauclair, 2011). The first evidence about the existence of this phenomenon origins in the 1950's. Around that time, a researcher named Solomon Asch (1951) confirmed, that a person placed under pressure of a majority with different opinion will most likely yield and adjust. In his experiment he ordered one person, a critical subject, to say which line, out of three possibilities, was matching the one given in an example. The subject was confronted with the contradictory answers of seven other group members, who were purposely giving them wrong. As a result, a stunning 1/3 of the critical subjects fully conformed with the rest of the group, giving the wrong answers 11 out of 12 times (Asch, 1951). This experiment is considered to be the first of many which proved that an individual's psychological processes are prone to the influences of the group. Later on, with better understanding of the social influence phenomenon, more advanced research followed, giving more insights into human psyche. Kelman (1958) argued that is it not enough to know that the change of attitude or behavior has happened, but that the reasons behind it should also be known. That knowing the motivational processes would help to determine the consequences of the new posture and its implications. Therefore, he introduced three varieties of social conformity: compliance, identification and internalization (Kelman, 1958). Nowadays, in social psychology books, when regarding social influence, the most often discussed and described types are: conformity, obedience, social loafing, attitude change and persuasion (Fischer & Vauclair, 2011). Out of the aforementioned, non-exhaustive, list of social influence mechanisms, conformity is the one most related to the scope of this research, as it analyses the change in people's behavior due to being influenced by others. Therefore, its three types will be discussed in the subchapter 2.2.1.

2.2.1 Social influence measurement

Social influence can be measured in two ways: direct or indirect. The first option includes asking the subject straightforward if he/she has been influenced in any way by their social environment. One of indirect measurements involves more sophisticated questions, which ask what the environment of the person would think about a certain matter that subject is or isn't doing. Another way is to identify what does the social environment of the subject do (or doesn't do) and confirm that subject does (or doesn't) do the same (Blais, Galais & Coulome 2019).

2.2.2 Mechanisms of social influence

Conformity is the act of changing one's opinion, action or attitude to fit with the responses of others. It is distinguished from normative behavior by the fact that a subject suddenly contradicts their previous opinion and agrees with the opinion of the rest of the group. This is caused by a perceived or actual pressure exerted on the subject by the rest of the group (Cialdini & Trost, 1998). When conforming, every individual tries to achieve their own goal, such as, for example, building and maintaining social relationships, effectivity or maintaining a positive self-concept (Cialdini & Trost, 1998; Cialdini & Goldstein, 2004). Conformity can take three main forms: compliance, internalization and identification (Kelman, 1958). All three types are described below.

Compliance

Compliance, also called normative conformity, is a particular type of response to a request. The request can be direct, such as a person asking for donations, or in a less obvious form, such as political advertisements showing the qualities of a candidate, silently asking for a vote. Once the request is made, the target uses their feelings to assess if the compliance will happen. What distinguishes this type of conformity is the fact that the subject knows that they are being targeted (Cialdini & Goldstein, 2004).

Compliance is the type of social influence which is hard to find in research regarding travel behavior, however, there are examples to be found. Emond and Handy (2012) checked which factors influence children to go to school by bike. Out of all surveyed students, only 33% have responded that they usually use this transportation mode to go to school. This 33% has been subjected to different types of social influences, exerted by their peers as well as their parents. In case of the first group, most of their peers were also using a bike as the main transportation mode. The parents' group mostly verbally encouraged their children to use a bike. It can be therefore concluded that the children were responsive to compliance exerted by their parents, proving social influence phenomenon's existence in travel mode choice.

Internalization

Internalization, also called informational conformity, is accepting and believing the judgements of the group. A subject is certain that the group judgement gives an accurate representation of the reality, accepts it as a norm and follows it in order to behave correctly (Holzhausen, 1993). A popular example of this phenomenon is following a religion. The believer subjects to shared meanings and social habits which are practiced and in turn gets support and guidance from the community (Ryan, Scott & King, 1993)).

An interesting internalization example can be seen in the research of Caiati, Rasouli and Timmermans (2019) who have investigated the willingness of adopting MaaS (Mobility as a Service). In their stated choice experiment, they have asked the respondents to assess the probability of buying a Maas subscription based on various factors presented. One of them was percentage of relatives, friends and colleagues already using MaaS. The results have shown, that positive reviews of the service coming from the society in general positively and significantly influence the intention of buying the subscription.

Identification

Freud was one of the first who described social influence mechanism called identification. He described it as “the earliest expression of an emotional tie with another person”. Identification is a process in which an individual adopts and follows the values and behaviors of another person. The person does not necessarily have to be famous, although it is a very often observed phenomenon (Fraser & Brown, 2002). Lasswell (1956) used this concept and related it to nationalism as a form of mass identification.

In the context of travel behavior, this type of social influence can be seen in the study carried out by Paez and Scott (2005). In their Monte Carlo simulation, they have tested the quickness of telecommuting adoption. After creating the social network, the adopters were divided into two waves: 1 and 2. Wave one included adopters who decided to telecommute without external stimuli- early adopters. The second included people who adopted telecommuting in second wave as well as people who continued to do so since wave 1. The second wave adopters was exposed to four different information types: (i) no social influence, (ii) influence from previous adopters only, (iii) influence from previous nonadopters only, (iv) influence from both adopters and nonadopters. The results have shown, that when the second wave adopters were exposed to the influence of previous adopters, their increase in numbers was 24% more than in the first wave. On the other hand, when exposed to influence of the nonadopters, the number of second wave adopters decreased by 7%. It can be therefore said, that when exposed to social influence, people tend to adopt new technology much quicker.

2.2.3 Social influence and its role in attitude and behaviour change

Human behavior is hard to predict (Minitab blog, 2013). However, it is appropriate and accurate prediction provides useful data to a wide variety of people, companies and governments. It is useful when predicting if there is a chance of the new product being successful on the market, it helps to predict election outcomes, or it can indicate if citizens will like the new infrastructure development. In the past, there have been various attempts in trying to find out a precise way of human behavior prediction, from assessing general attitudes, through the locus of control, ending at the "Theory of Planned Behavior", which nowadays is the most widely used theory in human psychology (Abrahamse, 2019). It was created by Ajzen (1991), whose starting point was an assumption, that a person's behavior is influenced not only by personal traits but also by the particular occasion, situation and forms of action. The behavior, observed on various occasions and in different situations, tends to give more information about one's disposition than observing a single behavior in a one-time situation. Further, Ajzen writes, that personal traits influence behavior indirectly, and direct influence is exerted by the intention to carry out the behavior. Intention to carry out the behavior is, in turn, driven by the attitude towards behavior, subjective norm and perceived behavioral control (Fig. 3). The first factor refers to one's positive or negative mindset regarding a particular behavior. The second one refers to social pressure regarding carrying out (or not) of a certain act. The last factor is the ability to perform it out of own free will and succeeding at it. The ability to perform includes one's judgement on how well he/she can execute a certain behavior or deal with a situation. In general, the better attitude, more favorable subjective norm and bigger perceived behavioral control, the stronger the intention of performing a certain behavior, therefore the bigger likelihood of performing it (Ajzen, 1991).

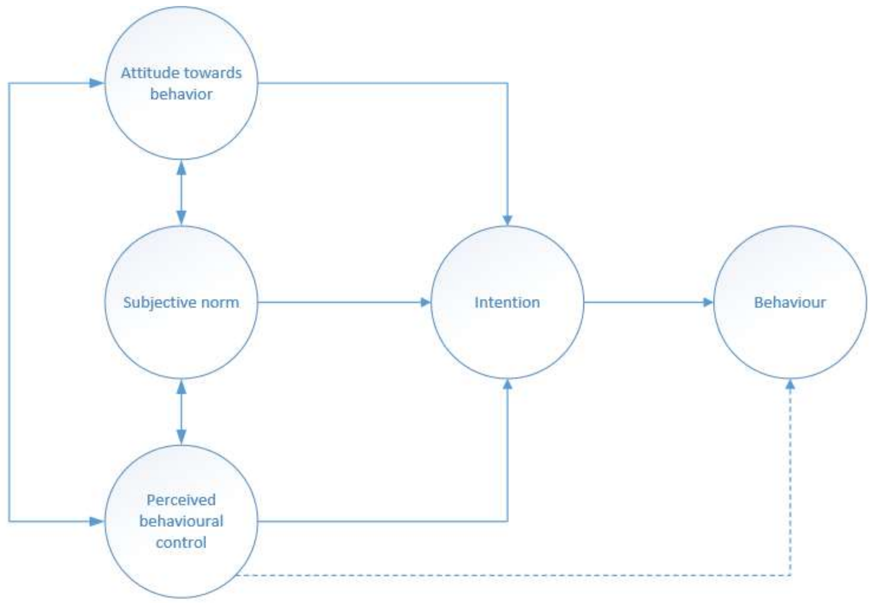


Fig. 3: The theory of planned behaviour (Ajzen, 1991)

Out of three factors driving the intention, attitude is most prone to be tempered with by the third parties. Normally, a persons' attitude- their way of responding to people, objects or events- is consistent with their knowledge and the state of mind. However, when someone tries to affect one's attitude by introducing new information, existing order is disturbed. New information is processed, while trying to rearrange the existing and the new piece of information to fit in, producing equilibrium again. In every person's mind there is a need of consistency between the cognition and beliefs, values and actions (Cohen, 1964). The process of purposely changing someone's attitude about something is considered as social influence. Therefore, using one's influence to change another person's attitude can ultimately lead to a change in behavior.

The act of influencing does not always have to be successful. Cohen (1959) has presented, that one's personality traits do not necessarily have to determine the persuasion easiness. However, there are factors which increase the likelihood of being persuaded (influenced). Some of these are: low self-esteem, perceptual dependence or social isolation. He has hypothesized that one's self-esteem is a function of the differences between person's ideals and their rate of success at achieving those ideals. In his attempt in confirming that, he found out that people with low self-esteem are more likely to be influenced by the ones with high self-esteem than the other way around. Moreover, people with low self-esteem are less likely to try to influence someone. A relatable theory has been tested by Leventhal and Perloe (1962) in which undergraduate students received persuasive communications about the Army and the life in it. Half of the subjects have received positive and optimistic communications, while other half received the negative, pessimistic and even hostile ones. The results showed that students who were said to have high self-esteem were more easily influenced by the positive communications, while the ones with low self-esteem were more likely to be influenced by the negativity.

Social influence can be divided into three different levels: direct, less direct and indirect level (Sherwin, 2014). The direct level occurs through the interaction with our loved ones: partners and families. The second type, less direct, concerns the influence exerted by peers, friends and colleagues and the third one includes the social and cultural context. According to Sherwin's theory (2014), the closest relatives, who represent the direct level of social influence, are those who have the biggest influencing power. As a person grows up, they take over the habits, attitudes and behaviors from the closest relatives. At a later point in life, the person potentially moves in with their partner. The constant interaction produces new customs, as the partners are being exposed to each other's behaviors and therefore adapt them. The results of her experiment in the context of cycling adaptation turned out to be confirming the theory. The subjects, varying from regular cyclists to non-cyclists, when asked about the reasons to start cycling have indicated the direct of influence, mentioning their family and partners as the reasons. However, a large number of people stressed that they have been influenced by their friends. According to them, it was a great way to start and sustain the habit of cycling (Sherwin, 2014).

2.3 Parking attributes

A car park plays an important role in the congestion degree inside city. Depending on their location, price and other attributes, they can be fundamental in encouraging or restricting the access into the centers (Ferilli, 2008). It has been researched, that the factors influencing driver's choice of parking can be divided into tangible and intangible factors. The intangible factors relate to one's subjective feelings, such as the feeling of safety, convenience or comfortability. It is impossible to measure them directly, but it is possible to rate or compare them to other factors. Tangible factors on the other hand, relate to the factors which can be physically measured. Those can include: trip characteristics, socio-economic background, and parking conditions. Trip characteristics mainly focus on the trip purpose, socio-economic background of the driver and parking conditions related to parking attributes (Teknomo & Hokao, 1997). In the research regarding parking choice, a lot of attention has been given to researching the important and less important parking attributes. Of course, the ideal parking spot would be free of charge and as close to the destination as possible, with the possibility of seeing the destination from the car. Moreover, the it should be easily accessible, without a having to spend a lot of time cruising for parking (Robertson, 2007). Unfortunately, most of the times it proves to be impossible to find it and certain trade-offs have to be made. From literature research it is clearly visible that the most often recurring parking attributes are: parking cost (fee), walking distance (to the destination) and access time (location). The other attributes vary from research to research, however, it is common to include the type of parking facility, parking availability (Ji, Deng, Wang & Liu, 2007), expected search time or waiting time (Chaniotakis & Pel, 2015).

The first decision that driver has to make when choosing a parking is to choose the parking type. They can be broadly categorized into "on-street", "off-street", "multi-story", "surface", "underground" and "illegal" (Brooke, 2015). The preference of the parking type is highly dependent on the trip purpose and duration. The on-street parking is easily accessible and more convenient than an off-street facility. Probably that's why a strong link between the preference of the on-street parking and shorter errand duration has been established (Hunt & Teply, 1993; Kobus, Gutierrez-i-Puigarnau, Rietveld & Van Ommeren 2012; Ma, Sun, He & Chen, 2013; Golias, 2002). Golias (2002) has found, that the choice between off- and on-street parking is highly dependent on parking duration: with increasing time, the preference for off-street parking increases. It finds a confirmation in conclusions made by Kobus et al (2012) who have found out, that the probability of using on-street parking is much higher when the parking duration is short, and it decreases sharply with increasing parking time. On the other hand, Teknomo and Hokao (1997) come to different conclusions: their findings have shown that it is the off-street and multi-story parking which is in bigger demand. Their research is confirmed by findings of Lambe (1996), who concludes that people value the fact that they do not have to walk on the street and choose for the parking attached to their destination. Lastly, Morency and Trepanier (2008) have found that women have a preference for interior parking.

The parking fee- the price charged for using a parking facility- is often studied when researching parking choice influencing factors. The prices can be charged in differently, for example, in an hourly or daily manner. They vary depending on the type of facility chosen: on-street parking can be free of charge or paid with the curb-side meters in which a certain amount of money has to be inserted for the expected parking duration. In the case of off-street parking, the fees are dependent on the location, parking quality as well as car park ownership (publicly or privately owned) (Brooke, 2015). Parking pricing has been found to be enormously influential in the matter of congestion. Anderson, De Palma (2004) and Shoup (2005) have stated that if parking prices are not structured with relation to the distance to the city center, the driver will try to park as close as possible to the center, contributing to the traffic problems. If such law is enforced, the drivers have been noticed to park further from the destination in order to avoid the higher charges (Ferilli, 2008; Westin & Gillen, 1978). However, according to Exel and Rietveld (2009) this statement holds only if the traveler is forced to pay for the trip him/herself. If the parking is subsidized by employer, the drivers are less price-sensitive. Price-sensitivity has been found to be related to the trip purpose. The fact that various researches conducted have indicated that in work- or business-related trip, the charge for the parking is not of utmost importance, seem to be a confirmation of that statement (Teknomo & Hokao, 1997; Hensher & King, 2001; Bonsall & Palmer, 2004; Kelly & Clinch, 2006). Teknomo and Hokao (1997) link the price-insensitivity of business or work travelers to the higher value of time, as the trip is often limited by a certain time constraint (Bonsall & Palmer, 2004). On the other hand, when carrying out a trip without time constraints, such as in the case of shopping, the motorists show a preference for a less-pricy or free parking spot and are willing to spend more time looking for it (Teknomo & Hokao, 1997; Morency & Trepanier, 2008; Van der Waerden, 2012). Price-sensitivity has also been discovered in the case of long duration parking. Kobus et al (2012) and Tsamboulas (2001) have examined the motorists who reacted negatively when being offered an increase in the parking charges, as long-time parking increases the cost more substantially when compared to the short-time parking. Ma et al, (2013) have found a connection between free and illegal parking. In case of short parking time, the drivers were risking a fine in order to avoid payment. When it comes to socio-demographic characteristics of drivers and their willingness to pay, the studies have come to the following conclusions: Morency and Trepanier (2008) have concluded that free parking is preferred by younger people. The contradictory statement has been made by Anastasiadou et al (2009), who stated that the older respondents were less likely to pay. Van der Waerden (2006), seems to be confirming both of those researches and stating that both older and younger people were more likely to change the mode of transport if asked to pay for parking. When considering differences between genders, it has been found that men are favoring the subsidized parking (Morency & Trepanier, 2008) and are also more likely to accept the increase in the parking charges than females (Tsamboulas, 2001) who pay much more attention to the parking price than males (Mo & Zhang, 2008). It has been also found by Bonsall and Palmer (2004) that wealthier people tend to choose parking closer to the destination in order to avoid long walking distance. It can be linked to the fact that that wealthier people pay less attention to parking fees but consider the distance and parking quality to be more important (Ferilli, 2008).

