Neighborhood preferences measured through video application: The added value of using multimedia

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Summary

Introduction
Nowadays, quality of life is widely discussed topic in literature. Residential satisfaction can often be used as an indicator for quality of life. Therefore, the research into people's neighborhood preference has gained in importance. Especially for policymakers and municipalities, the research into people's neighborhood preferences has a high priority. Because with this information neighborhoods can be adapted to attract a certain target group to improve social cohesion within the community. This study was executed to gain more knowledge into the overall neighborhood preference of people. In addition, more information was gathered about the preferences of socio-demographic sub- groups. By answering the first research question (RQ) of this study more insight will be gained into the neighborhood preferences of people.

''What are the neighborhood preferences of people and are there observable differences between sub-groups?''

Stated preference (SP) surveys are the most commonly used survey type to investigate neighborhood preferences of people. Due to fast technological advances, more SP research surveys are executed using multimedia, deviating from the conventional text surveys. Several studies have compared the use of multimedia to text using a SP survey, but their conclusions are inconclusive and sometimes contradictory to each other. In order to make compelling statements regarding people's neighborhood preferences, both methods were compared and evaluated regarding their usefulness in neighborhood studies. One group of subjects participated in a text-only SP survey about neighborhood preferences while another group took part in a video-based SP survey, representing the multimedia part. Furthermore, the added value of the use of a video in neighborhood preference studies was investigated.

''Are there differences between the preferences of the video-based group and the text-only group?

''What is the added value of video based SP questionnaires?''

Method
Based on a literature study, six neighborhood attributes and their levels were selected (Table 1). All six attributes and their levels can be visually represented in different ways, based on people's imagination, which made the outcomes of the comparison between the two methods interesting.

Attributes that could not be visually presented like 'money' , 'proximity to city center' or 'location' were not included in this study. In almost all residential SP studies, the attribute 'money' is included, to later on express how much people are willing to pay for an increase in preference per attribute. However, in this report the main focus was on people's neighborhood preference aside from what they would be willing to spend for two reasons. Firstly, in the Netherlands there is no municipal fee for the quality level of the neighborhood. Therefore, people do not pay for the neighborhood directly (monetary value). The second

point is that this study aimed to find the actual neighborhood preference of people aside from a monetary value or proximity to a city center.

Table 1. Overview attributes and levels

Attribute	Levels
Street design	1. Primarily for cars 2. For cars/pedestrians and bicycles
Parking type	1. On street 2. Designated parking places
Speed slowing measures	1. No 2. Yes, speedbumps
Playground in neighborhood	1. No 2. Yes
Pond in the neighborhood	1. No 2. Yes
Type of green	1. No green 2. Low (grass) 3. Medium (bushes) 4. High (trees)

For the multimedia part of this study, the use of four different levels of multimedia; pictures, panorama, a video and an interactive VR world were considered. Based on the limited timespan of the research and the control of the researcher on what people see the choice was made to use a video to represent the neighborhood.

A fractional factorial design of 16 neighborhoods, instead of 128, was used in this study due to practical constrictions of the number of respondents and the time a person would be willing to spend filling in the survey. Also, with the use of a fractional factorial design a good representation could be presented of the total 128 possibilities.

The drawing package Blender Render was used to produce the videos, because it was available as an open source program to increase transparency and reproducibility of the study. In addition, Blender Render could be used to create high quality textures in the video experiment, to make the environment more lifelike. All rendered movies had the same duration and the attributes that were not measured (for instance lampposts) had the same location color and amount in every movie. This was done to make sure that these variables did not create bias and were not measured in the online survey.

In order to make sure that the experiment methods were comparable, both contained exactly the same questions and attributes. Both survey types were made with the 'Berg enquete system', which is an online survey platform that allows to embed movies and/or pictures. The (16) rendered movies were included as YouTube video's into the survey.

Since a 10 point rating scale without middle (neutral) option was used to score each neighborhood, an ordinal regression was used to analyze the data. In order to perform an ordinal regression, the levels of each attribute were recoded as dummy variables.

Results

The socio-demographics of both experiments were comparable, which allowed to compare the outcomes of both experiment types. In total 565 people opened one of the surveys, from which 212 respondents completed either one of the surveys. In the video survey the completion rate was lower compared to the text experiment. This could be related to the duration time, which was a few minutes longer compared to the text-only survey. Another reason could be that several respondents that were recruited through a company had to quit the video survey because the company blocked the YouTube video's.

Two unexpected findings were detected in the SPSS output of the ordinal regression. Based on literature, it was expected that respondents would enjoy the video survey more compared to the text-only survey. To test this, all respondent were asked to indicate on a seven point Likert scale how much he or she enjoyed to fill in the survey. Unexpectedly, the text-only survey scored slightly higher compared to the video experiment, which was the opposite of what was initially expected. Secondly, in the video experiment all respondents see the same representation of each attribute, while in the text-only experiment they are left to their imagination. Therefore, a better model fit was expected for the video experiment. However, in this study both experiment types had an overall good model fit, but the text-only experiment scored a lot better in terms of model fit (prediction).

The part-worth utilities of both experiments types were converted into the relative importance of each attribute, which made them comparable. The ranking of all attributes from both methods is shown in Table 2. In both experiment types, the attribute 'green type' displayed the highest relative importance (±50%). However, the relative importance of the other attributes were different between the two experiment types, which resulted in a different ranking in attribute importance (Table 2).

In both experiment types, differences were found between different sub-groups. Not all of these differences in sub-groups were consistent between the two experiment types. Those that were consistent between the survey types are considered as solid evidence. For instance, the relative importance of the presence of a playground and the presence of speedbumps was higher in a household with children compared to a household without children (in both experiment types).

Table 2. Relative importance ranking of the attributes

	Video experiment	**Text-only-experiment**
1	Green type	Green type
2	Parking type	Presence playground
3	Street design	Speed slowing measures
4	Presence pond	Parking type
5	Presence playground	Presence pond
6	Speed slowing measures	Street design

Conclusion

The answer to the first RQ is that there are observable difference between the sub-groups. However, the experiment types contradicted each other in some sub-groups and therefore, only differences that were found in both experiment types were considered as 'true'. The differences between experiment types could be caused by the low amount of respondents per sub-group. The overview of the overall preference of people is shown in Table 2 for both experiment types. The answer to the second question is that there are indeed differences between the two experiment types in attribute importance (Table 2).

Researchers need to be very careful when using a multimedia survey and consider if using multimedia has added value (RQ 3) for the specific research they want to perform. For overall preferences the use of a text-only SP survey should be sufficient. The pitfall in using multimedia is that attributes and levels can be shown in multiple ways, which can deviate from how the neighborhood is actually going to be. Therefore, using multimedia is advised only in situations when the representation of the attributes is the same as how they are going to be made in the real neighborhood, or when the attribute cannot be explained in a few words (text).

Samenvatting

Introductie
Kwaliteit van leven is tegenwoordig een veelbesproken onderwerp in de literatuur. Woontevredenheid kan worden gebruikt als een indicator voor de kwaliteit van leven. Hierdoor is onderzoek naar wijkvoorkeuren van mensen belangrijker geworden. Vooral voor beleidsmakers en gemeenten heeft onderzoek naar wijkvoorkeuren van mensen een hoge prioriteit. Door deze informatie kunnen wijken aangepast worden om bepaalde groepen mensen aan te trekken en daarmee de sociale cohesie binnen de wijk te verbeteren. Deze studie was uitgevoerd om een beter beeld te krijgen van de wijkvoorkeuren van mensen. Daarnaast is meer informatie verkregen over de voorkeuren van socio-demografische subgroepen. Door de eerste hoofdvraag van dit onderzoek te beantwoorden is meer inzicht verkregen in de wijkvoorkeuren van mensen.