The walking distance can be described as the distance which one needs to walk from car to the location of entering the destination. Despite different trip purposes, all drivers want to find a parking place as close as possible to the destination, ideally in a parking garage attached to the building (Ma et al, 2013; Lambe, 1969). It has been proven to be true in the case of work- of business-related trips (Griffioen-Young et al, 2004) as well as ordinary shopping or private business, such as doctor visit (Lambe, 1969, Kobus et al, 2012). Lambe (1969) has postulated that the smaller the walking distance, the higher the willingness to pay. It finds confirmation in the results of Anderson et al (2006) who has stated that a person is willing to pay almost USD 0.50 per minute in order to park closer to the destination. Axhausen and Polak (1991) on the other hand, have checked the value of walking-to-the-destination time and have judged it to be more important than the in-car access and parking search time. Van der Waerden (2017) has researched the motorists' departure decisions and has proven that a big part of the society accounts for walking distance when choosing the departure time, especially when the final destination is work related. On average, the drivers try to find a spot from which the walking distance is equal to approximately 5 minutes (Ma et al, 2013). It has also been found that the closeness to the destination increases the probability of a driver being aware of the parking. The probability decreases with the walking distance (Van der Waerden & Timmermans, 2014). Bonsall and Palmer (2004) have come to the conclusion that females are much less inclined to choose for a long walk to the destination. Moreover, they have found out that with higher income the probability of choosing a car park with long walk time is smaller.

Another attribute which is being mentioned often is the security of a parking facility. According to the RAC Foundation (2005), the drivers are willing to pay 10% more for a parking if it is secure and well lit. After conducting their research, Teknomo and Hokao (1997) have come to the conclusion that it is the security of parking which is the most important attribute for the drivers who chose for off-street/multi-story parking. This seems to be confirmed in the research of Golias (2002) according to whom bigger preference for off-street parking and security goes along with the parking of longer duration. While both sexes consider the security to be important when choosing a parking place, a bigger number of females find it especially important when deciding where to park in a facility (Caicedo, Robuste & Lopez-Pita, 2006). Moreover, security has been found to be an important reason for choosing travelling by car over any other mode of transport. This effect correlated with the increased age of a respondent: the higher the number, the smaller the tendency to seek new challenges (Paulssen, Teme, Vij & Walker, 2014).

There are other attributes which can be found in the literature, however they appear with lesser frequency. For example, Bonsall and Palmer (2004) have included waiting time in their experiment and have proven that it is often taken into account by the travelers when scheduling when to leave home. It has been proven to be true in cases of both, shopping- and work-related errands. Moreover, they have also shown that females are more discouraged by a visible queue, as they trust the Parking Guidance and Information (PGI) time estimation more. In general, the driving simulation results have shown that people, once they became more acquainted with the city tend to follow the PGI instructions less and rely on their knowledge more. This is not the case when the unfamiliarity with the city is high. Then, people trust the PGI more, take its advice into the account. For example, in the case of PGI saying that a certain parking facility is full, half of the respondents would head to another parking nearby (Bonsall & Palmer 2004). When it comes to the parking duration, Van der Waerden (2012) has postulated that there is a significant difference between the weekly and non-weekly shoppers: The second group values the parking with no time restriction much more than the first. On the other hand, weekly shoppers like to park as close to the entrance as possible (Van der Waerden, 2012). Differences in parking behavior between males and females have been found by Salomon (1986) who concluded that females spend less time searching for a parking spot than males. Fletcher (1995) on the other hand has found that males are more likely to park illegally- in the designated spaces for disabled users.

Table 1: Overview of parking attributes

Researched attributes	Reference
Parking tariff	Anderson & De Palma, 2004; Shoup, 2005; Ferilli, 2008; Westin & Gillen, 1978; Exel & Rietveld, 2009; Teknomo & Hokao, 1997; Hensher & King, 2001; Bonsall & Palmer, 2004; Kelly & Clinch, 2006; Morency & Trepanier, 2008; Tsamboulas, 2001; Ma et al, 2013; Anastasiadou et al, 2009; Van der Waerden, 2006, Bonsall & Palmer 2004
Walking distance	Ma et al, 2013; Lambe, 1969; Griffioen-Young et al, 2004; Kobus et al, 2012; Anderson et al, 2006; Axhausen & Polak, 1991; Van der Waerden, 2012; Van der Waerden & Timmermans, 2014; van der Waerden, 2017; Bonsall & Palmer, 2004
Parking type	Hunt & Teply, 1993; Kobus et al, 2012; Ma et al, 2013; Golias, 2002; Teknomo & Hokao, 1997; Lambe, 1969; Morency & Trepanier 2008; Fletcher, 1995
Security type	RAC Foundation 2005; Teknomo & Hokao 1997; Golias, 2002; Caicedo et al, 2006
Waiting time	Bonsall & Palmer, 2004
Search time	Salomon, 1986
Parking duration	Van der Waerden, 2012

2.4 Parking models

In an attempt to understand people's travel behavior, researchers have been busy creating parking models which could help to get more insight into that subject. Over the years, many parking models have been developed and they vary among each other: they tackle different problems or try to find the answers in different ways. Parking models can be divided into two main types: spatially implicit and explicit models (simulations) (van der Waerden, 2012; Martens, Benenson & Levy, 2010). The first type is considered to be the predecessor and focuses on the driver's parking choice in an urban situation, where they are placed in a non-specified city and streets. An exemplary parking model is the one made by Arnott and Inci (2006), which focuses on a big problem occurring in downtown parking: congestion. The model's assumptions are simple and uniform when portraying the drivers and the conditions. The drivers are homogenous, risk neutral and they travel by car. Their travel starts and ends in different downtown areas; however, the covered distance is always equal. When close to the destination, the driver starts looking for an on-street parking place. In case the driver notices a vacant spot, he/she parks there; otherwise, drives around the block to find another. Once parked, each motorist will spend the exact same time outside of the car and, once done running errands, will exit downtown. Arnott and Inci were the pioneers in creating models which look at the parking process from the economic perspective; they did not pay attention to the parking attributes, nor to the psychological aspects of the drivers (Arnott & Inci, 2006). Since 2006, the models have been substantially improved, and now include many different factors that are important when choosing a parking spot, sometimes even account for people's different preferences. The first generation of models, which example of is the model made by Arnott (2006), is used to provide information about the dynamic parking patterns in urban districts, resulting in more information about the relation between parking policy and the parking conditions. That is why the models are said to portray the parking process from the economical point of view. (Martens et al, 2010). The second group of parking models covers the simulations in spatially explicit environment. It places a driver in a forced, but real situation: for example, in the streets that the driver is familiar with, to see his/her behavioral reactions in a given traffic situation (Martens et al, 2010). The number of existing researches focusing on the driver's behaviors in a simulation is limited. One prominent example is the PARKIT, developed in 2004 by Bonsall and Palmer. Their simulator allowed them to check the behavioral responses of "drivers", who had to carry out few driving simulations. Each simulation was different in terms of the given journey information (required arrival time), context (trip characteristics) and audio-visual stimuli (roadside signs, PGI) (Bonsall & Palmer, 2004). The driver's reactions and changes in their parking choices were carefully observed and with the help of the mathematical models provided a lot of new insight into the traffic behavior of car drivers.

According to the specification made by Young (2008), the models can also be divided based on the problem they take on. When considering this division type, there are five different types of models: parking design models, parking allocation models, parking search models, parking choice models and parking interaction models. The parking design models are focused locally, restricted to a certain parking facility and are created to check its performance. Parking allocation models research the number of arrivals to a facility in a bigger scale, up to a regional level. The third type, parking search models are designed to work on a metropolitan level in order to collect information about the existing systems to facilitate the parking search. Parking choice models check the responses of the motorists when faced with a change in the state of the parking facility. Lastly, the parking interaction models are representing the behavioral response of drivers who have been faced with a change in a parking policy (Van der Waerden, 2012). The model type which relates to the aim of this research the closest is the parking choice model, as it focuses on the behavior of drivers who must react to imposed parking conditions. Similar model has been created by Chaniotakis and Pel (2015), who have tested the driver's behavior when faced with uncertain parking situation. In their stated preference experiment, they have included 6 attributes: (i) parking type, (ii) parking fee, (iii) walking distance, (iv) travel time to parking location, (v) probability of parking upon arrival and (vi) probability of parking after 8 minutes. Each respondent had to choose one out of two presented alternatives. For the data analysis, three models were created: multinomial logit, mixed logit and panel mixed logit model. The models were characterized by the $R^2=0.114$ for the multinomial, $R^2=0.115$ for the mixed logit and $R^2=0.300$ for the panel effect mixed logit. The researchers have concluded, that the most important parking attribute was the parking tariff, followed by the probability of parking after 8 minutes. Other attributes were characterized by much lower part-worth utility (Chaniotakis & Pel, 2015).

Research of Iqbal (2018) and Laro (2018) is one of the few existing examples of applying social influence in the context of parking. The survey, created by Iqbal, was analyzed with the help of statistical models by Laro. The following attributes were employed: (i) parking tariff, (ii) walking distance, (iii) parking type, (iv) security type, (v) opinion family member, (vi) opinion friend, (vii) opinion colleague, (viii) opinion expert. The opinions which the groups were expressing were either of positive or neutral kind. The results have shown, that the most important parking attributes are parking tariff and security type. When it comes to social influence, Laro found, that advice coming from the family was the most important. The respondents seemed to be particularly eager to accept the advice regarding safety of the parking. The MNL model has performed below expectations, with $R^2_{adj}=0.074$, while the mixed logit model was characterized by $R^2_{adj}=0.184$.

2.5 Conclusions

Chapter 2 depicts the mechanisms and underlying psychology of decision-making, choice behavior and social influence. It explains, that every individual has an attitude towards a certain object or person. That attitude, coupled with two other factors, influences intention of performing a certain behavior. Therefore, it can be said, that by influencing someone's attitude, it is possible to influence their decision-making process, eventually leading to a behavior change. Next subchapters give an overview of the parking attributes. Out of many mentioned, it becomes clear, that only few of them matter in the process of parking spot selection: (i) the parking tariff, (iv) walking distance, (iii) parking type and (iv) parking security.

3. Research approach

3.1 Introduction

In the research regarding individual's preferences it is important to a use framework which focuses on finding out the underlying factors that guide one's behavior. In other words, to try to figure out why a certain person prefers one alternative to another (Hensher et al, 2005). Choice analysis, which focuses on explaining different behavioral responses, tries to establish just that. One's choice in choice analysis is seen as a final result of a decision-making process, which, in order to be completed, needs to follow some steps. Right after noticing the problem, one needs to determine the possible alternatives in a given situation. It does not mean that literally every existing alternative will be taken into account, just the ones of which the decision maker is aware and only the ones that are available at the moment of choosing (Majumder, 2015). Then, all alternatives need to be carefully evaluated and relatively best one should be chosen. However, it should be noted, that not all decisions are a result of a well-thought decision-making process. On the contrary, some choices are a result of habit, conventional behavior, intuition or imitation (Ben-Akiva & Lerman, 1991). Each person is different and faces choice situations in a different way, what can lead to variability in individuals' choices, also known as the society's heterogeneity. Moreover, some people can be additionally constrained- for example, by their income which does not allow to choose the most tempting alternative (Ben-Akiva & Lerman, 1991; Hensher et al, 2015).

The description of the decision-making process is relatively simple. However, its implementation in modelling is not so. The researcher should first come up with a set of alternatives to choose from. All alternatives should be mutually exclusive and collectively exhausting (Train, 2002). From all possible alternatives, also called universal set of alternatives, choice sets should be created. A choice set is then presented to the decision-maker. All presented alternatives should be feasible within their constraints, for example physically and timely available and affordable. Based on the feasibility of each alternative for each person, its attractiveness can be substantially increased or decreased, as the decision maker assigns a certain degree of attractiveness to every alternative. This "attractiveness index" is scientifically referred to as utility (Ben-Akiva & Lerman, 1991). It is assumed that the way to choose one, most appealing alternative leads through trade-offs, which are made by comparing different alternatives and choosing the one with the highest utility (Hensher et al, 2015).

The utility, denoted by the symbol U, consists of two main parts, V and ε, both of which are equally important to the researcher, as the first captures the influences observed by the researcher, while the latter the unobserved ones. It is the analyst's job to try to explain the underlying factors in both parts of the utility. It is assumed that both components are independent and additive, resulting in the following formula (Hensher et al, 2005):

$$U_i = V_i + \varepsilon_i$$

Where:

U_i- utility, alternative *i*

V_i- observable component of utility, alternative *i*

ε_i- residual, unobservable component of utility, alternative *i*

V_i, also referred to as the representative component of utility, can be decomposed to a linear expression in which each attribute is weighted by a unique weight, β, to account for each attribute's specific input:

$$V_i = \beta_{0i} + \beta_{1i} * f(X_{1i}) + \beta_{2i} * f(X_{2i}) + \cdots \beta_{Ji} * f(X_{Ji})$$

β_{0i}- alternative-specific constant

β_{1i}- weight associated with attribute X_1, alternative *i*

3.2 Setting up a choice experiment

The SP approach can be generally divided into two branches- preference and choice approach. Both belong to a domain of measures called "dominance measures", in which the respondent is faced with a task of assigning the relative preferences. When using the preference approach, the respondents are asked to express their subjective feelings in a form of ranking or rating. They can be assessing alternatives as a whole (decompositional preference) or the attribute levels separately (compositional preference). In the first case, the importance scores are derived based on the alternatives that were chosen, while the second case derives the utilities based on the attribute levels and their relative attractiveness (Kemperman, 2000). There are various issues associated with the preference approach, as it is complex and assumes high abilities of respondents to rate their preferences. When using this approach, the experiment construction should be considered especially careful, as the task difficulty increases with the number of options, substantially decreasing the data reliability. On the other side of the spectrum there is the choice approach, in which the respondent has to choose one out of few possible alternatives. It delivers less information- about one preferred alternative over the others, however, it is characterized by bigger reliability and smaller bias (Hensher et al, 2000). Hensher et al (1988) compared the two approaches and have concluded, that the choice designs were the easiest for the respondents to complete. Moreover, they were more successful in identifying the respondents' actual preferences than when using the preference approach (Hensher et al, 1988).

In order to properly develop a stated choice experiment, is it necessary to follow a certain order of tasks which is shown in Fig. 4. The first step, problem refinement, is there to fully understand the undertaken topic. Well researched and understood topic is necessary to set up a survey with appropriate questions, which in turn helps to find answers to the given problem. The general problem definition, made in Chapter 1, covers the existing parking problems in the cities and offers a new approach to solve them. In order to check the solution's validity, a SP experiment is created. Its alternatives, along with the parking attributes of the facility, include also a social influence factor. While the parking attributes have been researched numerous times, combining them with the social influence factors may give new insights into the psychology of parking. The literature research has shown, that it is possible to define different groups of social influence. The direct group includes the closest family and significant others, less direct: friends and colleagues, while the indirect one the social and the cultural context (Sherwin, 2014). This information helps to define the social influence and further refine the problem. It shows, that it is not enough to measure the social influence per se, but it is also important to know which group influences a person the most, if at all. Therefore, the social influence will be measured by the percentage of family, friends, colleagues and others parking at a certain parking.

The second step, stimuli refinement, is composed of two stages regarding the attributes. Stage one includes the identification of all possible attributes within the context of the research. Afterwards, the researcher must decide if he/she wants to exclude some of them or not, as there are two different ways of approaching the topic. In the case of attributes exclusion, it is necessary to decide which ones are important for the research. This is the downside of this approach, as different people can have a different opinion about which attribute is meaningful, and which not. Another, less often employed option, is to produce an experiment with all the discovered attributes. In that case, each respondent is given a certain number of alternatives distributed in such a way to make them manageable to study afterwards. This method is in general much more complex and delivers a large body of material, that is why, for the sake of simplifying, the first method is chosen (Hensher et al, 2005). After the attributes have been chosen, their levels need to be set. The researcher has to decide how many levels should be assigned to each attribute. In that case, the rule "the more, the better" holds, as with increasing number of levels, more information regarding the utility relationships can be obtained. However, this seemingly easy-looking task turns out not to be so, as there are several traps which a researcher needs to look out for. When labelling the attributes, they must be unambiguous, because sometimes, despite having the same name, they mean different things to decision makers. This can lead to a big amount of unobserved variability in the results and inability to properly assess the outcome. The attribute sets should also be constructed in a way to avoid inter-attribute correlation, as the inappropriate attribute connection leads to biased results (Hensher et al, 2005).

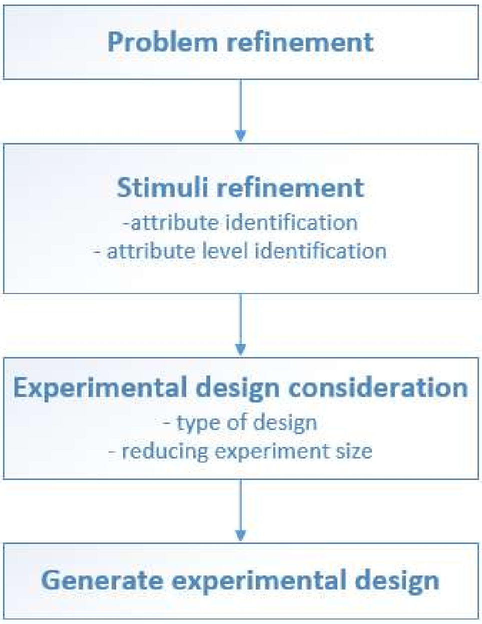


Fig. 4: Steps in setting up a choice experiment (Hensher et al, 2005)

After attributes and corresponding attribute levels have been chosen, the researcher can choose an experimental design to generate the alternatives. The aim of this step is to define the combinations of the levels of attributes in a certain way, in order to avoid their correlation. The two most popular designs are full and fractional factorial design. The full factorial design covers all possible combinations of all attribute levels. The total number of combinations is described by the formula: L^A, where L is the number of levels and A the number of attributes. For example, in the case of an experiment design with 3 levels and 2 attributes, the full factorial design equals to: $L^A= 3^2 = 9$ alternatives. In case the number of alternatives is not feasible to work with, it is possible to use to fractional factorial design, which uses only a fraction of all possible combinations. That, however, needs to be carried out according to the mathematical rules driving statistics, as a random alternative selection can produce inefficient designs, which cannot guarantee the effects being independently estimated. When designing a fractional factorial design, it needs to be cared for, that it is orthogonal. Orthogonal design ensures, that all the attributes are independent of each other: in other words, it prevents between-attribute correlation (Hensher et al, 2005). In mathematical form, the design orthogonality ensures, that once the attribute levels are coded, the multiplication of each column by other equals to 0 ("Orthogonal designs", Minitab support). Another condition of obtaining efficient fractional design, is to determine the main and interaction effects between the variables. The main effects describe the effect which an independent variable exerts on the dependent one, while the interaction effects focus on the effects which two independent variables together have on the dependent variable (Frost, 2017). The main and interaction effects should be established and taken into account by the analyst while creating the fractional design, as they may affect the utility of alternatives (Hensher et al, 2005).

According to Kroes and Sheldon (1988), one respondent can fairly assess from 9 up to 16 different alternatives, the reliability decreasing with the growing number to judge. In case of this study, the full factorial design will reach at least few thousand combinations, therefore the data collection process would prove to be unfeasible, extensively time- and money-consuming. Wanting to avoid bias and unreliable data, it has been decided to use the fractional factorial design.

3.3 Discrete choice models

3.3.1 Coding

Coding should always be carried out when dealing with categorical variables, as it allows the analyst to find the linear and non-linear relations between the levels of attributes (Hensher et al, 2005). The two most popular coding types are dummy and effects coding. In both cases the number of coded levels equals to K-1, where K is their total number. Such a way of work is required in order to avoid linear dependencies in the model (Daly et al, 2016). However, both coding types vary in a fundamental assumption: in case of dummy coding, the Kth level is omitted and used as the reference (base) level. In effects coding, the attribute levels utility is compared to the grand mean- the mean utility of all the attribute levels and allows to determine the utility of the omitted level too (Thompson, UCLA slideshow). Table 2 is illustrating the effects coding using an example of an attribute with three levels.

Table 2: Effects coding

Attribute level	Coding		Part-worth utility
1€	1	0	$\beta_{1i} * 1 + \beta_{2i} * 0 = \beta_{1i}$
2€	0	1	$\beta_{1i} * 0 + \beta_{2i} * 1 = \beta_{2i}$
3€	-1	-1	$\beta_{1i} * (-1) + \beta_{2i} * (-1) = -(\beta_{1i} + \beta_{2i})$

The first two levels are coded in the exact same way as in dummy coding. The difference appears in the third one: in the case of effects coding, the level is denoted as $-(\beta_{1i} + \beta_{2i})$. When the dummy coding is employed, the third level becomes confounded, as it equals not to the utility of this level, but rather to the average overall utility, what is not desired in the research (Hensher et al, 2005). That is why, the effects coding is chosen instead of the dummy coding.

3.3.2 Multinomial logit model

The multinomial logit model (MNL) is the most commonly used model from the logit family. It is considered to be the basic model, from which several others have been derived (Bhat, 2002). In this type of model, it is assumed, that a decision-maker *n* faces *J* alternatives. The utility in the MNL model consists of component V_{nj}, which is known to the analyst, and component ε_j, which is unknown, resulting in: $U_{nj} = V_{nj} + \varepsilon_{nj}$ (Train, 2002). What is important, is that the MNL model is derived under assumption, that ε_i component is independently and identically distributed (IID). The independence assumption states, that there are no common, unobserved factors affecting the utilities of alternatives. The identical distribution insinuates, that the variances of the unobserved effects are equal for all alternatives *j* (Bhat, 2002; Hensher et al, 2015). This assumption allows for the coefficients normalization and ultimately leads to obtaining the following formula:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1} e^{V_{nj}}}$$

Where:

P_{ni} - probability that individual *n* chooses alternative *i*

$e^{V_{ni}}$ - exponential function of the observed utility of alternative *i*

$\sum_j e^{V_{nj}}$ - sum of exponential function of all the observed utilities

As it was mentioned before, the MNL is derived under certain assumptions, from which IID is not the only one. The second assumption states, that the MNL accounts for the homogeneity of society. In other words, it is assumed that there are no taste variations among the individuals in the society. Another limiting assumption states that the error covariance is identical among all the alternatives for all the individuals. All three assumptions, even though convenient, can be violated and therefore lead to biased results. That is why, the MNL model has been used as the base on which other models have been developed in order to relax the three strict assumptions (Bhat, 2002). MNL model is also characterized by the independence of irrelevant alternatives (IIA), which states, that the ratio of two choice probabilities is not dependent on the existence (or absence) of other alternative in the given choice set (Hensher et al, 2015).

Binary logit model

Binary logit model is a special case of multinomial logit model, in which exactly two alternatives are judged (Ben-Akiva & Lerman, 1991). This type of model is practical and feasible to work with and is often used in order to analyze one part of many in an experiment. The outcome is often described using 0 or 1, where 1 denotes an event of interest happening, while 0 the event not happening. In this case, the dependent variable is binary, and the choice outcome is described as a function of the independent variable (Söderbom, 2010).

$$P_{n1} = \frac{e^{V_{n1}}}{e^{V_{n1}} + 1}; P_{n2} = \frac{1}{e^{V_{n2}} + 1}$$

Where:

P_{n1}- probability, that individual *n* chooses alternative 1
P_{n2}- probability, that individual *n* chooses alternative 2
$e^{V_{n1}}, e^{V_{n2}}$- exponential function of the observed utility

3.3.3 Latent class model

The latent class (LC) model, like many others, has been developed based on the MNL model. The LC model accommodates the heterogeneity which appears in the society. Unlike the MNL model, in which it is assumed, that the parameters are continuously distributed among all the individuals, LC model assumes their distribution in a discrete form. In other words, it is assumed, that the sample population is made of *C* groups of individuals. Each group is heterogeneous and has its own parameter (Hensher et al, 2015).

The LC model can be divided into two groups: with fixed and random parameters. The first one, also called standard LC model, will be used in this experiment. It assumes, that the parameters within one group are fixed, however, they vary between different groups:

$$P_{ni} = \frac{e^{V_{nC}}}{\sum_{j \in C} e^{V_{nC}}}$$

Where:
P_{ni}- probability that individual n chooses alternative i
$e^{V_{nC}}$- exponential function of the observed utility for individual n, belonging to class C
$\sum_{j \in C} e^{V_{nC}}$- sum of exponential function of all the observed utilities

3.3.4 Model evaluation

There exist many ways to evaluate how reliable the model is. Two most often employed methods are likelihood-ratio test, which describes how well the model fits the data (goodness-of-fit) and McFadden's R^2, which indicates how much of variation is explained by the model. Both are shortly described below.

Likelihood-ratio test

The likelihood-ratio test (LRS) tells the analyst how well the created model fits the data. It is based on the method of maximum log-likelihood estimation. When using the maximum log-likelihood theory, the created model maximizes the probability that observed data are present in this model (Field, 2013). Among others, maximization process includes identifying the parameters β which fit the data best. Moreover, the log-likelihood function is always negative and approaches its maximum when it reaches the parameters which fit the model best (Hensher et al, 2015). The maximum log-likelihood formula can be written as:

$$LL(\beta) = \sum_{n} \sum_{i} (P_{ni})^{y_{ni}}$$

Where:
P_{ni}- probability that individual *n* chooses alternative *i*
y_{ni}- choice index: equal to 1 or 0, depending on the choice outcome

The null model is a model which does not take into account the parameters used to estimate the full model (Gotelli, 2001). It is obtained by using the following formula:

$$LL(0) = n * \ln(1/a)$$

Where:

n - total number of observations

a - total number of alternatives

The LRS's value depends on the sample size, therefore it should be used to compare models with the same number of parameters only ("What is log-likelihood?", MiniTab Support). The LRS formula uses both maximized and null model to obtain a result:

$$LRS = -2(LL(\beta) - LL(0))$$

Where:
LRS- ratio test statistic
$LL(\beta)$- maximized model
$LL(0)$- null model

In the LRS formula, the multiplication by two is carried out so that the obtained value can have the same distribution as χ^2 and therefore be compared. If the critical value of χ^2 is exceeded, the parameters do indeed improve the performance of the model (Silvey, 1970).

McFadden's R^2

McFadden's R^2 also bases on the maximum likelihood theory. It can be interpreted as "how well the created model explains the variance existing in the model", with the higher the value, the better (Walker & Smith, 2016). The R^2 can take values from 0 to 1. The formula divides the maximized model by the null model (Hensher et al, 2015):

$$R^2 = 1 - \frac{LL(\beta)}{LL(0)}$$

Where:
R^2- prediction power of the model
$LL(\beta)$ – maximized model
$LL(0)$- null model

Models with bigger number of parameters tend to have higher log-likelihood, what leads to an indication of higher predicting powers than in reality. In order to avoid that, R^2_{adj} has been invented. The formula varies from the standard R^2 by subtracting the number of parameters from the maximized model, what "penalizes" it for taking into account too many variables which do not influence the dependent variable. It is necessary to use the R^2_{adj} if one wants to compare models with different numbers of predictors (Train, 2009).

$$\mathrm{R}^2{}_{adj} = 1 - \frac{LL(\beta) - K}{LL(0)}$$

Where:
$\mathrm{R}^2{}_{adj}$- prediction power of the model
$LL(\beta)$ – maximized model
$LL(0)$- null model
K- number of estimated parameters

3.4 Research construction

3.4.1 Attribute choice

A vast number of different types of parking attributes has been researched over the years. However, not all of them have been deemed important to the car drivers. Table 1 ("Overview of parking attributes") in section 2.2 highlights the attributes which have been declared to be important by the researchers. The more researches have declared the attributes significant, the higher probability that it truly is so, therefore, four most often appearing attributes in the reviewed articles have been chosen for the experiment: (i) parking tariff, (ii) walking distance, (iii) parking type and (iv) security type. For the sake of appropriate attribute level justification, it should be mentioned, that the SP experiment will place the respondent in a hypothetical situation of going shopping to the city center by car.

The "parking tariff" is considered to be one of the most important attribute in the research. The literature review states, that the price-sensitivity changes with the trip purpose: if one has to pay him/herself, the preference for cheaper, or free parking goes up (Teknomo & Hokao, 1997; Morency & Trepanier, 2008; Van der Waerden, 2012). It is assumed, that a person running private errands such as shopping, does indeed pay out of her/his own pocket. Therefore, this attribute is of high importance in this experiment. In the Netherlands, where free parking in the city center is rare, if not non-existent, this level is omitted. The parking fees are varying enormously, depending on the city, time and day of arrival and the parking itself. Van Ommeren (2012) has stated, that in 2012, an average hourly fee in a city center of a Dutch city was about 1.5€. On the other hand, looking at parking prices in medium-sized cities, it is possible to find a parking spot in the strict center for as little as 2.60-2.90€ per hour (based on the data retrieved from www.parkopedia.nl). With increasing distance, the prices decrease to as low as +/-1.2€. For the sake of simplicity in the data analysis, the levels of 1, 2 and 3€ will be taken into account. Choosing such levels will potentially allow to estimate the preferences on the level of 4€/hour.

According to Ma et al (2013) and Lambe (1969), the drivers want to have the shortest "walking distance" possible. However, as it is not always possible, the drivers do their best to park within a 5-minute walk from the destination (Ma et al, 2013). An average person walks about 1.4m per second, what gives the walking distance of about 420 meters. On the other hand, 700 meters has been found a "maximum reasonable walking distance" in studies on catchment areas regarding public transport stops. (Kittelson & Associates, 2003). Considering given information, it is reasonable to choose the walking distance of 100, 300 and 500 meters, 100 meters being the ideal walking distance to the destination, 300 meters being the average and 500 meters being the relatively long walking distance. Just like in the case of parking tariff, with the chosen levels, it will be potentially possible to estimate the preferences on the level of 700 meters, being the maximum "reasonable" walking distance.

The attribute "parking type" will be given three levels: on-street, parking lot and parking garage. According to various sources mentioned in the literature review, the preference for on-street parking is related to the shorter duration of the stay, which decreases with the prolonging duration (Golias, 2002; Hunt & Teply, 1993). On the other hand, some researchers have found a preference for off-street and multi-story parking, despite the length of stay (Teknomo & Hokao, 1997). As going to shop is a highly subjective matter and may last for a really short or really long period, depending on the person, their shopping needs, preferences and budget, all three levels should be considered in the research.

When it comes to the "security type", the existing body of research proves that it is an important factor when choosing a parking spot. However, it is rarely specified which exact type of security would be the most satisfactory for a driver. That is why, three most often encountered security types are used in the experiment: cameras, personnel, and the third option "no security".

The social influence factors are treated as attributes and measured along with the parking ones, in the same choice sets. From the examples shown in the literature review, a conclusion can be drawn, that there are three different levels of social influence: direct, less direct and indirect (Sherwin, 2014). From those three levels, four social influence groups are created and included in the research as attributes: family, friends, colleagues and others. Previous research carried out by Iqbal (2018) and Laro (2018) showed an approach, where the four groups were giving their opinions about the parking facility, such as "closest", "cheapest", "safest" or "no opinion". There is a possibility, that the given advice was too vague for the respondents, therefore the obtained results are not fully satisfactory. A different method of social influence evaluation is employed in this study: the percentage related to the number of people from social influence groups parking at a certain parking facility. Using the low (10%), medium (50%) and high (90%) percentage of people parking as the attribute levels allows to see how the driver's attitude towards the parking changes. For example, social influence estimation this way has been carried out by Rasouli and Timmermans (2013), who have tested the vehicle attributes, social influence and social network in relation to the latent demand for electric cars.