'' Wat zijn de wijkvoorkeuren van mensen en zijn er waarneembare verschillen tussen subgroepen? ''

'Stated preference (SP)' enquêtes zijn het meest gebruikte type als het gaat om het onderzoeken van wijkvoorkeuren van mensen. Vanwege de snelle technologische ontwikkelingen worden meer SP enquêtes uitgevoerd die gebruik maken van multimedia, afwijkend van de traditionele tekst enquêtes. Meerdere studies vergelijken het gebruik van multimedia in SP enquêtes met het gebruik van tekst in SP enquêtes, maar hun conclusies en resultaten zijn tegenstrijdig. In deze studie worden twee enquêtes vergeleken, namelijk een die gebruik maakt van multimedia (video) en een traditionele tekst enquête.

'' Zijn er verschillen tussen de voorkeuren van de video groep en de groep met alleen tekst?''

'' Wat is de meerwaarde van op video gebaseerde SP vragenlijsten? ''

Methode
Op basis van een literatuurstudie zijn zes 'attributes' en corresponderende onderliggende levels gekozen. Alle zes 'attributes' en hun onderliggende levels kunnen op verschillende manieren visueel worden weergegeven. 'Attributes' die enkel als tekst weergegeven konden worden, zoals afstand en geld, zijn niet gebruikt in deze studie. Voor het multimedia gedeelte van deze studie zijn vier soorten overwogen; foto's, panorama, video en een interactieve virtual reality (VR) wereld. Op basis van de beperkte tijdspanne van het onderzoek en de controle van de onderzoeker op wat mensen zien, is ervoor gekozen om een video te gebruiken om de wijk te visualiseren.

Het tekenpakket Blender Render werd gebruikt om de video's te produceren, omdat het beschikbaar was als een open source-programma om de transparantie en reproduceerbaarheid van het onderzoek te vergroten. Daarnaast kan Blender Render worden gebruikt om hoogwaardige 'textures' te maken in het video-experiment, waardoor de virtuele omgeving meer levensecht wordt. Alle filmpjes hadden dezelfde duur en de objecten die niet werden gemeten (bijvoorbeeld lantaarnpalen) hadden in elke film dezelfde locatie, kleur en aantal. Dit is gedaan om ervoor te zorgen dat deze variabelen niet werden gemeten in de online enquête. De video's zijn als YouTube video verwerkt in de online enquête door middel van het Berg enquête systeem. De respondenten van de enquêtes werden gevraagd om elke wijk te beoordelen op een 10 puntenschaal, zonder neutrale (midden) optie.

Resultaten
De socio-demografische gegevens van beide experimenten waren vergelijkbaar, waardoor de resultaten van beide soorten experimenten vergeleken konden worden. In totaal hebben 565 mensen een van de enquêtes geopend, waarvan 212 respondenten de enquêtes hebben ingevuld. In de video-enquête was het voltooiingspercentage lager in vergelijking met de tekst-enquête. Dit kan te maken hebben met de duur van de video-enquête, welke een paar minuten langer was in vergelijking met de enquête alleen voor tekst.

Op basis van de literatuur werd verwacht dat respondenten het leuker zouden vinden om de video-enquête in te vullen. Onverwachts scoorde het tekstonderzoek iets hoger in vergelijking met het video-experiment, wat het tegenovergestelde was van wat aanvankelijk werd verwacht. Tevens was een betere model fit (voorspelling) verwacht voor het video-experiment, omdat alle respondenten in het video-experiment dezelfde weergave van elk ‘attribute’ te zien kregen. Terwijl respondenten in het experiment met alleen tekst aan hun verbeelding worden overgelaten. In deze studie hadden beide typen experimenten echter een goede overall-fit, maar het experiment met alleen tekst scoorde duidelijk beter in termen van model fit (voorspelling).

De waardes van beide soorten experimenten werden omgezet in het relatieve belang van elk ‘attribute’, waardoor ze vergelijkbaar werden. De rangorde van alle ‘attributes’ van beide methoden is weergegeven in Tabel 1. In beide soorten experimenten vertoonde het ‘attribute’ type groen het hoogste relatieve belang (± 50%). Het relatieve belang van de anderen was echter verschillend tussen de twee experimenttypen, wat resulteerde in een andere rangschikking in attribuutbelang (Tabel 1)

Tabel 1. Volgorde relatief belang ‘attributes’’

	Video experiment	**Tekst experiment**
1	Groen type	Groen type
2	Parkeer type	Aanwezigheid speeltuin
3	Straat design	Snelheid vertragende maatregelen
4	Aanwezigheid vijver	Parkeer type
5	Aanwezigheid speeltuin	Aanwezigheid vijver
6	Snelheid vertragende maatregelen	Straat design

In beide experiment soorten werden verschillen gevonden tussen subgroepen. Niet al deze verschillen in subgroepen waren consistent tussen de twee experimenten. Degenen die consistent waren tussen beide soorten enquêtes worden beschouwd als solide bewijs. Het relatieve belang van de aanwezigheid van een speeltuin en de aanwezigheid van verkeersdrempels was bijvoorbeeld hoger in huishoudens met kinderen in vergelijking met een huishouden zonder kinderen (in beide soorten experimenten).

Conclusie

Het antwoord op de eerste onderzoeksvraag is dat er een waarneembaar verschil is tussen de subgroepen. De uitkomsten van de ‘attributes’ in de twee experimenttypen spreken elkaar in sommige subgroepen tegen en daarom worden alleen verschillen die in beide experimenttypen naar voren kwamen als 'waar' beschouwd. Het lage aantal respondenten per subgroep kan de oorzaak zijn van verschillen tussen de experimenttypen. Het overzicht van de algemene wijkvoorkeur van mensen is weergegeven in Tabel 1 voor beide soorten experimenten (onderzoeksvraag 1). Het antwoord op de tweede vraag is dat er inderdaad verschillen zijn tussen de twee soorten experimenten (video en tekst), zoals weergegeven in Tabel 1.

Onderzoekers moeten heel voorzichtig zijn bij het gebruik van een SP enquête die gebruik maakt van multimedia en overwegen of het gebruik van multimedia een meerwaarde heeft (onderzoeksvraag 3) voor het specifieke onderzoek dat ze willen uitvoeren. Voor algemene voorkeuren zou het gebruik van een SP-enquête met alleen tekst voldoende moeten zijn. Een valkuil bij het gebruik van multimedia is dat ‘attributes’ en de onderliggende levels op verschillende manieren kunnen worden getoond, wat kan afwijken van hoe de buurt er in het echt uit komt te zien. Daarom wordt het gebruik van multimedia alleen geadviseerd in situaties waarin de representatie van de ‘attributes’ hetzelfde is als hoe ze in de echte buurt worden gemaakt, of wanneer de ‘attributes’ niet in een paar woorden (tekst) kunnen worden uitgelegd.

Abstract
Residential satisfaction is often seen as an indicator for quality of life, which makes research into people's neighborhood preferences an important topic. Traditionally a stated preference study (SP) contains written attributes (text), which leave the respondent to make mental images for him- or herself. With current progress in virtual reality (VR) applications more SP surveys are performed with the use of multimedia. This study adds to the neighborhood preference literature, as well to the discussion whether multimedia application in SP surveys has added value. In this study six neighborhood attributes have been used and presented to two different respondent groups. One group filled in the conventional text-only experiment, while the other group carried out the video experiment. Both experiment designs used a ten point rating scale to express neighborhood preference and were analyzed using an ordinal regression.