An overview of attributes and their levels is presented in the table below (Table 3).

Table 3: Attributes and their levels

	Level 1	Level 2	Level 3
Parking tariff	1 €	2 €	3 €
Walking distance	100 meters	300 meters	500 meters
Parking type	Off-street parking	Parking garage	On-street parking
Level of security	Security cameras	Security personnel	No security
% of family members	10%	50%	90%
% of friends	10%	50%	90%
% of colleagues	10%	50%	90%
% of others	10%	50%	90%

Out of the chosen attributes and their levels, it is possible to create a full factorial design which will have 3^8 =6561 choice alternatives. The time necessary to collect enough data to carry out the sample analysis would be unfeasible, therefore fractional factorial design is employed. In order to correctly estimate the necessary number of alternatives, Addelman's tables are used. Employing the tables allows to estimate the main effects without correlation, at the same time substantially decreasing the number of necessary combinations (Addelman, 1960). In the case of an experiment with 8 attributes, each of three levels, the minimum number of alternatives equals to 27. They can be seen in Appendix I.

3.4.2 Data collection

The data was collected using the TU/e's own survey system, called BergSystem. The survey was spread with the help of Panelclix, an online marketing panel (www.panelclix.nl), which helps with market researches. The members of the panel who expressed a wish to take part in the survey were first asked if they were over 18 years and had a valid driver's license. In case any of those questions were answered negatively, the potential respondent was not allowed to continue. Once answering the questionnaire, one additional question was asked to assess the eligibility: how often a person travels by car to the center. In case the answer was "never" or "rarely", the respondent was also denied the participation. The survey was divided into three main parts: a set of questions which focused on the respondent's background, the actual choice experiment, and questions regarding personal characteristics. All three are shortly described below.

The first set of questions was presented in the form of ratings and focused on the driver's habits regarding visiting the city center: their frequencies and time. Further, the respondent was asked how often they follow others when considering the transportation mode, route and parking type choice. The questions were to give more information about the driver's familiarity with the city's streets. Moreover, the mode, route and parking type choice are the most important decisions which one must make when deciding on travelling. They are also strictly interrelated, as the outcome of one choice may influence another (Van der Waerden, 2012).

The second part of the survey involved the SP experiment, which consisted of two parts. Before accessing the questions, the respondents were asked to place themselves in a hypothetical situation of going shopping into the city center by car. They were also shown an example question, to make them fully understand what type of questions would be presented further. The first part of the SP experiment, evaluation of one alternative, was a series of yes/no questions (binary questions), in which the respondent had to answer if they would park in a parking spot with presented attributes (Fig. 5). In the second one, evaluation of two alternatives, the respondent was facing two possible options and had to state which parking spot he/she would choose. There was also “none of the above” option, in case none seemed appealing (Fig. 6). This study focuses on the first part of the SP experiment: one-alternative choice.

After answering the questions regarding the SP experiment, followed a part regarding the social background of the respondents. They were asked about the age group, highest obtained education level and the gender.

Dit is een voorbeeldvraag!

Hieronder ziet u een beschrijving van een parkeergelegenheid die beschikbaar is bij uw bestemming. Daarnaast ziet u het gebruik van uw sociale netwerk. Ga er van uit dat u van plan bent bij de getoonde parkeergelegenheid te parkeren om te gaan **winkelen** in het stadscentrum. Geef aan het einde van de tabel aan, of u te getoonde parkeergelegenheid zou kiezen om uw auto te parkeren.

Voorbeeld evaluatie TAAK	Kenmerken	Parkeergelegenheid
Parkeergelegenheid	*Parkeertarief*	1 euro
	Loopafstand	500 meter
	Type parkeergelegenheid	Straatparkeren
	Veiligheidsniveau	Beveiligingspersoneel
Sociale netwerk	*Gebruik door Familieleden*	10 procent
	Gebruik door Vrienden	90 procent
	Gebruik door Collega's	50 procent
	Gebruik door Anderen	10 percent
Zou u de getoonde parkeergelegenheid gebruiken om uw auto te parkeren?		Ja Nee

Fig. 5: Evaluation of one alternative

Dit is een voorbeeldvraag!

Nu ziet u een beschrijving van twee verschillende parkeergelegenheden die beschikbaar zijn bij uw bestemming. Naast de parkeerkenmerken ziet u het gebruik van uw sociale netwerk. Ga er van uit dat u van plan bent bij een van de getoonde parkeergelengenheden te parkeren om te gaan **winkelen** in het stadscentrum. Geef aan het einde van de tabel aan welke parkeergelegenheid uw **voorkeur** heeft. Mocht u geen voorkeur hebben voor een van de getoonde parkeergelegenheden, dan kunt u de 'Geen van beide' optie gebruiken.

Voorbeeld evaluatie TAAK	Kenmerken	Parkeergelegenheid I	Parkeergelegenheid II	Geen van beide
Parkeergelegenheid	*Parkeertarief*	1 euro	3 euro	
	Loopafstand	500 meter	100 meter	
	Type parkeergelegenheid	Straatparkeren	Straatparkeren	
	Veiligheidsniveau	Beveiligingspersoneel	Geen beveiliging	
Sociale netwerk	*Gebruik door Familieleden*	10 procent	10 procent	
	Gebruik door Vrienden	10 procent	10 procent	
	Gebruik door Collega's	10 procent	50 procent	
	Gebruik door Anderen	90 procent	10 procent	
Welke parkeergelegenheid heeft uw voorkeur?				

Fig. 6: Evaluation of two alternatives

3.5 Conclusions

The designed SP experiment was carried out using the fractional factorial design, with the conservation of the orthogonality rule and accounting for the main effects. Out of 6561 (3^8) possible alternatives, 27 were chosen and presented to the respondents in an online survey. The survey collected three different types of information: about the driver's personal experiences, their parking preferences and personal characteristics. The importance of the following parking attributes was checked: (i) parking tariff, (ii) walking distance, (iii) parking type, and (iv) security type. The social influence attributes were measured in the percentage form: connecting the percentage of (i) family, (ii) friends, (iii) colleagues and (iv) others parking at a said parking facility. In total, one respondent was presented with 18 out of 27 alternatives: 6 in the binary choice questions ("yes/no" answer) and 12 in 6 choice sets, in which a respondent had to choose one alternative out of two possibilities (or "none of the above" option). The number of questions each respondent had to answer was 12. The collected data were analyzed with the use of binary logistic and LC model.

4. Data Analysis

4.1 Introduction

The survey was spread with the use of the Panelclix panel (www.panelclix.nl), an online platform which allows the users to fill in questionnaires in return for a small incentive. It was available online from 01.10.2019 until 31.10.2019. The members, after expressing their will to participate, were asked preliminary questions about the driver's license possession and frequency of going to the center by car as the driver. After being deemed eligible, they were allowed to further fill in the questionnaire.

4.2 Sample analysis

The survey received 617 responses, out of which: 1 has not given their consent necessary to proceed, 6 did not have a driver's license, which was necessary to take part in the survey, and 7 did not drive by car to the city center. These 14 responses were removed from the dataset, leaving 603 respondents. Some details of the respondents are presented in Table 4.

Table 4: demographics of the respondents

Total number of valid responses	603	
Gender		
	#	%
Male	309	51.2%
Female	294	48.8%
Age (years)		
	#	%
<25	50	8.3%
25-34	160	26.5%
35-49	160	26.5%
50-65	156	25.9%
>65	77	12.8%
Highest education level		
	#	%
Secondary school (VMBO, MAVO, HAVO, VWO)	157	26.1%
Vocational education (MBO)	186	30.8%
Academic education (HBO, WO)	260	43.1%

The respondent's distribution according to gender is almost equal, with a slight female dominance (51.2%). All age groups are present in the survey, however, middle groups are higher in numbers: with about 26% each, while the group of people below age of 25 and above 65 make only 21% of the sample. Most of the respondents have an academic diploma (43%), followed by a vocational education (31%). In the third place, there are secondary school diploma holders (including professional level), with 26% of total.

4.3 Comparison to the general Dutch society

One of the assumptions of quantitative research is that the sample represents the entire population (Fowler, 2009). That is why, it is important to check if collected data actually correspond with data of the population which it is supposed to mirror. In case of this study, comparison is made between the sample and entire Dutch society. The Dutch Central Bureau of Statistics, CBS for short, is a center which possesses information about every person which is registered in the Netherlands. Statistical data with which the sample is compared can be found on the website www.cbs.nl.

When comparing the collected sample with entire Dutch population, it seems to fit the general population quite well (Fig. 7). The differences in the number of female and male respondents vary marginally. However, discrepancies do appear in case of the age group 25-65, the academic and secondary education level. The collected sample has a higher number of people between ages of 25-65 and more people who have finished their academic education. At the same time, it has less respondents whose highest education level is secondary school (CBS, 2019). This can be attributed to the fact, that, in general, younger as well as higher educated people tend to be willing to answer questionnaires much more often than the rest of the society. All in all, however, the sample reflects the Dutch nation well enough to represent it.

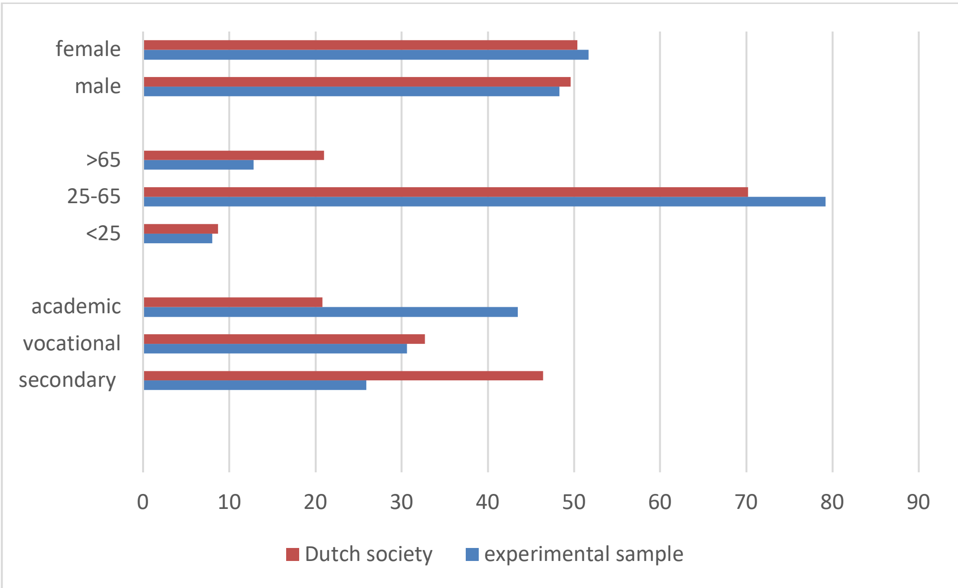


Fig. 7: Comparison of the sample with the Dutch society (CBS)

4.4 Respondents' experiences

The first part of the survey considers the driver's personal experiences. It includes the questions about the frequency of the city center visits, the time strip in which those visits take place, as well as the questions about following other people in the route, transportation mode and parking facility choice. The following figures show the respondents' answers.

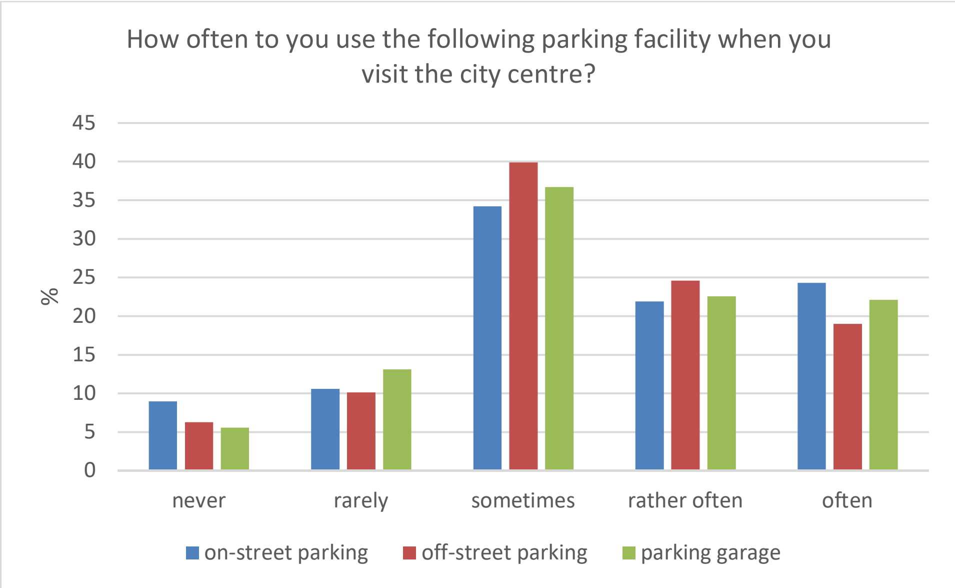


Fig. 8: Frequency of using certain parking facility type

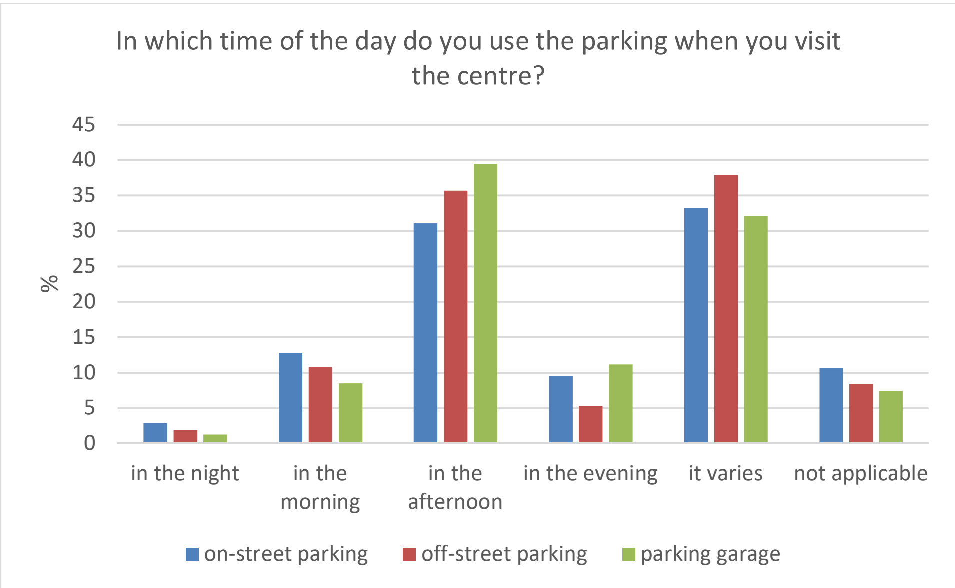


Fig. 9: Times of visiting the centre

In general, it can be said, that most of the drivers in the collected sample park at certain parking types “sometimes”. There are no big differences in the driver’s choices when choosing parking facility type. When regarding time of the day, “in the afternoon” and “it varies” indications prevail.

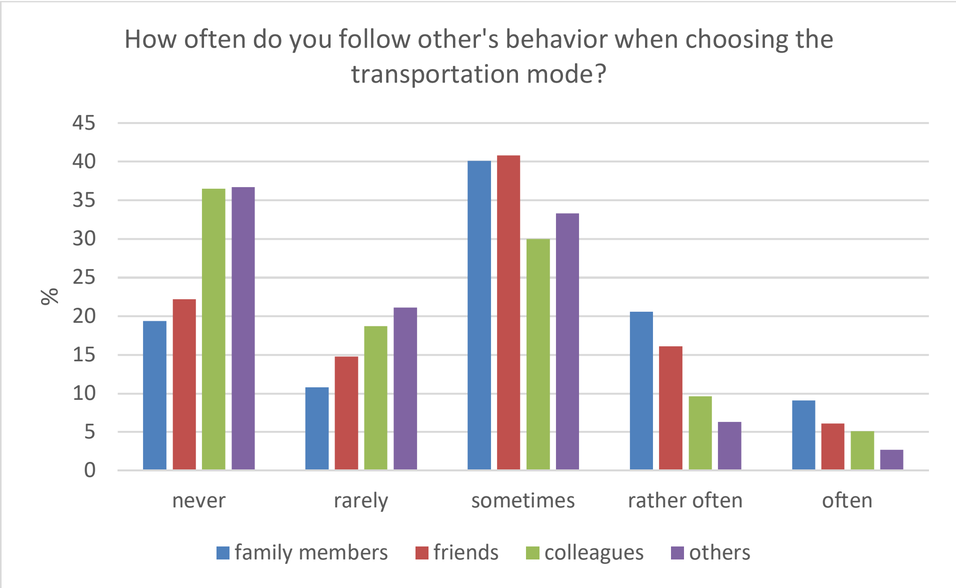


Fig. 10: Following others in choosing the transportation mode

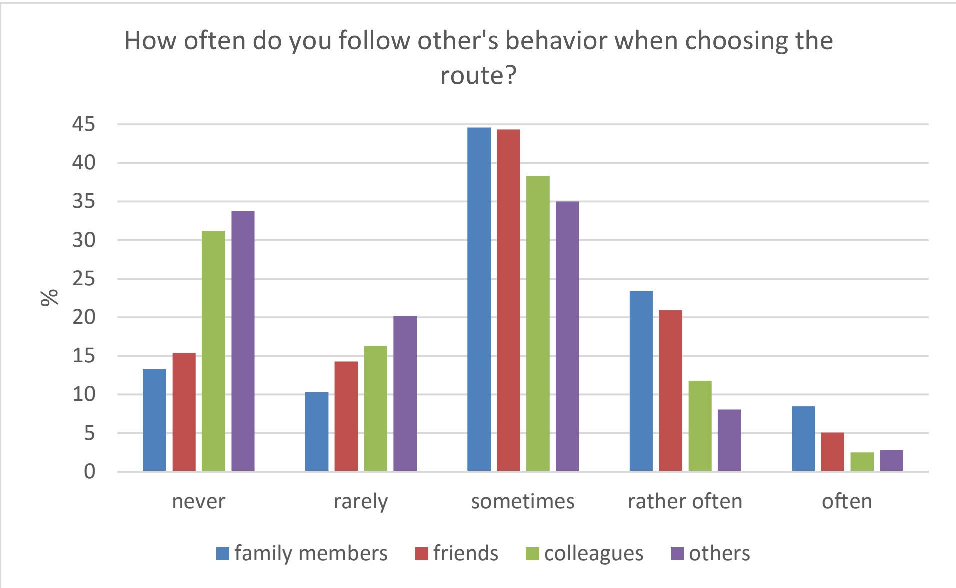


Fig. 11: Following others in choosing the route

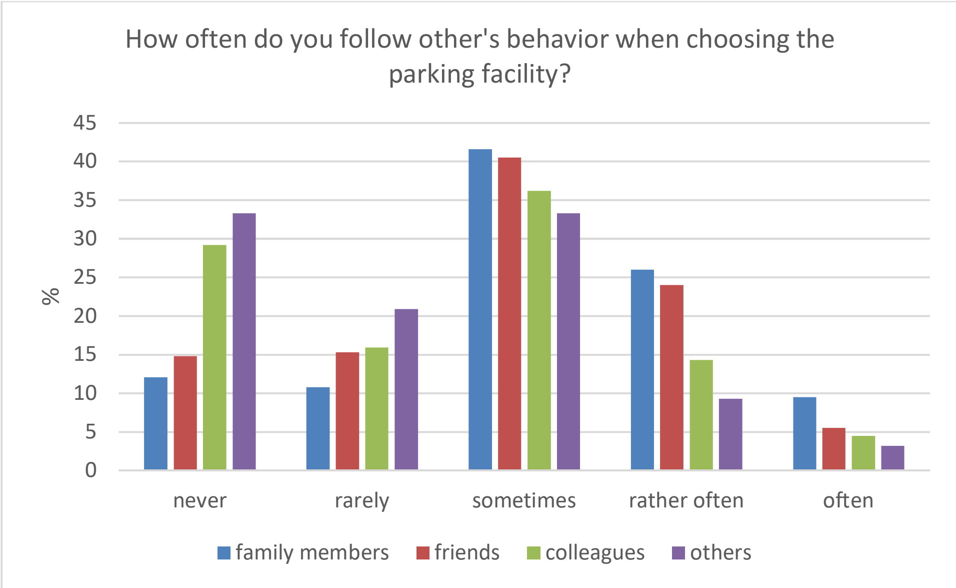


Fig. 12: Following others in choosing the parking facility

Further, the respondents were asked to indicate how often they follow others in the matters of choosing: transportation mode, route and the parking type. There is a visible trend among drivers who admit to following other's choices or behavior quite often: they tend to do it with people with whom they have closest relations much more often than strangers. The groups "colleagues" and "others" are followed much less often than the other two. Overall, the conclusion can be drawn, that the likeness of following decreases with the closeness of the connection. The results seem to be in accordance with the literature review: the most influencing groups are indeed family and friends, while the least followed group is the others group.

4.5 Stated choice experiment

The collected data was divided into two subsets: one regarding the evaluation of one alternative, and second concerning the evaluation of two alternatives. This study concerns only the first data subset: one-alternative evaluation (see Chapter 3, Fig. 6).

4.5.1 Binary logit model

The processed dataset considered the binary questions. The respondents were presented with 6 questions, in which they were asked to state if they would park there. Only one alternative per question was assessed, and the possible answer was "yes" or "no". In total, in the first part of the questionnaire, each person assessed 6 out of 27 alternatives. The survey was constructed in such a way, so that each alternative had been evaluated similar number of times- about 134. In total, all the alternatives have been evaluated 3618 times. In Appendix II, the crosstabulation of alternatives is shown.

The binary logistic regression model was created in NLogit software. By default, it displays only first two levels of each attribute. However, because of the effects coding, it is possible to calculate beta for the third level with the use of the following formula: $-(\beta_{1i} + \beta_{2i})$. As a rule of thumb, when attribute's significance level is p> 0.05, it is deemed insignificant. The attribute levels, along with their parameters and significance are displayed in Table 5.

Table 5: Binary logit model, part-worth utilities

	Full model, N=603	
	β	Sig. z
Tariff 1€	0.781	0.000
Tariff 2€	0.023	0.687
Tariff 3€	-0.804	
Walking distance 100 m	0.365	0.000
Walking distance 300 m	0.039	0.475
Walking distance 500 m	-0.404	
Off-street parking	0.123	0.043
Parking garage	0.159	0.007
On-street parking	-0.282	
Security cameras	0.305	0.000
Security personnel	0.159	0.006
No security	-0.464	
10% of family parks there	-0.194	0.000
50% of family parks there	0.019	0.740
90% of family parks there	0.175	
10% of friends park there	-0.154	0.006
50% of friends park there	-0.100	0.083
90% of friends park there	0.254	
10% of colleagues park there	-0.005	0.926
50% of colleagues park there	-0.019	0.734
90% of colleagues park there	0.024	
10% of others park there	-0.46	0.402
50% of others park there	0.037	0.505
90% of others park there	0.423	
Constant	0.961	0.000
LL(β)	-2014.780	
n	3618	
LL(0)	-2507.806	
LRS	-986.053	
R^2	0.196	

*Base level


Parking tariff
1,2
0,7
0,2
-0,3
-0,8
-1,3
1 €
2 €
3 €
Walking distance
1,2
0,7
0,2
-0,3
-0,8
-1,3
100 m
300 m
500 m
Security type
1,2
0,7
0,2
-0,3
-0,8
-1,3
Security cameras
Security personnel
No security
Parking type
1,2
0,7
0,2
-0,3
-0,8
-1,3
Off-street parking
Parking garage
On-street parking

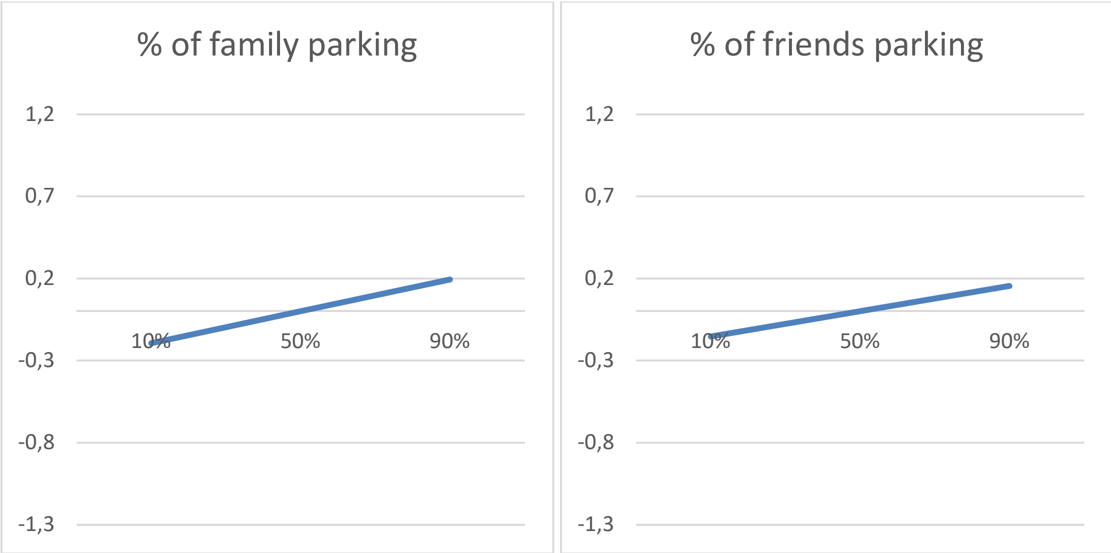


Fig. 13: Part-worth utilities, binary logit model

The results show, that drivers pay special attention to the parking price. The 1€ price has the highest part-worth, indicating, that it is the most desirable. The preferred walking distance is the shortest- 100 meters. Parking garage is characterized by the highest preference, while the lowest belongs to on-street parking. When it comes to security, drivers strongly prefer to have it rather than not. The obtained results seem to match ones of other researchers, who have stated, that when going shopping, the preference for the cheapest parking is the highest (Teknomo & Hokao, 1997; Morency & Trepanier, 2008; Van der Waerden, 2012). Moreover, the results agree with findings of Teknomo & Hokao (1997) and Lambe (1996) who have stated, that the preference for off-street and parking garage is higher than for on-street parking.

The social influence factors show, that "colleagues" and "others" groups do not matter when choosing a parking facility, as they are deemed to be insignificant. When it comes to family and friends, however, they prove to be influential. The preference of parking is high if 90% of friends or family park there and it decreases with decreasing percentage.

Having the R^2_{adj} value equal to 0.091 (from the range 0 to 1), it can be said, that the model performs below expectations. However, it should be noted, that trying to predict human behavior is a much more complicated process than experimenting with machines (Pituch & Stevens, 2016). Moreover, when dealing with human behavior, it is rare to obtain R^2 value higher than 0.5, deeming the obtained result acceptable (Minitab blog, 2013). When looking at LRS=-986.053 it can be said, that the data fits the model quite well, as the closer to 0, the better the goodness-of-fit.

The R^2_{adj} can be compared to the value obtained by Laro (2018), R^2_{adj}=0.074, as binary logit model is a special case of the MNL model with two options. It can be said, that the binary logit model shows a slight improvement in the prediction accuracy than its predecessor. The improvement, despite being relatively small, indicates, that changing the way of social influence factors inclusion from opinions to a percentage of people parking at a certain facility is a step in a right direction.

4.5.2 Binary logit model detailing

The literature research shows, that people tend to park differently depending on their age, sex and the income level. For example, Morency and Trepanier (2008) have stated, that young people pay much more attention to the price and they prefer to park in a free spot the most. Moreover, they have discovered a preference of women using interior parking. Tsamboulas (2001) has found out, that females pay much more attention to parking pricing than males. Bonsall and Palmer (2004) on the other hand, have concluded that females are less likely to choose a parking spot which requires a long walking distance to the destination. They have also found out, that people with higher income prefer to park closer to the destination. As relatively higher income often comes with high education, it could be said, that people with higher education level prefer smaller walking distance. They also prefer to pay more for the place which ensures that their car is safe (RAC Foundation, 2005). Therefore, it may be interesting to check if the model will perform better with only a certain group of respondents out of entire sample is taken into account.

Binary logit model with respect to gender

The first division which is be made is between men and women. The outcome of the model with significant parameters only can be seen in the table below. For full model output, refer to Appendix III.

Table 6: Binary logit model with gender differentiation, part worth utilities

	Women, N=309		Men, N=294	
	β	Sig. z	β	Sig. z
Tariff 1€	0.703	0.000	0.864	0.000
Tariff 2€	0.135	0.093	-0.085	0.280
Tariff 3€	-0.838		-0.779	
Walking distance 100 m	0.451	0.000	0.287	0.000
Walking distance 300 m	0.045	0.566	0.326	0.673
Walking distance 500 m	-0.496		-0.613	
Off-street parking	0.168	0.050	0.070	0.424
Parking garage	0.135	0.106	0.185	0.027
On-street parking	-0.303		-0.255	
Security cameras	0.245	0.005	0.366	0.000
Security personnel	0.205	0.014	0.105	0.205
No security	-0.450		-0.471	
10% of family parks there	-0.233	0.003	-0.165	0.034
50% of family parks there	0.041	0.608	0.007	0.931

90% of family parks there	0.192		0.158	
10% of friends park there	-0.168	0.035	-0.129	0.101
50% of friends park there	-0.086	0.292	-0.128	0.124
90% of friends park there	0.254		0.257	
10% of colleagues park there	0.059	0.458	-0.063	0.414
50% of colleagues park there	-0.035	0.649	0.077	0.319
90% of colleagues park there	-0.024		-0.014	
10% of others park there	0.021	0.796	-0.112	0.149
50% of others park there	-0.043	0.796	0.112	0.149
90% of others park there	0.022		0.000	
Constant	1.031	0.000	0.900	0.000
LL(β)	-1005.056		-1000.604	
n	1854		1764	
LL(0)	-1285.095		-1222.712	
LRS	-560.078		-444.215	
R^2	0.218		0.182	

The obtained results indicate, that when women only are taken into account, the preference for 1€ parking is lower than when compared with the general population. On the other hand, preference for closely located parking spot is higher. Women do not have preference regarding parking type, also their preference for security cameras is only slightly higher than for the presence of security personnel. When considering social influence, women tend to be influenced by friends and family. The obtained results only agree with the conclusions of Bonsall and Palmer (2004) who have deducted, that women prefer shorter walking distances than men. The results contradict contradicts the results obtained by Morency and Trepanier (2008), who have concluded, that women prefer interior parking.

The second model, including men only, also shows the preference for 1€ parking and smallest walking distance. In this case, the parking type does prove to matter: men prefer parking garage the most; they also have the highest preference for security cameras being present. Men tend to be slightly less influenced by their family members than women. They also prove not to be influenced by their friends, colleagues or others at all.

The model representing women only predicts on a higher level than the full model. The model representing men, however, performs in a poorer way. The R^2_{adj} equals to 0.083 and 0.097 respectively for men and women. On the other hand, LRS ratio is much closer to 0, therefore indicating, that the goodness-of-fit of the model is better than for the full one.

Binary logit model with respect to age

The obtained models with respect to the ages "<25 years old", "25-65 years old", ">65 years old" cannot be assessed in a reliable way: the two abject samples have the number of observations equal to 300 and 462 respectively. According to McFadden's rule of thumb: "(…) sample sizes which yield less than thirty responses per alternative produce estimators which cannot be analyzed reliably by asymptotic methods.'' (McFadden, 1984). In order for those two groups to be deemed reliable, at least 810 responses are needed. The groups are divided in such a way to create three models with the following division: people below 35, people between 35 and 49 and people from 50 up. The first group can be described as "young adults", while people from the age of 50 as "seniors". The middle group can be referred to as "adults".