In total 215 respondents completed either one of the survey types. The overall model fit of the text-only experiment was better compared to the video experiment. Additionally, respondents slightly enjoyed the text-only experiment more. In both experiment types the attribute 'green type' scored almost 50% on relative importance of the whole attribute set. The other five attributes showed a different importance order between the two experiment types. The results indicate that respondents that filled in the text-only survey thought more about how important they considered the individual attributes, while in the video experiment the larger visual attributes gained importance. This raises the question if the application of multimedia may lead to incorrect preference scores. Researchers need to be very careful when using a multimedia survey and evaluate if using multimedia has added value for the specific research they want to perform. For overall preferences the use of a text-only SP survey should be sufficient. The pitfall in using multimedia is that attributes and levels can be shown in multiple ways, which can deviate from how the neighborhood is actually going to be. Therefore, using multimedia is advised only in situations when the representation of the attributes is the same as how they are going to be made in the real neighborhood, or when the attribute cannot be explained in a few words (text).

Keywords:

Neighborhood preference, attribute visualization, stated preference, presentation style

List of abbreviations

ASVV	Aanbevelingen voor verkeersvoorzieningen (Recommendations for traffic services)
CBS	Central Bureau of Statistics
CM	Choice modelling
CV	Contingent valuation
fps	Frames per second
HD	High definition
MAV	Multi-attribute valuation
RC	Revealed choice
RQ	Research question
SAS	Statistical Analysis System
SC	Stated choice
SP	Stated preference
SPSS	Statistical Package for the Social Sciences
Std.	Standard
TU/E	Eindhoven University of Technology
VR	Virtual reality
VS	Versus
2D	Two-dimensional
3D	Three-dimensional
720p	1.280 pixels horizontally and 720 pixels vertically
1080p	1.920 pixels horizontally and 1.080 pixels vertically

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1. Introduction

In this introduction the topic, research questions and aim of the thesis are presented. In addition, the research method that was used to answer these research questions is discussed. The outline of the introduction is structured in sections to provide a clear overview of the research that has been conducted in this study. Therefore, the introduction will discuss the problem framework and definition, research goal, research boundaries, research design, the social and scientific importance of this study. At the end of this chapter a reading guide is added to provide the reader with a clear overview of the organization of this report.

1.1 Problem definition

Social separation is a problem that often occurs in residential areas where only one layer of the population is present (for instance the Dutch 'vogelaarwijken') (Kullberg & Permentier, 2013). One way to increase social coherence in a neighborhood is to make areas attractive for people from other classes of society. This can be done in two ways, namely by changing the housing stock or through making the neighborhood attractive for other socio-demographic groups. The first method, to change the housing stock, is a rather difficult approach since often houses are owned by the people residing there. Secondly, by making the neighborhood more attractive for other socio-demographic groups the quality of life of people will indirectly increase. The second manner is easier for policy makers to implement, while they do not deal with multiple owners. By making the neighborhood more attractive for other socio-demographic groups, the quality of life of people will increase, even if they already live in the type of neighborhood they prefer.

Until now the most commonly used method to gain knowledge about residential preferences of different layers of the population have been text surveys. Recently, rapid technical advances in the field of virtual reality (VR) have led to the idea to implement multimedia as an additional method to investigate the preferences of people. However, the use of multimedia for this purpose is under discussion. multimedia gives the possibility to find people's preference more accurate for attributes that are very visual, instead of only using text. For example the square meters of a house can probably better be shown as text-only, instead of processing in a virtual world. For instance architectural style or types of green can probably better be visualized through multimedia instead of text-only, because multimedia is less biased by the person's imaginative capabilities.

1.2 Research question(s)

The research problem is twofold, namely the neighborhood preferences themselves and the differences in outcomes between the use of multimedia and text-only surveys. In the academic literature, researchers do not agree on the use of multimedia in stated preference (SP) surveys. By using two survey types (multimedia and text-only), more insight will be gathered in the (un)likeness they have. The research will add to the literature on residential preferences. The study is divided in a technical part, in which the multimedia model was developed, and a part in which the outcome in residential preferences between different layers of the population is investigated.

Three main research questions were formulated for this study. The first focusses on people's neighborhood preferences, while the second and third question focus on differences between the models and the added value of video-based questionnaires.

1 What are the neighborhood preferences of people and are there differences observable between sub-groups?

This question contributes to the SP literature on neighborhood choice, which will be discussed further on in this report. A lot of research has been performed in this area, except not with the use of video application. Hence, this study will add to the already existing literature with the use of video as an innovative element. Primarily the influence of house prices, house attributes, distances to public transport, work and others on residential preferences are investigated in current literature. In this study, neighborhood preferences will be investigated, without taking into account housing attributes or using monetary values.

2 Are there differences between the preferences of the video-based group and the text-only group?

The second main question focusses on the difference between both survey versions (text-only and video). In the literature not all studies agree that there are prominent differences between the two tests types. Researchers do not agree on these differences and argue that one method might be better than the other, while some say they are a lot alike. Until now only one study has been executed with a respectable amount of respondents (Patterson, Darbani, Rezaei, & Zacharias, 2017)*. While others have been done with a lower number of respondents and are difficult to base conclusions on.*

3 What is the added value of video-based SP questionnaires?

With this research, more information will be gathered on the (un)likeliness of the two methods and their applicability in neighborhood studies. By answering this research question the added value of using multimedia in SP neighborhood surveys should become evident and it will add to a more consistent way of using multimedia. Additionally, previous research focusses on a combination of text and multimedia against a text-only study. The aim of these studies was to investigate if the use of text is less important in a multimedia study as compared to a text-only study. In contrast to this previous research, this study will solely focus on visual attributes and therefore compares a multimedia study with a text-only study.

The first research objective is to investigate people's residential preferences and compare these between different sub-groups of the population. The second objective aims to compare the video group with the text-only group, while the third objective examines if the video experiment has added value compared to the text-only experiment. The set of attributes in this study are subjected to the use of video and the drawing capabilities of the researcher. This means that not all attribute types can be used or extreme precaution would be necessary when drawing them. In the literature a lot of concerns are expressed on 'hidden' attributes that could affect people's choice. The possible effects of these hidden attributes will be taken into account and are minimalized when creating the virtual world.

1.3 Research design

The first step in designing the research is to define the attributes and their corresponding levels. After deciding on the attributes the profiles can be determined. Subsequently, the surveys are developed (Figure 1). These steps will take less time for the text-only survey compared to the video survey. The video survey will require more time, because the virtual world has to be created and integrated into the online survey. When both the video and text-only survey are completed, an expert panel will be asked to compare both survey types and evaluate if they are similar and comparable in terms of outcome. When they are not similar, the critique will be processed and the improved version is presented to the panel of experts. When the surveys are approved, both will be executed. This will take time, because enough respondents need to be recruited for both surveys (twice as much respondents are needed). Subsequently the socio-demographics of both respondent groups will be investigated using descriptive statistics to investigate, whether these are comparable between groups. If the socio-demographics are consistent between the respondent groups, the data will be analyzed and the preferences between the two methods can be compared and conclusions can be drawn.