Table 7: Binary logit model with age differentiation, part worth utilities

	Young adults, N=210		Adults, N=160		Seniors, N=233	
	β	Sig. z	β	Sig. z	β	Sig. z
Tariff 1€	0.749	0.000	0.740	0.000	0.862	0.000
Tariff 2€	0.059	0.542	-0.058	0.594	0.030	0.739
Tariff 3€	-0.808		-0.682		-0.892	
Walking distance 100 m	0.389	0.000	0.178	0.105	0.473	0.000
Walking distance 300 m	-0.095	0.307	0.126	0.245	0.108	0.224
Walking distance 500 m	-0.294		-0.304		-0.581	
Off-street parking	0.033	0.743	0.064	0.584	0.251	0.015
Parking garage	0.375	0.000	0.057	0.610	0.045	0.634
On-street parking	-0.408		-0.121		-0.296	
Security cameras	0.234	0.026	0.332	0.005	0.397	0.000
Security personnel	0.202	0.050	0.117	0.302	0.133	0.157
No security	-0.436		-0.449		-0.530	
10% of family parks there	-0.229	0.015	-0.214	0.051	-0.173	0.054
50% of family parks there	0.056	0.557	-0.085	0.425	0.070	0.453
90% of family parks there	0.173		0.299		0.103	
10% of friends park there	-0.166	0.082	-0.229	0.033	-0.109	0.227
50% of friends park there	-0.136	0.177	-0.046	0.686	-0.104	0.267
90% of friends park there	0.302		0.275		0.213	
10% of colleagues park there	0.045	0.634	-0.189	-0.080	0.077	0.390
50% of colleagues park there	-0.056	0.553	0.077	0.482	0.054	0.541
90% of colleagues park there	0.011		0.112		-0.131	
10% of others park there	-0.023	0.808	0.024	0.828	-0.138	0.122
50% of others park there	0.034	0.723	-0.100	0.348	0.148	0.114
90% of others park there	-0.011		0.076		-0.01	
Constant	0.974	0.000	1.014		0.945	0.000
LL(β)	-698.104		-528.376		-769.877	
n	1260		960		1398	
LL(0)	-873.365		-665.421		-969.020	
LRS	-350.523		-274.091		-398.283	
R^2	0.201		0.206		0.206	

Young adults have the highest preference for the 1€ parking; the part-worth utility however, is slightly lower than for the full model. They also prefer smaller walking distance. When it comes to parking facility type, they prefer parking garage the most and on-street parking the least. Young adults like to have any type of security present, with a small preference for security cameras. They tend to be influenced by their family only, as the other social influence factors are non-significant.

The second model, concerning adults, shows similarities to the one of young adults. Also in this case, there is strongest preference for 1€ parking, 100 meters walking distance and security cameras being present. On the contrary to young adults, the adults group does not show any preference regarding parking facility type. They are also not influenced by their family, colleagues or others, however, they seem to take their friends' opinions into account.

The model representing the seniors is characterized by the highest part-worth utilities for 1€ parking tariff and 100 meters walking distance out of all presented binary logit models. They prefer security cameras as security type and tend to like off-street parking the most. They are not prone to be influences by any groups. The obtained results seem to contradict the conclusions made by Morency and Trepanier (2008), who have stated that young people pay the most attention to the parking pricing: in case of this sample, it is the seniors who pay most attention to it.

The model representing seniors, with R^2_{adj}=0.105, has higher predicting power than the other two and full model. The LRS ratios of models are much closer to 0 than in the case of full model, indicating, that the goodness-of-fit is better.

Binary logit model with respect to education level

The third possible distinction made is with respect to the highest obtained education level.

Table 8: Binary logit model with respect to the education level, significant parameters only

	Secondary, N=157		Vocational, N=186		Academic, N=260	
	β	Sig. z	β	Sig. z	β	Sig. z
Tariff 1€	0.613	0.000	0.824	0.000	0.861	0.000
Tariff 2€	0.045	0.680	0.007	0.939	0.023	0.796
Tariff 3€	-0.658		-0.831		-0.884	
Walking distance 100 m	0.316	0.005	0.369	0.000	0.414	0.000
Walking distance 300 m	0.108	0.309	-0.053	0.585	0.046	0.595
Walking distance 500 m	-0.424		-0.316		-0.460	
Off-street parking	0.143	0.226	0.044	0.672	0.210	0.012
Parking garage	0.157	0.165	0.253	0.017	0.085	0.364
On-street parking	-0.300		-0.297		-0.295	
Security cameras	0.413	0.000	0.357	0.001	0.211	0.038
Security personnel	0.081	0.473	0.198	0.053	0.185	0.051
No security	-0.494		-0.555		-0.296	
10% of family parks there	-0.194	0.077	-0.142	0.144	-0.221	0.010
50% of family parks there	0.106	0.339	-0.054	0.584	0.015	0.086
90% of family parks there	0.088		0.196		0.206	
10% of friends park there	-0.112	0.303	-0.146	0.141	-0.202	0.020
50% of friends park there	0.026	0.815	-0.052	0.615	-0.219	0.017

90% of friends park there	0.086		0.198		0.421	
10% of colleagues park there	0.107	0.329	-0.059	0.547	-0.033	0.703
50% of colleagues park there	0.049	0.640	0.016	0.869	-0.009	0.919
90% of colleagues park there	-0.156		0.043		0.042	
10% of others park there	-0.103	0.340	-0.080	0.415	0.006	0.949
50% of others park there	0.187	0.918	0.003	0.976	-0.014	0.870
90% of others park there	-0.084		0.077		0.008	
Constant	0.988	0.000	0.8000	0.000	1.076	0.000
LL(β)	-525.604		-635.336		-836.063	
n	942		1116		1560	
LL(0)	-652.9446		-773.552		-1081.3096	
LRS	-254.681		-276.432		-490.493	
R^2	0.195		0.179		0.227	

The group of secondary-educated people does not pay a lot of attention to parking attributes in general, in comparison with other groups. The type of parking does not matter to them, neither does the percentage of family, friends, colleagues or others parking at a certain parking. The part-worth utility regarding 1€ parking is the smallest out of all models, showing the preference of 1€ parking smaller than in other two cases. The same can be said about walking distance equal to 100m- preference exists, yet in comparison with other two groups it is much smaller. On the other hand, cameras preference is characterized with the highest part-worth utility in all groups, indicating, that the security attribute is important to this group.

Vocationally trained respondents show a high preference for the 1€ parking, as well as 100 meters walking distance. The most often chosen parking type is parking garage, followed by off-street parking. Just like the secondary educated respondents, vocationally educated show the highest preference for security cameras and are in general not prone to be influenced by others.

The academics are characterized by second highest 1€ parking preference (in binary logit models). At the same time, they pay the least attention to the security of the parking. Those two conclusions contradict the results obtained by the RAC Foundation (2005), which stated, that people with relatively high income (therefore often higher education) prefer to pay more just to ensure that their car is safe. On the other hand, their preference for shortest walking distance turned out to be confirmed. When considering social influence, this group is characterized by being the most influenced by family and friends. Only academics have shown sensitivity to the attribute level "50% of friends park there", what, as a result, indicated, that the influence of their friends is bigger than their family.

The model representing secondary school graduates performs worse than the full model, with R^2=0.062. The vocational school graduates' model explains the variance in the model slightly better than the full binary logit model- R^2=0.094. The improvement is also visible in the case of the academics, with R^2=0.101. On the other hand, this model is characterized by the worst fit of the data, while the best belongs to secondary educated.

4.5.3 Latent class model

The LC model divides the respondents into different groups based on the answers they give. Each class is distinguished by a pattern of conditional probabilities, which determines how likely it is that the variables will take specified values (Sinharay, 2010). In simple words, it means, that the groups share similar opinions or behavior.

In case of this sample, the maximum number of groups that could be created is 2. When trying to divide the respondents into more groups, the software returns an error about variance matrix being singular and exits the optimization.

Just like in the case of binary logit model, parameters with significance level higher than 0.05 are deemed insignificant and part-worth utilities of each attribute are calculated (Table 9). The members of latent class 1 are more inclined to use the offered parking; moreover, they also show signs of being influenced by their family members. Second latent class, on the other hand, is less inclined to park at a facility and tends not to be influenced. That is why, class 1 will be named the "influenced", while class 2 "not influenced".

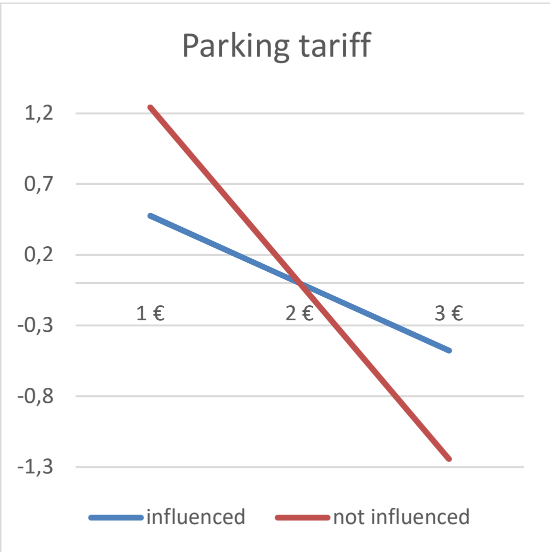
Table 9: Latent class model, part-worth utilities

	Full model, N=603			
	Latent class 1: influenced		Latent class 2: not influenced	
	β	Sig. z	β	Sig. z
Tariff 1€	0.476	0.024	1.242	0.000
Tariff 2€	0.257	0.144	0.076	0.411
Tariff 3€	-0.733		-1.318	
Walking distance 100 m	0.594	0.005	0.475	0.000
Walking distance 300 m	-0.099	0.520	0.049	0.581
Walking distance 500 m	-0.495		-0.524	
Off-street parking	-0.059	0.740	0.234	0.030
Parking garage	0.615	0.008	-0.070	0.524
On-street parking	-0.556		-0.164	
Security cameras	0.250	0.177	0.415	0.000
Security personnel	0.398	0.041	0.189	0.036
No security	-0.648		-0.604	
10% of family parks there	-0.591	0.001	-0.702	0.496
50% of family parks there	0.060	0.690	0.050	0.581
90% of family parks there	0.531		0.652	
10% of friends park there	-0.217	0.175	-0.023	0.800
50% of friends park there	0.026	0.893	-0.163	0.803
90% of friends park there	0.191		0.186	
10% of colleagues park there	0.011	0.941	-0.022	0.808
50% of colleagues park there	-0.045	0.749	0.034	0.703
90% of colleagues park there	0.034		-0.012	
10% of others park there	-0.140	0.373	0.027	0.759
50% of others park there	0.017	0.910	-0.017	0.861

90% of others park there	0.123		-0.01	
Constant	2.338	0.000	-0.030	0.823
Probability	0.520		0.480	
LL(β)	-1852.774			
n	3618			
LL(0)	-2507.806			
LRS	-1310.065			
R^2	0.261			

*Base level

Figures below display the part-worth utilities of each attribute level. Note, that the lack of bars corresponds to the insignificant attributes.



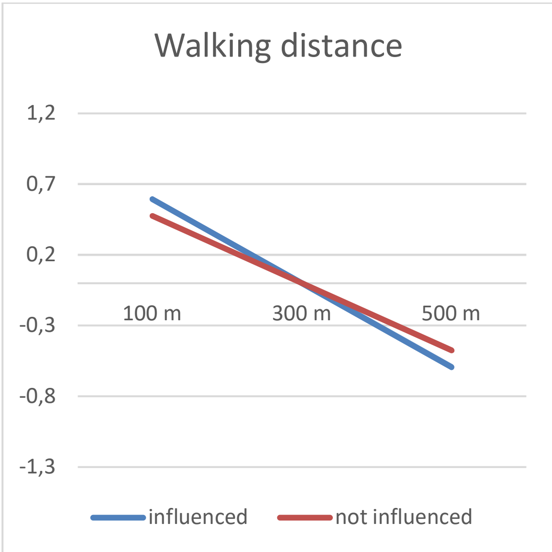


Fig. 14: Part-worth utilities, LC model

Overall, 52% of respondents is estimated to belong to class 1: "influenced", while 48% to the "non-influenced" class. Both groups are showing very different parking characteristics preferences. "Influenced" show the highest preference for parking garage. They also strongly prefer 100 meters walking distance. Third attribute level characterized by the highest part-worth utility is the 90% of family parking at that certain parking facility, indicating, that latent class 1 is the most prone to be socially influenced by their family. This group also displays preference for the 1€ parking tariff and security personnel. Latent class 2, "not influenced", is characterized by a very strong preference of 1€ parking- it is the highest out of all created groups. They also show a preference for 100 meters walking distance, as well as off-street parking and security cameras.

Based on the obtained constants for the two groups it can be said, that people who have been assigned to class 1 are more likely to park at provided parking facility, while class 2 is not.

When regarding the social influence, the “influenced” group is strongly influenced by percentage of family members parking at a certain parking, what cannot be said about the second- they prove to be non-responsive to social influence from any of the groups. The part-worth utility for 90% of family parking at a certain parking is the highest out of all obtained models, indicating, that for respondents assigned to class 1, this factor is of big importance.

McFadden’s R^2 indicates, that the model has an average predicting power, at the level of R^2_{adj}=0.254. LRS=-1310.065 shows, that the goodness-of-fit is also average. Yet still, the obtained LC model predicts on a higher level than the binary logit models. This indicates, that the members of society indeed show different parking preferences and a statistical model should be able to accommodate the heterogeneity of society. Allowing the taste variations tends to deliver better performing models.

The LC model assigned each respondent to latent class 1 or 2 with a certain degree of probability of belonging to that said class. In order to describe what characterizes members of “influenced” and “non-influenced” groups, the respondents were matched with their personal characteristics and divided into classes corresponding with their answers. The results are shown in Fig. 16. When looking at the results, it can be said, that women are more prone to be influenced than men: there are more women belonging to latent class 1, and more men belonging to latent class 2. Moreover, more respondents with secondary education belong to the “influenced” group, while more academically trained to the “not influenced”. When comparing the age structure, the number of respondents belonging to latent class 1 and 2 is similar. A conclusion can be drawn that women and people with lower education degree are more prone to respond to social influence, while men and highly educated people not.

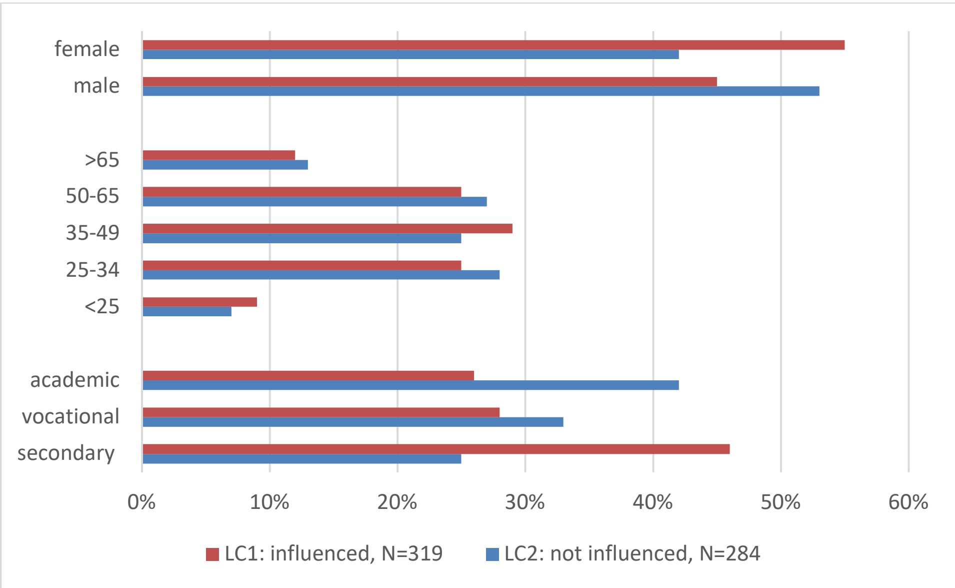


Fig. 15: Personal characteristics comparison

4.5.3 Conclusions

The analysis of parking attributes shows, that cheap price and short walking distance are very important factors when choosing a parking facility. When it comes to the parking type, respondents agree about the smallest preference of on-street parking. They also pay a lot of attention to security measures: they value it, if any security type is present.

The importance of social influence is visible only in cases of some groups. The respondents, if at all, are influenced by their family; only two cases deemed social influence of friends significant. When looking at personal characteristics, it can be said that young people, along with highly educated, tend to be more influenced than older respondents and the ones with lower education. Moreover, women show more tendency to be influenced than men.

Out of all obtained models, the LC model performs best, explaining 25% of the variance in the model (R^2_{adj}=0.254). When looking at the LRS of the models, a conclusion can be drawn, that models which divided the respondents based on their age, gender or education level, fit the data better than general models.