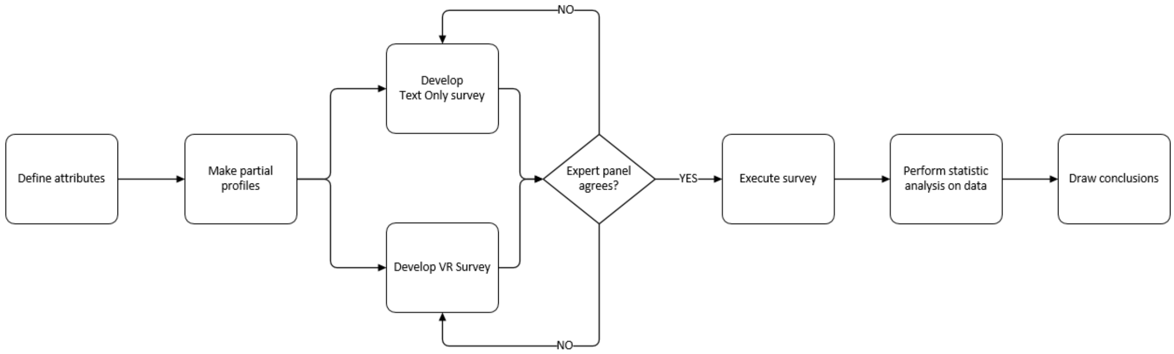

Figure 1. Research design

1.4 Expected results

The results of this study can provide municipalities, project developers and other instances with a good view on which attributes people value in a neighborhood. The expected neighborhood preferences per attribute will be discussed in section 3.2 Attributes survey. In addition to neighborhood preferences of different sub-groups, the outcome between the traditional text-only and the video-based survey is investigated. Since all of the chosen attributes can be visually pictured in many different ways, a difference in neighborhood preferences is expected between the two methods. In the text-only survey people have to imagine the surrounding, which is likely to deviate from the neighborhood that is used in the video experiment. For example, because all attributes can have different sizes, shapes or locations.

1.5 Research limitations

At the start of the research project the researcher had limited knowledge on how to design a virtual world. Since learning how to build a virtual world requires a lot of time and the project was bound to time restrictions, the choice was made to create a video representation. Developing an interactive VR world would cost too much time and the control of the researcher would be less. A good representation of the neighborhood is sufficient for this study, however, the video design may lack supplementary details. Since neighborhood preferences are compared between two experiment types, twice the amount of respondents are required. Therefore, finding the amount of respondents for two studies will be challenging. The research focusses on the environment (neighborhood) and not on housing attributes or distances to for example the city center.

1.6 The practical and scientific importance

This research will provide municipalities, project developers and other instances with better knowledge on how to improve neighborhoods and attract specific socio-demographic groups. Based on this research, measures can be taken in neighborhoods to improve quality of life, as well as attract other socio-demographic groups.

The scientific importance of this study is twofold, finding people's preference and finding the differences and added value of video-based survey in comparison with a text-only survey. First, with this study more insight in people's neighborhood preferences will be gained and add to neighborhood preference research. This study is unique because it solely focusses on neighborhood attributes aside from non-visual attributes (e.g. money and distances). The second important contribution to literature is the comparison between the conventional text-only and the video survey. Previous research does not agree on whether the use of multimedia has added value. With this study more research will be obtained about the similarities and differences between the two methods. Subsequently a decision can be made on what the added value of using multimedia in SP neighborhood studies is.

1.7 reading guide

This research paper is divided in four chapters, the current chapter is the first and presents the introduction to the problem and the limitations of this study. The second chapter discusses previous literature to get a better perspective on the problem and the research that has already been performed on this matter. The methodology of the study is explained in chapter three of this paper. The fourth chapter presents the outcomes of the analysis and a conclusion based on all chapters forms the last fifth chapter. Additionally, this last chapter gives directions for future studies in the neighborhood and multimedia field.

2. Literature review

Before the actual experiment can be executed, a literature study needs to be done to discuss other research in the field and determine how to perform the research.

2.1 Neighborhood preference

In this first section the importance of performing neighborhood research will be discussed, as well as the factors that influence the preference of people. Additionally an overview of the attributes that are used in residential and neighborhood studies will be provided.

2.1.1 The importance of residential and neighborhood satisfaction

When choosing a place to reside, people want to achieve a good level of quality of life. Housing satisfaction is often an indicator of quality of life (Ahn & Lee, 2016) is one of the domains under residential satisfaction. Residential satisfaction has been defined in literature as the level of pleasure one receives from living in a specific place (Ahn & Lee, 2016). A survey which was performed by the Dutch ministry (Het ministerie van Binnenlandse Zaken en Koninkrijksrelaties, 2016) showed that 97% of the people who find their residential area (very) attractive expressed that their neighborhood is nice and 65% feels attached to their neighborhood. Individuals are more likely to have place attachment, when they are more satisfied with the physical and social characteristics of the neighborhood (Mesch & Manor, 1998, p. 514). Also Sirgy and Cornwell (2002) found that neighborhood features affect quality of life through the mediating effects of community satisfaction, housing satisfaction and home satisfaction (Sirgy & Cornwell, 2002). Thus, when people are less satisfied about their neighborhood this results in a lower quality of life. This is the case in multiple neighborhoods, as discussed in sub-section 1.1 Problem definition. The research into people's preferences regarding their surroundings is very important to ensure a good quality of life within a community

2.1.2 Factors that influence residential and neighborhood preferences

When choosing a place to live, people need to decide on a type of dwelling in a certain kind of residential area (Vasanen, 2012). City management can influence the characteristics of the house, neighborhood, and resident, thus the habitability of a residential setting (Erdogan, Akyol, Ataman, & Dokmeci, 2007). The topics housing choice and housing preference have been studied from various angles. Some of these angles are; life course, family events, geographical changes and households seeking housing that corresponds with their needs (Vasanen, 2012).

Residential preferences are influenced by many factors. When going through the life cycle (e.g., changes in income, education level, age and household composition) people have different needs and therefore wishes in their residential state. For example when a child is born and a family expands, their wishes and needs change. Larger families need more rooms and value a safe environment with a playground for the child (Patterson et al., 2017; Jansen et al., 2009; Nijenstein et al., 2015; Heins, 2004, Badland et al, 2012; Vasanen, 2012). Families with children prefer to live further away from the city center, while the adolescent and older respondents favor to live centrally (Lindberg, Hartig, Garvill, & Garling, 1992). Van Cauwenberg et al. (2016) found that among older adults the sidewalk evenness is a very important attribute, while the attribute traffic calming device had a very low importance. The neighborhood preferences in the study executed by Badland et al. (2012) are different between groups of people. Preference differences are found in the group age, education level and household income. However Badland et al. (2012) only focusses on the urban style preference of people. Lindberg et al. (1992) looked at the influence of the life cycle stages on preferences on housing as well as neighborhood preference. Since people's neighborhood preferences change when going through the life cycle it is very important in neighborhood studies to include descriptive questions regarding, among others, education level, age and household income (Michaelson, 1977).

Patterson et al. (2017) use current dwelling tenure type, while Liao et al. (2015) look at multiple neighborhood and dwelling characteristics of the current dwelling of the respondents. These studies show that not only socio-demographic groups can be formed, but also groups of people, based on their current residential/neighborhood characteristics. Additionally, the Dutch 'Woon onderzoek' (Rijksoverheid, 2012), which is a large survey executed by the Dutch government, uses demographics to find preferences of groups of people. These demographics of the respondents and their preferences can be important knowledge for policy makers as well as developers and other instances. Thus, together these studies indicate that the current living situation of people influences their residential and neighborhood preferences. Therefore when performing neighborhood research it is very important to take these into account. In section 3.5 Survey the factors (e.g. socio-demographics and neighborhood characteristics) that are examined in this study are discussed.

2.1.3 Attributes residential and neighborhood preferences

The attributes in this study are based on a literature study. For this purpose relevant studies that used text and/or multimedia methods are reviewed in Table 3. The article title as well as the purpose of each research is as well summarized in Table 3. In addition, a column showing the number of participants was added to give an idea about on how many respondents participated in each study. One of the most used attributes is the attribute price, however this will not be used as indicated earlier, because the focus of this research lies on the actual preferences, without the influence of price. Another attribute that is often used, is the proximity or distance to something, this can be city center, park, supermarket, transit. Only visual attributes will be used in this study, therefore the proximity or distance attribute will not be used. Some studies in Table 3 only focus on housing attributes and others on a combination of housing and neighborhood attributes. the attributes that have to do with housing will not be examined further.

Louviere and Timmermans (1990) use multiple neighborhood attributes, such as greenery, playgrounds and the amount of traffic in the neighborhood. Liao et al. (2015) and Tian et al. (2015) use in their studies the neighborhood attributes; street design and the parking availability in the neighborhood. The type of car parking is used as a neighborhood attribute by Molin et al. (1996). Traffic calming device is an attribute used by Van Cauwenberg, et al. (2016), which is an attribute that can be placed in the category of safety related attributes within the neighborhood. Vos et al. (2016) use in their study the neighborhood attributes presence of bike lanes and the presence of green, which have been mentioned earlier, because other studies also used these attributes.

Additionally in the study performed by Heins (2004), respondents were asked which attributes they considered important in a rural residential environment (Appendix A – Frequently stated preferences). Typical characteristics of the rural landscape such as nature, open spaces, water and animals are much valued among the characteristics of the residential environment (Heins, 2004). Quietness and safety are considered very important social characteristics of the residential environment, as can be seen in Appendix A – Frequently stated preferences. Both were considered as reject-inducing attributes by almost all respondents and even 90% considered them essential (Heins, 2004).

Table 3. Attributes other studies

Article	Participants	Purpose	Key Attributes	Methods
Alternate methods of conjoint analysis for estimating housing preference functions: Effects of presentation style (Orzechowski, Arentze, Borgers, & Timmermans, 2005)	35 Text only 29 multimedia	Whether the two different presentation styles result in different housing preference	-Price -Number of bedrooms -Dormer window -House (incl. extensions)	-Text only -Multimedia -Discrete choice model
Comparing text-only and virtual reality discrete choice experiments of neighbourhood choice (Patterson, Darbani, Rezaei, & Zacharias, 2017)	184 Text only 184 multimedia	Compare the statistical choice model results obtained from two DCEs with different representation methodologies	-Dwelling type -Space between buildings -Depth front yard -Travel time work (car) -Travel time work (PT) -Travel time to shops -Home value	-Text only -Multimedia Respondent can navigate through environment -Discrete choice model
The effects of pre-experimental training on the validity and reliability of conjoint analysis: the case of housing preference (Maciej, Arentze, Borgers, & Timmermans, 2012)	64 participants	Examine the effects of pre-experimental training on the internal, external and predictive validity of the estimated conjoint choice model.	-Price -Number of bedrooms -Dormer window -House (incl. extensions)	-Text only -Multimedia -Discrete choice model
The impact of including images in a conjoint measurement task: evidence from two small-scale studies (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009)	28 respondents	examine the impact of including images in a conjoint measurement task	-Dwelling type -Architectural style -Costs -Residential environment -Number of rooms	-Text only -Images combined with text -Discrete choice model
Beyond demographics: human value orientation as a predictor of heterogeneity in student housing preferences (Nijenstein, Haans, Kemperman, & Borgers, 2015)	667 participants	choice heterogeneity in students' housing preferences in the Netherlands	-Price -Dwelling size -Cycling time -Bathroom -Kitchen -Walking time to park -Walking time to supermarket -Outdoor space	-Text only -Discrete choice

Article	Participants	Purpose	Key Attributes	Methods
Hierarchical Information Integration Applied to Residential Choice Behavior (Louviere & Timmermans, 1990)	76 participants	introduce, discuss and apply a recently proposed research approach for studying complex decision making called hierarchical information integration	-Distance to parking -Amount of traffic -View -Privacy -Greenery -Playgrounds	-Text only -Discrete choice
Rural living in city and countryside: Demand and supply in the Netherlands (Heins, 2004)	112 participants	Most frequently stated preferences	See Appendix A – Frequently stated preferences	-Indicate most important attribute
Association of neighbourhood residence and preferences with the built environment, work-related travel behaviours, and health implications for employed adults: Findings from the URBAN study (Badland, et al., 2012)	1616 participants	Association of neighbourhood residence and preferences with the built environment, work-related travel behaviours, and health implications for employed adults	-Walkability -Urban style	-Interview
Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis (Liao, Farber, & Ewing, 2015)	1053 respondents	comparing preferences with actual residential locations and travel patterns in the two distinctive subregions	-Distance to work -Distance to PT -Street design -Dwelling price -Distance to shops etc. -Housing types -Parking availability	-Discrete choice model -Internet survey
Desire for Smart Growth: A Survey of Residential Preferences in the Salt Lake Region of Utah (Tian, Ewing, & Greene, 2015)	1227 households	How do preferences vary from region to region? More conservative parts of the country, such as the Salt Lake region of Utah, may still favor conventional suburban neighborhoods	-Proximity to work -Proximity to destination -Housing composition -Parking availability -Home prices -Bicycle/pedestrian streets -Proximity to transit	-Discrete choice -Online survey -Text only
Predicting consumer response to new housing : a stated choice experiment (Molin, Oppewal, & Timmermans, 1996)	95 respondents	summarize some of the methodological discussion related to alternative ways of eliciting consumer preferences.	-Tenure -Size living room -Type building -Monthly costs -Depth backyard -Green space -Car park -Bedrooms -Shopping center	-Discrete choice Survey -Text only

Article	Participants	Purpose	Key Attributes	Methods
Street characteristics preferred for transportation walking among older adults: a choice-based conjoint analysis with manipulated photographs (Van Cauwenberg, et al., 2016)	1030 participants	investigate the perceived influence of a large set of micro-scale environmental factors on a street's appeal for transportation walking using manipulated photographs of a street among a large sample of older adults	-Sidewalk -Separation from traffic -Obstacle on sidewalk -Traffic volume -Speed limit -Traffic calming device -Overall upkeep -Vegetation -Benches	-Combination text and pictures -Conjoint based choice model
Visual preferences in urban street scenes (Nasar, 1984)	29 Japan 17 US	Perform a cross-cultural comparison between Japan and the US on visual preferences in urban street scenes	-Nature -Vehicles -Cleanliness -Orderly/chaotic -Closed/open -Simple/diverse	-Video and pictures -7 point bipolar rating scales
Urban sprawl: neighbourhood dissatisfaction and urban preferences. Some evidence from Flanders (Vos, Acker, & Witlox, 2016)	1878 respondents	Comparison between people's preferences and their current satisfaction regarding the neighbourhood	-Traffic safety -Presence of bike lanes -Presence of green -Social safety -Proximity of diverse activities	-Internet survey -Very dissatisfied-Very satisfied scale

2.2 Stated preference survey

The multiple ways that can be used to investigating people's neighborhood preferences are discussed in this section.

2.2.1 Stated preference and revealed models

One way to gain more insight in the residential preferences of social groups and on how to improve these is by means of performing surveys. There are two modelling approaches that can be distinguished in people's preference, these are revealed choice (RC) and stated choice (SC). Revealed models are based on observational data of households' actual (housing) choices in real markets, while stated preferences and choice models are based on people's reactions to hypothetical (housing) choices (Timmermans, Molin, & Noortwijk, 1994, p. 215).