5. Conclusions

5.1 Summary and conclusions

The SP experiment carried out in this thesis was created to check the existence of social influence in the context of parking. For many years, social influence phenomenon has been researched in various contexts. However, the number of publications relating it to parking problems is limited. The main focus of previous studies has been put on the parking attributes. Therefore, with social influence factors inclusion, there was hope to explain and understand people's parking choices behavior better. The SP experiment contained 8 attributes: 4 related to the parking facility, 4 to social influence context. Before choosing the parking attributes, the existing body of research was checked for the ones deemed significant. Out of all found ones, four were chosen: (i) parking tariff, (ii) walking distance, (iii) parking type and (iv) security type. Attributes regarding social influence were also chosen based on previous research, which indicated, that there exist three types of influence: direct, less direct and indirect. This information enabled creating the four social influence groups, which included: (i) family, (ii) friends, (iii) colleagues and (iv) others. Each attribute was given three levels.

The experiment was spread through internet in a form of online survey. Within a month, 603 respondents completed the full questionnaire. Collected data was analyzed with two models: binary logit and LC model. The first one was later divided, and respondents were subdivided into groups, corresponding to their gender, age and education level. The LC model, on the other hand, divided the respondents based on the responses they were giving.

The analysis of the full binary logit model has shown, that parking tariff is the most important attribute. Respondents highly value their walking time, as 100 meters walking distance turned out to be the second most important attribute. They also show a preference for security cameras and parking garage. Moreover, they seem to be prone to social influence of their family and friends. After the model sub-division, results change. Parking tariff still is the most important factor, however, in case of men, adults and secondary educated people, security proves to be more important than the walking distance. In case of women, adults and secondary educated, parking type does not matter. Seniors, secondary and vocationally educated tend to not respond to social influence at all. Other groups have shown to be responsive to the influence of their families or friends (or both). No groups have shown sensitivity to the influence from colleagues or others.

The second created model, LC model, divided respondents based on their answers. Looking at part-worth utilities, two groups could be distinguished: people responsive to influence, and people not responsive to it. Here, the preferences of respondents differ from the ones in the binary logit model. The latent class 1, "influenced", shows the highest preference for parking garage, followed by 100 meters walking distance. Then, there is social influence attribute, with the 90% of family using a certain parking. The members of those groups also show a preference for 1€ parking and security personnel. The second group, "not influenced", shows a very high preference for 1€ parking. Slightly smaller preference can be seen for 100 meters walking distance and security cameras. Both groups prefer on-street parking the least. Carrying out further analysis, it was possible to match the respondents with their personal characteristics. The results have shown, that more women and secondary educated people belong to class 1 ("influenced"), while class 2 ("not influenced") was characterized by a bigger number of men and people with higher education.

The social influence aspect present in the study tested the extent to which people internalize with others. The process of internalization, an act of changing one's behavior or beliefs due to influence of another person, has been confirmed to exist between those who have stronger bonds with each other. Family members and (in some cases) friends, representing the direct and less direct social influence respectively, have proven to be of importance. A high percentage of the group members using a certain parking facility gives the driver information, that it may fulfil his/her needs as well, as often people who are bound by strong ties of love and friendship have the similar expectations and needs, therefore increasing the chance that the parking facility will fit the other person's needs as well.

By including social influence factors in the study, there was hope, that more of model's variance could be explained. While parking attributes and their levels were the same, the employed strategy of social influence attributes inclusion was different than the one of Laro (2018) and Iqbal (2018). Instead of stating the advice given by a member of family, friends, colleagues or others, the percentage of respective group members using a certain parking facility was given. With better quantified level of attributes, there was hope for achieving better results. Comparing the R^2_{adj} it can be said, that this method showed an improvement, and the models created in this study outperform their predecessors slightly. This indicates, that changing the way of social influence inclusion is a step in a right direction. However, there is still room to improve the model's general performances. The binary logit model performed below expectations (R^2_{adj}=0.094), while the LC model performed in an average way (R^2_{adj}=0.254). Looking at the differences in the variance explanation, it can be concluded, that when analyzing human behavior, statistical models should account for the heterogeneity of society. The lower value of the R^2_{adj} in binary logit models indicates, that treating the entire society in a homogenous way delivers worse results.

The aim of this thesis was to investigate to what extent parking and social influence attributes play role in choosing a parking spot. With the obtained results, the research questions can be answered. Parking attributes play major role in this context, however, social influence also can be of importance. Individual's preferences are strongly related to gender, age and education and they can vary among the respondents with different personal characteristics and backgrounds. The extent to which a person responds to social influence is also of subjective matter. The probability of being influenced is higher, if the influencer comes from the person's family. At the same time, people do not seem to be responsive to influence coming from the colleagues or others. With a different social influence modelling approach than the one presented by Iqbal (2018) and Laro (2018), there was hope of achieving better results. The created models, however, did not improve the prediction accuracy in a significant way.

5.2 Discussion and recommendations

Results of this study indicate, that in order to influence people to change their parking habits, it is necessary to look into the family connections closely, as it is family which possesses the most influential power. In order to lead drivers away from the parking facilities in the city centers, it is important to look into the way family members communicate and act upon it, trying to stimulate more discussion about parking facilities. One way to help with that is to invest in development of advertising, both on and offline.

What is also of importance, is to notice, that people with similar backgrounds and environments share similar parking preferences. The person's environment and the nature of social contacts shapes their world-view and personality, therefore shaping what they like and what is important to them. In order to influence different groups, various communication ways should be undertaken. For example, elderly may not be active internet users, while youngsters may not read newspapers. In order to maximize the potential outreach, it is necessary to think of various ways of advertisement.

The analyzed sample had 603 Dutch respondents. While sample size and diversification are more than satisfactory, it could prove to be useful to include expats in the study too. The Netherlands has a big expat community (CBS, 2019), who contribute to the number of drivers significantly and may have different view on parking attributes. Moreover, relative importance of attributes depends on the trip characteristics. This study was carried out in the context of going shopping, therefore does not reflect on different contexts, such as going to work or running short errands. Previous studies of Iqbal (2018) and Laro (2018) have deemed the influence of colleagues and experts insignificant. This study further confirms their results. Therefore, in the next study more emphasis should be put on the influence of family and friends. Social influence attributes are hard to quantify and research. Both studies, despite different inclusion approaches, did not achieve fully satisfactory results. It is possible, that a different way of including social influence attributes is necessary. The term "family" is broad, as it covers both close and extended family. With further specification of the "family", obtaining better results may be possible. It is also worth noting, that this study focuses on one-alternative evaluation only. It is possible, that analysis of the second part of the questionnaire, two-alternative choice, will allow to draw more conclusions. Still, this study provides a lot of insights and a good basis to further research the social influence in the context of parking. It proves, that when it comes to the parking spot choice, parking attributes are the most important. The social influence context also exists, but in a more selective, less strong manner.

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Appendices

Appendix I:

- **Full list of alternatives**

Alternative 1	
Parking tariff	2 €
Walking distance	300 meters
Parking type	Off-street
Level of security	No security
% of family members	50%
% of friends	50%
% of colleagues	50%
% of others	90%

Alternative 2	
Parking tariff	1 €
Walking distance	500 meters
Parking type	Off-street
Level of security	Security cameras
% of family members	10%
% of friends	90%
% of colleagues	90%
% of others	10%

Alternative 3	
Parking tariff	1 €
Walking distance	300 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	10%
% of friends	90%
% of colleagues	90%
% of others	10%

Alternative 4	
Parking tariff	3 €
Walking distance	100 meters
Parking type	Parking garage
Level of security	No security
% of family members	50%

Alternative 16	
Parking tariff	2 €
Walking distance	300 meters
Parking type	On-street
Level of security	Security personnel
% of family members	90%
% of friends	90%
% of colleagues	10%
% of others	10%

Alternative 17	
Parking tariff	1 €
Walking distance	300 meters
Parking type	Off-street
Level of security	Security cameras
% of family members	50%
% of friends	90%
% of colleagues	10%
% of others	50%

Alternative 18	
Parking tariff	2 €
Walking distance	300 meters
Parking type	Parking garage
Level of security	Security cameras
% of family members	10%
% of friends	10%
% of colleagues	90%
% of others	50%

Alternative 19	
Parking tariff	3 €
Walking distance	300 meters
Parking type	On-street
Level of security	Security cameras
% of family members	10%

% of friends	90%
% of colleagues	50%
% of others	10%

Alternative 5	
Parking tariff	1 €
Walking distance	500 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	90%
% of friends	50%
% of colleagues	10%
% of others	90%

Alternative 6	
Parking tariff	3 €
Walking distance	300 meters
Parking type	Parking garage
Level of security	No security
% of family members	10%
% of friends	90%
% of colleagues	10%
% of others	90%

Alternative 7	
Parking tariff	3 €
Walking distance	500 meters
Parking type	On-street
Level of security	Security cameras
% of family members	50%
% of friends	50%
% of colleagues	10%
% of others	10%

Alternative 8	
Parking tariff	1 €
Walking distance	300 meters
Parking type	On-street
Level of security	No security
% of family members	90%
% of friends	10%

% of friends	10%
% of colleagues	90%
% of others	50%

Alternative 20	
Parking tariff	2 €
Walking distance	100 meters
Parking type	On-street
Level of security	Security personnel
% of family members	10%
% of friends	90%
% of colleagues	50%
% of others	50%

Alternative 21	
Parking tariff	2 €
Walking distance	100 meters
Parking type	Parking garage
Level of security	No security
% of family members	90%
% of friends	90%
% of colleagues	10%
% of others	10%

Alternative 22	
Parking tariff	3 €
Walking distance	300 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	50%
% of friends	10%
% of colleagues	90%
% of others	10%

Alternative 23	
Parking tariff	1 €
Walking distance	100 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	50%
% of friends	50%

% of colleagues	90%
% of others	90%

Alternative 9	
Parking tariff	2 €
Walking distance	100 meters
Parking type	Parking garage
Level of security	Security cameras
% of family members	50%
% of friends	10%
% of colleagues	10%
% of others	90%

Alternative 10	
Parking tariff	3 €
Walking distance	100 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	90%
% of friends	10%
% of colleagues	10%
% of others	50%

Alternative 11	
Parking tariff	2 €
Walking distance	500 meters
Parking type	Off-street
Level of security	No security
% of family members	10%
% of friends	50%
% of colleagues	10%
% of others	50%

Alternative 12	
Parking tariff	3 €
Walking distance	100 meters
Parking type	On-street
Level of security	Security cameras
% of family members	10%
% of friends	50%
% of colleagues	90%

% of colleagues	90%
% of others	50%

Alternative 24	
Parking tariff	1 €
Walking distance	100 meters
Parking type	Off-street
Level of security	Security cameras
% of family members	90%
% of friends	90%
% of colleagues	50%
% of others	90%

Alternative 25	
Parking tariff	3 €
Walking distance	500 meters
Parking type	Parking garage
Level of security	No security
% of family members	10%
% of friends	90%
% of colleagues	50%
% of others	50%

Alternative 26	
Parking tariff	1 €
Walking distance	100 meters
Parking type	On-street
Level of security	No security
% of family members	10%
% of friends	10%
% of colleagues	10%
% of others	10%

Alternative 27	
Parking tariff	2 €
Walking distance	500 meters
Parking type	On-street
Level of security	Security personnel
% of family members	50%
% of friends	90%
% of colleagues	90%

% of others	90%

% of others	90%

Alternative 13	
Parking tariff	3 €
Walking distance	500 meters
Parking type	Parking garage
Level of security	Security personnel
% of family members	10%
% of friends	10%
% of colleagues	50%
% of others	90%

Alternative 14	
Parking tariff	3 €
Walking distance	300 meters
Parking type	On-street
Level of security	Security cameras
% of family members	90%
% of friends	50%
% of colleagues	50%
% of others	50%

Alternative 15	
Parking tariff	2 €
Walking distance	500 meters
Parking type	Parking garage
Level of security	Security cameras
% of family members	90%
% of friends	10%
% of colleagues	50%
% of others	10%

Appendix II:

- **SPSS, alternatives crosstabulation**

		Option		Total
		Ja	Nee	
prop.CARD_	1	89	44	133
	10	99	35	134
	11	68	67	135
	12	76	58	134
	13	54	80	134
	14	76	58	134
	15	99	35	134
	16	104	30	134
	17	122	12	134
	18	103	31	134
	19	83	51	134
	2	114	20	134
	20	105	30	135
	21	95	39	134
	22	75	59	134
	23	121	13	134
	24	130	4	134
	25	65	68	133
	26	97	37	134
	27	93	41	134
	3	119	15	134
	4	82	52	134
	5	111	23	134
	6	64	70	134
	7	57	77	134
	8	100	34	134
	9	112	22	134
Total		2513	1105	3618

Appendix III:

- **NLogit Binary logit model, full model**

```
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -2014.79977
Estimation based on N =   3618, K =  17
Inf.Cr.AIC  =   4063.6 AIC/N =    1.123
Model estimated: Dec 09, 2019, 09:19:42
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -2226.4621  .0951 .0908
Response data are given as ind. choices
Number of obs.=  3618, skipped    0 obs
--------+--------------------------------------------------------------------
        |                 Standard            Prob.      95% Confidence
   KEUZE|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
  ICONST|      .96066***      .04147    23.16  .0000      .87937   1.04194
    TAR1|      .78077***      .06456    12.09  .0000      .65424    .90730
    TAR2|      .02263         .05607      .40  .6865     -.08726    .13251
    DIS1|      .36456***      .05682     6.42  .0000      .25320    .47591
    DIS2|      .03913         .05475      .71  .4748     -.06818    .14645
    TYP1|      .12321**       .06089     2.02  .0430      .00387    .24255
    TYP2|      .15921***      .05903     2.70  .0070      .04352    .27490
    SEC1|      .30531***      .06200     4.92  .0000      .18379    .42684
    SEC2|      .15843***      .05869     2.70  .0069      .04340    .27346
    FAM1|    -.19396***       .05507    -3.52  .0004     -.30190   -.08603
    FAM2|      .01863         .05603      .33  .7396     -.09120    .12845
    FRI1|    -.15396***       .05549    -2.77  .0055     -.26273   -.04520
    FRI2|    -.10021*         .05788    -1.73  .0834     -.21366    .01324
    COL1|    -.00516          .05523     -.09  .9256     -.11341    .10309
    COL2|      .01866         .05489      .34  .7339     -.08892    .12623
    OTH1|    -.04649          .05552     -.84  .4024     -.15530    .06233
    OTH2|      .03728         .05589      .67  .5048     -.07227    .14683
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

- **NLogit Binary logit model, women only**