On first sight the revealed modelling approach seems the most appropriate and accurate. However the pitfall is that it does not necessarily say much about how people would actually like to live. The stated modelling approach has a better fit with underlying preferences, because it looks at how people would like to live. Therefore, in this study the stated preference (SP) approach will be applied.

2.2.2 The applicability of stated preference surveys

The SP surveys encompass a large number of research tools (Figure 2) that are designed to help understand people's preferences, and they are used in many disciplines. Some of these disciplines are: marketing; transportation-, environmental- and health-economics; as well as land-scape research and urban planning (Patterson, Darbani, Rezaei, & Zacharias, 2017). In the field of residential preferences a SP survey is commonly used, as shown in Table 3. For instance Van Cauwenberg et al. (2016) use for their research into street characteristics a SP survey, to find the underlying preferences. Figure 2 shows two valuation methods that belong to SP studies. Public assets, including environmental assets can only be priced using the contingent valuation (CV), due to the fact that there is no market and therefore no compensation payment (money). In this survey type people are asked how much they are willing to pay for an improvement in for instance the neighborhood (Blore, 1996). In this study it is not important how much people are willing to pay, but the goal is to find out people's preferences, without the influence of money. Different attributes and their level's importance can be retrieved using the multi-attribute valuation (MAV), which can take multiple forms. On one side, of these forms the respondent is asked to select an alternative as the 'best' one. On the other side, attributes need to be numerically scored, between these two, more alternatives are possible (Westenberg & Koele, 1994).

There are two different types of MAV SP surveys; preference based conjoint analysis and choice modelling (CM). When looking at marketing research, conjoint analysis is the most used marketing research method for analyzing consumer trade-offs (Green, Krieger, & Wind, 2001). This survey type is based on economic research where housing research has a lot of common ground. By making a set of different attributes that consists of multiple levels the underlying preferences and magnitudes can be derived. This gives the possibility to make the ideal house/area for a certain group of people.

The last years CM has taken over the preference research in urban planning and housing research due to the fact that it lets people choose between options (set of attributes), which encompasses a better reality (Jansen, Coolen, & Goetgeluk, 2011). While conjoint analysis lets the respondent rate each set of attributes individually.

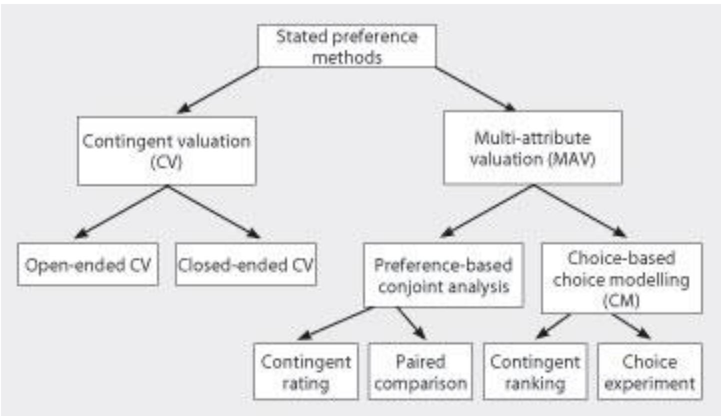

Figure 2. SP methods (The royal college of midwives)

2.3 The use of multimedia in stated preference studies

Traditionally SP studies are performed in text surveys, in recent years all sorts of multimedia surveys are used instead of text. In this chapter different studies that use multimedia will be discussed, as well as its added value.

2.3.1 Pros and cons multimedia in SP surveys

Traditionally, the profiles that are used in a SP survey consist of descriptions of attributes (e.g., dwelling type) and attribute levels (e.g., detached house) in the format of written text (also called verbal descriptions) (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009). Residential attributes are more visibly oriented than most economic research, for instance in laptop marketing research, where specs are valued, but cannot be expressed in tangible pictures. This led to the incorporation of pictures in housing preference research (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009). The reasons for using images according to Jansen et al. (2009) are:

- some attributes, such as architectural style, may be difficult to describe in a few words. Thus, one may opt to visualize such attributes;
- by visualizing attributes, respondents may better understand and therefore appreciate the various options, thus may make better choices;
- images may enhance the realism of the task, this may increase the external validity of the results;
- visualization may lead to a higher homogeneity of perceptions as it is less open to individual interpretation compared to written descriptions;
- the task may be more interesting and less fatiguing;
- nowadays respondents may be accustomed to the use of images due to technological advances over the years and may feel a lack of images as an omission in the measurement task (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009).

Drawbacks for using images are:

- when text surveys are used, there is more control over the experiment than when images are included in the experiment.
- visualization may lead to information being provided differently than the researcher actually intended (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009).

According to the review performed by Jansen et al. (2009) the results of studies are not consistent between pictures and text-only (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009). Based on their own results they are unfavorably disposed towards using images in a conjoint measurement task about general housing preferences (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009). With new upcoming technologies such as VR people's preference can be measured in a more lifelike environment. However, as just discussed there are proponents and opponents for using VR. Until now a few studies have been performed with the use of VR in the housing scene (Orzechowski et al. 2005, 2012; Patterson et al. 2017; (Dijkstra & Timmermans, Conjoint Analysis and Virtual Reality – a Review, 1998) and also in other markets (e.g. product preference) VR has already been used (Berneburg, 2007); (Dijkstra, Leeuwen, & Timmermans, 2003); (Bateman, Day, P.Jones, & Jude, 2009). A review performed by Ernst and Sattler (2001) investigated the use of text vs multimedia in studies across different fields. Their overview determines that the outcomes of the studies differ and are not consistent (Ernst & Sattler, 2001).

VR gives the possibility to further examine people's preferences. But whether VR gives a better representation of reality compared to text-only is still up to debate, due to the lack of research and the low numbers of respondents in the literature. The main findings are different between studies performed by Patterson et al (2017) and previous studies by Jansen et al. (2009) and Orzechowski et al. (2005), where attributes tended to have greater importance when presented visually. In Patterson's study, visual attributes did not have greater importance than text variables. 'It is not known a priori whether different presentation styles will result in (a) different estimated housing preferences and attribute utilities, (b) equal utilities but with a different error variance, or (c) equal utilities and the same error variance' (Orzechowski, Arentze, Borgers, & Timmermans, 2005).

Just as the pros and cons for using images, the same drawbacks and positive points could be translated to VR and other multimedia levels. Most research using multimedia focusses on a combination of housing and neighborhood characteristics, while almost none solely focusses on housing attributes. One of the studies that focusses on housing preferences is the study performed by Orzechowski et al. (2001), this is done by using not only a 3D representation, but also a 2D representation Probably the use of multimedia in housing preference research is more challenging as compared to neighborhood preference research. This is due to the fact that housing preferences mostly contain gross areas which are really difficult for people to see and understand through VR. Also the furniture, wall paint etc. will be taken into account by the respondent in a VR study. Neighborhood preferences are better suited, because there is less chance to include 'hidden' attributes and therefore influence people's choice. Also looking at literature it can be clearly seen that the inclusion of pictures and VR mostly is applied on residential preferences. An example is shown in Figure 3, this is an example of the VR study performed by Patterson et al. (2017). VR experiments give the possibility to show an actual environment, instead of a little and vague description. Also Bateman et al. have argued that the inclusion of visuals can enhance the evaluability of choice tasks (Bateman, Day, P.Jones, & Jude, 2009).

Figure 3. Residential VR application (Patterson, Darbani, Rezaei, & Zacharias, 2017)

Two built environment studies were executed by Orzechowski et al. (2005, 2012) with VR, however both report a low number of respondents. The study performed by Orzechowski et al. (2005) was performed on 29 subjects (Orzechowski, Arentze, Borgers, & Timmermans, 2005). In another study performed by Orzechowski et al. (2012) 36 respondents were included in the VR experiment (Orzechowsky, Arentze, Borgers, & Timmermans, 2012). The only study with a high(er) number of respondents is the study performed by Patterson et al. and included 184 respondents in the VR experiment, as can be seen in Table 3. One of the goals of this study is to evaluate a 'new' presentational method for neighborhood surveys. The main goal of this study is to find out accurate residential preferences through the application of VR instead of text. According to Patterson et al. (2017) these more precise residential preferences will be acquired, because respondents are not left to their own interpretation, but a VR model is shown. Advancements in how to present (develop) the VR world will be incorporated in this study (Patterson, Darbani, Rezaei, & Zacharias, 2017).

Most studies that compare any level of multimedia with text-only, use two different groups for both methods. One could opt for using just one group for both methods. The advantage of using just one sample is that the socio-demographics are exactly the same between the two methods. One of the drawbacks for using just one respondent group is that the task is doubled (higher burden) and therefore less sets can be included. Another important drawback is formulated in the research performed by Orzechowski et al. (2012), in this study the researchers conclude that pre experimental training influences the results. Thus, having just one respondent group for both methods is undesirable for this study.

2.4 Multimedia

In this section the different types of multimedia and their applicability on this study will be discussed.

2.4.1 Multimedia use in studies

Before a drawing package can be chosen to construct the virtual world, the type of multimedia needs to be determined. Four types of multimedia are considered for this study, these are based on usage in literature:

1. Pictures (Jansen, Boumeester, Coolen, Goetgeluk, & Mollin, 2009);
2. Panorama (Van Holle, et al., 2014);
3. Video (Krysan, Couper, Farley, & Forman, 2009);
4. Interactive VR world (Patterson, Darbani, Rezaei, & Zacharias, 2017).

The lowest level of multimedia is the use of pictures. Because the study focusses on multiple attributes throughout the neighborhood, multiple pictures would be necessary to give a good idea of the total neighborhood and the different attributes within it.

Another way of presenting the virtual world is through a panorama. The panorama allows the respondent to pan around from 1 viewpoint. Just like the use of pictures multiple panoramas would be necessary in order to show the neighborhood in a good manner and display all the attributes, of which some will have different locations.

The third type of multimedia, the use of a video to show the neighborhood and all the attributes and their levels. Just like the previous two the researcher is in control of what is shown and in which manner. Through this way the researcher can make certain that the respondent will see all the attributes. However just as the pictures it is not interactive for the respondent.

The highest type of multimedia is the use of an interactive VR world. This allows the respondent to 'walk' around through the virtual world, with the limitations the researcher has set. The use of interactive VR should challenge the respondent more, which should lead to better results. However the respondent is in control and chooses what he/she sees, instead of the researcher.

2.4.2 The applicability of multimedia in this study

An overview of the four multimedia types that are considered and their applicability on this study are shown in Table 4, the explanation of the scoring is discussed after the table. The study is restricted by the researcher's designing capabilities, time and the amount of respondents. Based on these restrictions the applicability of each multimedia type on this study will be evaluated. In addition the goal was to use the highest level of multimedia, due to the fact that VR is gaining importance in research.

The scoring on amount of sets is included, because of the low(er) amount of respondents. With a lower amount of respondents it is important to let them rate more sets, in order to obtain more observations. The duration score is based on the researcher's capabilities. The scoring depends on the expected time the researcher needs to develop the multimedia survey. The third scoring point is the level of interaction between the multimedia level and the respondent. Because people are getting 'tired' of traditional research, a survey including interactivity could lead to better results. The scoring is based upon the interactivity scale from the article defining virtual reality: dimensions determining telepresence (Steuer, 1992). It is important that the respondent sees all attributes, which leads to the scoring point control of researcher. The goal was to use the highest multimedia level possible, with the set of restrictions, therefore the scoring point proximity to VR is included. The scoring is based upon the place of the multimedia level on the vividness and interactivity axis in the research performed by Steuer (1992).

Table 4. Applicability multimedia research project

	Pictures	Panorama	Video	Interactive VR
Amount of sets	++	+	++	-
Duration	++	+	+	--
Level of interaction	--	+	+/-	++
Control of researcher	++	+	++	-
Proximity to VR	--	+/-	+/-	++
Total	++	++++	+++++	+/-

Amount of sets

The research is limited through time, which means that the amount of respondents also will be limited. The amount of sets each respondent is presented with differs throughout the different levels of multimedia, because some ask more time to understand or walk through. There is no research done into the time a respondent needs to answer/rate one set for each of the multimedia types. Therefore the researcher's knowledge is used to score this point. A ++ score is given to both the use of either pictures or videos, because both are easy to understand and people do not have to be instructed (much). This allows the amount of sets to be higher than the other two that score lower and results in higher reliability with the same number of respondents. Panorama scores a +, because people need to be instructed a little on how it works. Also the respondent needs to go through multiple panoramas to see a whole set of attributes. Therefore the amount of sets will be lower compared to the other two that were earlier mentioned. Interactive VR scores the lowest, due to the fact that people need to be instructed the most. Walking through VR worlds is still no common practice for respondents, while the use of videos and pictures is. Also due to the fact that people navigate themselves through the world, they will probably take more time to go through one environment in comparison to the other three types of multimedia.

Duration (development time)

The interactive VR type scores the lowest (most time needed), because the world needs to be made and afterwards restrictions need to be built in and a way must be found to navigate people through. Panorama and video score both +, because for both a virtual world needs to be created and afterwards rendering and testing is needed, before the respondents can fill in the questionnaire. The use of pictures scores ++ (least time needed), because only a partial world needs to be designed. The respondents will only see a few shots throughout the environment, when pictures are used. Also using pictures in the online questionnaire is easier and quicker implemented, due to the fact that less testing is needed.

Level of interaction
Studies show that when the interaction is higher, respondents are more committed, which leads to better results in reliability (Patterson, Darbani, Rezaei, & Zacharias, 2017). Pictures involve (almost) no interaction with the respondent, which is why it scores low in this category. The use of a video has more interaction, but is still not interactive. The panorama level lets people look around from one central viewpoint, which leads to a + as score. The highest level of interaction is the interactive VR world in which the respondent is free to 'walk' around throughout the environment.

Control of researcher
Also a point that needs to be taken into account is the control that the researcher has on what the respondents see. Due to the fact that a whole neighborhood is used and attributes are spread throughout it, it is important that the respondent sees all attributes in each set. Because the control of the researcher is low, the interactive VR scores the lowest (Patterson, Darbani, Rezaei, & Zacharias, 2017). In a panorama the researcher can choose the location(s), which allows the researcher to have more control. However the control is more limited than with a video or pictures. In a panorama for example people can choose to only pan to the left and therefore miss one of the attributes. In a video and with the use of pictures, the researcher has control of what is shown and in what way.

Proximity to VR
One of the goals of this study is to find people's underlying preferences for neighborhood attributes, through the application of VR. The higher the level of VR, the bigger the difference is with the text-only questionnaire. Pictures score the lowest (--), due to the fact that there is not much VR in a picture. The video and panorama contain virtual reality, however it is still less than an interactive VR world where people can participate in themselves. Therefore panorama and video are scored +/- and the interactive VR type has a maximum score of ++.

2.5 Conclusion literature
In this chapter the importance of doing research into people's neighborhood preference was discussed. By increasing people's overall neighborhood preference, the quality of life of these people will increase too. For municipalities and other instances this study will provide insight in how to attract different social groups into specific neighborhoods. The traditional way of doing a conjoint analysis is a survey based questionnaire, where the attributes and their levels are presented as text. Over the years more researchers used multimedia instead of text to present attributes. In the academic literature there is no consensus on whether multimedia can be used instead of text. Some studies indicate that there are no differences and that a multimedia study increases reliability and represents the 'real world' better. Others find that both study types lead to different results, where through multimedia presented attributes gain importance.