```
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -1005.05573
Estimation based on N =   1854, K =  17
Inf.Cr.AIC  =   2044.1 AIC/N =    1.103
Model estimated: Dec 09, 2019, 09:20:05
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1123.7659  .1056 .0974
Response data are given as ind. choices
Number of obs.=  1854, skipped    0 obs
--------+--------------------------------------------------------------------
        |                 Standard            Prob.      95% Confidence
   KEUZE|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
```

ICONST	1.03144***	.05921	17.42	.0000	.91539	1.14749
TAR1	.70266***	.09023	7.79	.0000	.52581	.87951
TAR2	.13505*	.08029	1.68	.0926	-.02231	.29240
DIS1	.45148***	.08262	5.46	.0000	.28955	.61340
DIS2	.04503	.07850	.57	.5663	-.10883	.19888
TYP1	.16815*	.08593	1.96	.0504	-.00027	.33656
TYP2	.13592	.08414	1.62	.1062	-.02899	.30083
SEC1	.24473***	.08778	2.79	.0053	.07269	.41678
SEC2	.20463**	.08354	2.45	.0143	.04088	.36837
FAM1	-.23266***	.07871	-2.96	.0031	-.38692	-.07840
FAM2	.04122	.08047	.51	.6085	-.11650	.19893
FRI1	-.16783**	.07945	-2.11	.0346	-.32354	-.01212
FRI2	-.08614	.08170	-1.05	.2917	-.24627	.07399
COL1	.05921	.07970	.74	.4576	-.09701	.21542
COL2	-.03560	.07825	-.45	.6492	-.18898	.11778
OTH1	.02082	.08054	.26	.7960	-.13704	.17869
OTH2	-.04329	.07854	-.55	.5815	-.19721	.11064

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

- **NLogit Binary logit model, men only**

Discrete choice (multinomial logit) model
Dependent variable Choice
Log likelihood function -1000.60372
Estimation based on N = 1764, K = 17
Inf.Cr.AIC = 2035.2 AIC/N = 1.154
Model estimated: Dec 09, 2019, 09:20:24
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only -1101.6279 .0917 .0829
Response data are given as ind. choices
Number of obs.= 1764, skipped 0 obs

KEUZE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
ICONST	.90034***	.05876	15.32	.0000	.78516	1.01552
TAR1	.86409***	.09305	9.29	.0000	.68172	1.04645
TAR2	-.08549	.07919	-1.08	.2803	-.24070	.06972
DIS1	.28707***	.07940	3.62	.0003	.13146	.44269
DIS2	.03256	.07711	.42	.6728	-.11856	.18369
TYP1	.06965	.08705	.80	.4236	-.10096	.24026
TYP2	.18504**	.08345	2.22	.0266	.02148	.34860
SEC1	.36649***	.08837	4.15	.0000	.19328	.53970
SEC2	.10536	.08315	1.27	.2051	-.05762	.26833
FAM1	-.16498**	.07785	-2.12	.0341	-.31756	-.01240
FAM2	.00682	.07921	.09	.9314	-.14844	.16207
FRI1	-.12858	.07844	-1.64	.1012	-.28231	.02516
FRI2	-.12760	.08287	-1.54	.1236	-.29002	.03483
COL1	-.06336	.07764	-.82	.4144	-.21554	.08881
COL2	.07740	.07769	1.00	.3191	-.07487	.22968
OTH1	-.11220	.07770	-1.44	.1488	-.26449	.04010
OTH2	.11269	.08046	1.40	.1613	-.04500	.27038

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

- **NLogit Binary logit model, young adults**

```
Discrete choice (multinomial logit) model
Dependent variable              Choice
Log likelihood function     -698.10398
Estimation based on N =   1260, K =  17
Inf.Cr.AIC  =   1430.2 AIC/N =    1.135
Model estimated: Dec 31, 2019, 03:43:54
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only   -777.9740  .1027 .0904
Response data are given as ind. choices
Number of obs.=  1260, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
   KEUZE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
  ICONST|     .97420***      .07126    13.67  .0000       .83453   1.11386
    TAR1|     .74861***      .10989     6.81  .0000       .53322    .96400
    TAR2|     .05943         .09736      .61  .5416     -.13140     .25026
    DIS1|     .38875***      .09807     3.96  .0001       .19655    .58096
    DIS2|   -.09515          .09318    -1.02  .3072     -.27777     .08748
    TYP1|     .03344         .10210      .33  .7433     -.16667     .23355
    TYP2|     .37466***      .10595     3.54  .0004       .16701    .58231
    SEC1|     .23386**       .10483     2.23  .0257       .02839    .43933
    SEC2|     .20228*        .10323     1.96  .0501     -.00005     .40462
    FAM1|   -.22898**        .09425    -2.43  .0151     -.41370   -.04426
    FAM2|     .05651         .09617      .59  .5568     -.13198     .24501
    FRI1|   -.16655*         .09593    -1.74  .0825     -.35456     .02146
    FRI2|   -.13636          .10090    -1.35  .1766     -.33411     .06140
    COL1|     .04505         .09465      .48  .6341     -.14046     .23055
    COL2|   -.05580          .09410     -.59  .5532     -.24024     .12864
    OTH1|   -.02329          .09582     -.24  .8080     -.21109     .16451
    OTH2|     .03375         .09508      .35  .7226     -.15260     .22011
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

- **NLogit Binary logit model, adults**

```
Discrete choice (multinomial logit) model
Dependent variable              Choice
Log likelihood function     -528.37569
Estimation based on N =    960, K =  17
Inf.Cr.AIC  =   1090.8 AIC/N =    1.136
Model estimated: Dec 31, 2019, 03:43:07
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only   -576.8071  .0840 .0675
Response data are given as ind. choices
Number of obs.=   960, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
   KEUZE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
```

	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
ICONST	1.01376***	.08039	12.61	.0000	.85620	1.17131
TAR1	.73792***	.12431	5.94	.0000	.49428	.98155
TAR2	-.05831	.10932	-.53	.5937	-.27257	.15595
DIS1	.17776	.10955	1.62	.1047	-.03697	.39248
DIS2	.12622	.10868	1.16	.2455	-.08678	.33922
TYP1	.06435	.11745	.55	.5837	-.16584	.29454
TYP2	.05732	.11248	.51	.6103	-.16313	.27777
SEC1	.33206***	.11935	2.78	.0054	.09814	.56598
SEC2	.11739	.11386	1.03	.3025	-.10577	.34055
FAM1	-.21379*	.10949	-1.95	.0509	-.42840	.00081
FAM2	-.08546	.10717	-.80	.4252	-.29552	.12460
FRI1	-.22952**	.10783	-2.13	.0333	-.44085	-.01818
FRI2	-.04579	.11334	-.40	.6862	-.26792	.17635
COL1	-.18960*	.10839	-1.75	.0803	-.40205	.02284
COL2	.07662	.10900	.70	.4821	-.13702	.29026
OTH1	.02396	.11004	.22	.8276	-.19172	.23964
OTH2	-.10044	.10702	-.94	.3480	-.31019	.10931

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

- **NLogit Binary logit model, seniors**

```
Discrete choice (multinomial logit) model
Dependent variable                 Choice
Log likelihood function        -769.87726
Estimation based on N =    1398, K =  17
Inf.Cr.AIC  =    1573.8 AIC/N =    1.126
Model estimated: Dec 31, 2019, 03:38:54
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only    -870.7264  .1158 .1049
Response data are given as ind. choices
Number of obs.=   1398, skipped    0 obs
```

KEUZE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
ICONST	.94487***	.06899	13.70	.0000	.80965	1.08008
TAR1	.86176***	.10874	7.93	.0000	.64864	1.07489
TAR2	.03027	.09078	.33	.7388	-.14765	.20819
DIS1	.47335***	.09319	5.08	.0000	.29069	.65600
DIS2	.10806	.08878	1.22	.2236	-.06596	.28207
TYP1	.25077**	.10279	2.44	.0147	.04930	.45223
TYP2	.04497	.09452	.48	.6342	-.14029	.23023
SEC1	.39713***	.10493	3.78	.0002	.19147	.60279
SEC2	.13291	.09399	1.41	.1573	-.05131	.31713
FAM1	-.17261*	.08942	-1.93	.0536	-.34786	.00264
FAM2	.06987	.09313	.75	.4531	-.11266	.25240
FRI1	-.10921	.09050	-1.21	.2275	-.28659	.06817
FRI2	-.10391	.09356	-1.11	.2668	-.28729	.07947
COL1	.07725	.08988	.86	.3901	-.09892	.25341
COL2	.05410	.08860	.61	.5415	-.11956	.22776
OTH1	-.13820	.08947	-1.54	.1224	-.31356	.03715
OTH2	.14789	.09350	1.58	.1137	-.03537	.33116

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

- **NLogit Binary logit model, people with secondary education**

```
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -525.60363
Estimation based on N =     942, K =  17
Inf.Cr.AIC  =   1085.2 AIC/N =    1.152
Model estimated: Dec 12, 2019, 12:39:57
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only    -570.6097  .0789 .0619
Response data are given as ind. choices
Number of obs.=   942, skipped    0 obs
```

KEUZE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
ICONST	.98788***	.08079	12.23	.0000	.82955	1.14622
TAR1	.61315***	.12335	4.97	.0000	.37139	.85491
TAR2	.04521	.10969	.41	.6802	-.16977	.26020
DIS1	.31562***	.11274	2.80	.0051	.09465	.53658
DIS2	.10838	.10658	1.02	.3092	-.10051	.31727
TYP1	.14325	.11827	1.21	.2258	-.08856	.37506
TYP2	.15712	.11318	1.39	.1651	-.06470	.37894
SEC1	.41349***	.11977	3.45	.0006	.17875	.64822
SEC2	.08134	.11332	.72	.4729	-.14076	.30345
FAM1	-.19439*	.10988	-1.77	.0769	-.40975	.02098
FAM2	.10603	.11085	.96	.3388	-.11125	.32330
FRI1	-.11243	.10913	-1.03	.3029	-.32631	.10146
FRI2	.02622	.11209	.23	.8150	-.19348	.24592
COL1	.10742	.11009	.98	.3292	-.10835	.32319
COL2	.04951	.10597	.47	.6404	-.15819	.25721
OTH1	-.10290	.10794	-.95	.3405	-.31446	.10867
OTH2	.18712*	.11099	1.69	.0918	-.03041	.40466

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

- **NLogit Binary logit model, people with vocational education**

```
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -635.33601
Estimation based on N =    1116, K =  17
Inf.Cr.AIC  =   1304.7 AIC/N =    1.169
Model estimated: Dec 12, 2019, 12:36:43
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only    -712.4111  .1082 .0944
Response data are given as ind. choices
Number of obs.=  1116, skipped    0 obs
```

KEUZE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	

```
--------+--------------------------------------------------------------------
  ICONST|      .80036***       .07261     11.02  .0000       .65805     .94267
    TAR1|      .82357***       .11257      7.32  .0000       .60294    1.04420
    TAR2|      .00749          .09870       .08  .9395     -.18595      .20092
    DIS1|      .36885***       .09976      3.70  .0002       .17333     .56436
    DIS2|     -.05350          .09798      -.55  .5850     -.24553      .13853
    TYP1|      .04375          .10341       .42  .6722     -.15893      .24643
    TYP2|      .25342**        .10628      2.38  .0171       .04511     .46173
    SEC1|      .35717***       .10796      3.31  .0009       .14557     .56878
    SEC2|      .19837*         .10273      1.93  .0535     -.00298      .39972
    FAM1|     -.14204          .09718     -1.46  .1438     -.33250      .04842
    FAM2|     -.05445          .09946      -.55  .5841     -.24938      .14049
    FRI1|     -.14566          .09885     -1.47  .1406     -.33941      .04808
    FRI2|     -.05202          .10349      -.50  .6152     -.25486      .15082
    COL1|     -.05926          .09845      -.60  .5473     -.25222      .13371
    COL2|      .01599          .09733       .16  .8695     -.17477      .20674
    OTH1|     -.08023          .09850      -.81  .4153     -.27328      .11283
    OTH2|      .00288          .09776       .03  .9765     -.18873      .19449
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

- **NLogit Binary logit model, people with academic education**

```
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -836.06299
Estimation based on N =    1560, K =  17
Inf.Cr.AIC  =    1706.1 AIC/N =    1.094
Model estimated: Dec 12, 2019, 14:22:24
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only   -939.8933  .1105 .1007
Response data are given as ind. choices
Number of obs.=  1560, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
   KEUZE|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
  ICONST|     1.07623***       .06708     16.04  .0000       .94476    1.20770
    TAR1|      .86069***       .10576      8.14  .0000       .65340    1.06798
    TAR2|      .02311          .08944       .26  .7961     -.15218      .19840
    DIS1|      .41385***       .08977      4.61  .0000       .23790     .58979
    DIS2|      .04580          .08609       .53  .5947     -.12293      .21453
    TYP1|      .21041**        .10128      2.08  .0378       .01190     .40892
    TYP2|      .08457          .09320       .91  .3642     -.09811      .26724
    SEC1|      .21077**        .10162      2.07  .0381       .01160     .40993
    SEC2|      .18480*         .09478      1.95  .0512     -.00096      .37055
    FAM1|     -.22069**        .08584     -2.57  .0101     -.38892     -.05245
    FAM2|      .01496          .08775       .17  .8647     -.15703      .18694
    FRI1|     -.20254**        .08731     -2.32  .0204     -.37367     -.03141
    FRI2|     -.21892**        .09159     -2.39  .0168     -.39843     -.03941
    COL1|     -.03279          .08589      -.38  .7026     -.20112      .13555
    COL2|     -.00884          .08723      -.10  .9193     -.17981      .16213
    OTH1|      .00562          .08793       .06  .9490     -.16672      .17796
    OTH2|     -.01445          .08833      -.16  .8701     -.18758      .15868
--------+--------------------------------------------------------------------
```

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Appendix III:

- **NLogit, Latent class model**

```
Latent Class Logit Model
Dependent variable                 KEUZE
Log likelihood function      -1852.77399
Restricted log likelihood    -2507.80650
Chi squared [  35 d.f.]       1310.06501
Significance level                .00000
McFadden Pseudo R-squared       .2611974
Estimation based on N =    3618, K =  35
Inf.Cr.AIC  =    3775.5 AIC/N =    1.044
Model estimated: Dec 07, 2019, 15:28:55
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -2507.8065  .2612 .2540
Constants only  -2226.4621  .1678 .1597
At start values -2014.8084  .0804 .0714
Response data are given as ind. choices
Number of latent classes =             2
Average Class Probabilities
     .520  .480
LCM model with panel has      603 groups
Fixed number of obsrvs./group=         6
Number of obs.=  3618, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
   KEUZE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Utility parameters in latent class -->> 1
ICONST|1|    2.33796***      .25440     9.19  .0000     1.83934   2.83657
  TAR1|1|     .47584**       .21025     2.26  .0236      .06376    .88792
  TAR2|1|     .25656         .17572     1.46  .1443     -.08786    .60097
  DIS1|1|     .59376***      .17130     3.47  .0005      .25802    .92950
  DIS2|1|    -.09858         .15333     -.64  .5203     -.39909    .20193
  TYP1|1|    -.05930         .17894     -.33  .7403     -.41001    .29141
  TYP2|1|     .61504***      .23111     2.66  .0078      .16207   1.06801
  SEC1|1|     .24957         .18498     1.35  .1773     -.11299    .61213
  SEC2|1|     .39828**       .19521     2.04  .0413      .01568    .78087
  FAM1|1|    -.59079***      .17135    -3.45  .0006     -.92664   -.25495
  FAM2|1|     .05956         .14926      .40  .6899     -.23299    .35211
  FRI1|1|    -.21722         .16017    -1.36  .1750     -.53114    .09671
  FRI2|1|     .02567         .19096      .13  .8931     -.34861    .39994
  COL1|1|     .01137         .15450      .07  .9413     -.29145    .31419
  COL2|1|    -.04539         .14196     -.32  .7492     -.32363    .23285
  OTH1|1|    -.14041         .15778     -.89  .3735     -.44965    .16883
  OTH2|1|     .01746         .15519      .11  .9104     -.28670    .32163
        |Utility parameters in latent class -->> 2
ICONST|2|    -.03035         .14099     -.22  .8296     -.30669    .24599
  TAR1|2|    1.24161***      .13044     9.52  .0000      .98595   1.49726
  TAR2|2|     .07559         .09194      .82  .4110     -.10461    .25579
  DIS1|2|     .47544***      .09079     5.24  .0000      .29750    .65338
  DIS2|2|     .04902         .08888      .55  .5812     -.12517    .22322
  TYP1|2|     .23428**       .10793     2.17  .0299      .02275    .44582
  TYP2|2|    -.06961         .10920     -.64  .5238     -.28364    .14442
```

SEC1|2	.41542***	.10101	4.11	.0000	.21745	.61339
SEC2|2	.18858**	.08997	2.10	.0361	.01224	.36491
FAM1|2	-.07025	.10326	-.68	.4963	-.27264	.13214
FAM2|2	.04983	.09031	.55	.5811	-.12718	.22684
FRI1|2	-.02334	.09060	-.26	.7967	-.20091	.15424
FRI2|2	-.16275*	.09307	-1.75	.0803	-.34516	.01965
COL1|2	-.02202	.09081	-.24	.8084	-.20000	.15595
COL2|2	.03423	.08968	.38	.7027	-.14155	.21000
OTH1|2	.02746	.08965	.31	.7594	-.14825	.20317
OTH2|2	-.01661	.09481	-.18	.8610	-.20243	.16922
	Estimated latent class probabilities					
PrbCls1	.52015***	.06075	8.56	.0000	.40108	.63922
PrbCls2	.47985***	.06075	7.90	.0000	.36078	.59892

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.