Based on the control of a researcher, time restrictions and the level of interaction the choice was made to use a video to represent the multimedia part of this study (Table 4). From the literature review (Table 3) interesting/useful attributes such as street design, presence of a playground, safety, presence of green and parking were used in neighborhood studies. A set of attributes is chosen based upon the literature study in this chapter, the chosen attributes are discussed in 3.2 Attributes survey. These chosen attributes and their corresponding levels will be shown through a video to the respondents.

3. Methodology

In this third chapter the methodology that was used to execute this research is explained. This ranges from the virtual world itself, to the statistics what were used for deriving people's preferences.

3.1 Introduction

In the book conjoint measurement (Gustafsson, Herrman, & Huber, 2003, 2007) a flow diagram of steps is presented for executing a conjoint analysis. This flow diagram was used as starting point for this research, but was slightly changed to fit the current research (Figure 4). The second and third step have been exchanged, because in this research the use of a virtual world was previously determined (research questions) and based on this the collection design was chosen. An additional step of choosing a drawing package was added into the flow chart. The remaining steps were not changed in comparison with the original flow chart by Gustafsson, Herrmann and Huber (2003, 2007). All steps as shown in Figure 4 will be discussed in this chapter, except for how the stimuli were presented, this was already discussed in section 2.4 Multimedia.

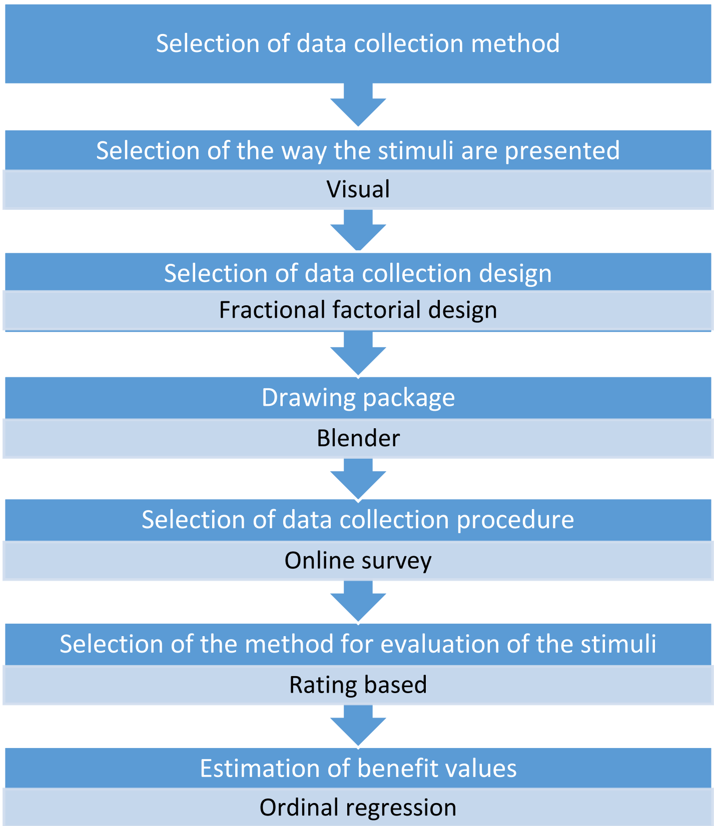

Figure 4. Partial flow diagram adapted from A. Gustaffson, A. Herrmann and F. Huber. Conjoint Measurement, Fourth Edition, Chapter 1, page 5, Springer, 2003, 2007 (Gustafsson, Herrman, & Huber, 2003, 2007).

3.2 Attributes survey

The attributes and their levels that are used in this study were based on Table 3 and are presented in Table 5. Six attributes were chosen, because more than six attributes in a SP survey are too confusing and are too much to process for the respondents (Caussade, Ortuzar, Rizzi, & Hensher, 2005).

Table 5. Attributes and levels

Attribute	**Levels**
1. Street design	1. Primarily for cars 2. For cars/pedestrians and bicycles
2. Parking type	1. On street 2. Designated parking places
3. Speed slowing measures	1. No 2. Yes, speedbumps
4. Playground in neighborhood	1. No 2. Yes
5. Pond in the neighborhood	1. No 2. Yes
6. Type of green	1. No green 2. Low (grass) 3. Medium (bushes) 4. High (trees)

1. Street design
The street outline was expected to be an important attribute for people, because this highly influences the appearance of the street and additionally could give a feeling of security. The attribute street design was used multiple times in previous studies, as can be seen in Table 3. The attribute was divided in 2 levels:
1) Primarily for cars, with a sidewalk;
2) For cars, but with separate sidewalk and bicycle lane.

2. Parking type
In the Netherlands 71.3% of the households own one or more cars (CBS, 2017). However, not everyone can park their car on their own property, which means that people have to park in public areas. This attribute was less used in literature as parking type, but more in terms of parking availability in the neighborhood (Table 3). Since house characteristics were not taken into account in this study, two levels were chosen:
1) On street parking;
2) Designated parking places next to the road.

3. Speed slowing measures
Safety is an important attribute for people, this can be incorporated by adding speed slowing measures for the cars. Heins (2004) showed in their research that safety is even an reject inducing attribute. In this case two levels were chosen:
1) No speed slowing measures;
2) Speed slowing measures, namely speedbumps.

4. Playground neighborhood
People with children are expected to exert positive value on a playground in the neighborhood. Only one study in Table 3 used the presence of a playground as an attribute (Louviere & Timmermans, 1990). This is another reason why this attribute was added, the attribute has two levels:
1) No playground;
2) Playground in the neighborhood.

5. Pond in neighborhood
In a lot of neighborhoods in the Netherlands a pond or a river goes through the residential area. This can give people a good feeling (nature), but it can also give a feeling of unsafety for children, because of safety risks. According to Heins (2004), water is a much valued characteristic of the residential environment. Just as the attribute playground, the pond consists of two levels:
1) No pond;
2) Pond in the neighborhood.

6. Green type
In a lot of different studies green was taken into account (Heins, 2004), as mentioned in Table 3. For this study different types of green heights were chosen and not the density or proximity of them. Four levels were chosen for this study:
1) No green;
2) Low green, namely grass;
3) Middle green, namely bushes;
4) High green, namely trees.

3.3 Method
As previously mentioned in sub-section 2.2 Stated preference survey there are two types of SP survey types. In this study a conjoint analysis was used due to the fact that discrete choice is a too high burden for respondents filling in the video experiment. This is caused by the fact that people first have to go through the first video environment and after this through the next before they choose between them. Also, these follow-up environments would probably be a high burden for the respondents and lead to people forgetting parts, which results in less trustworthy results (bigger variance). The research was performed as quantitative study, to contribute with larger number of respondents to the video research in residential preferences. The respondents were asked to participate in either the video or the text-only experiment in an online survey. In order to compare the results it was important that both sets of respondents were alike in terms of socio-demographics and to have a low bias.

3.3.1 Factorial design

The total amount of possibilities with the attributes and levels as shown in Table 5 is 2^5x4^1= 128, which is a so-called full factorial design. A full factorial design includes all possible combinations of the attributes levels. In most studies a fractional factorial design is used instead of a full factorial design. This design, involves selecting a fraction of the profiles constructed in a full factorial design (Rao, 2014). For this experiment it was important to find an efficient factorial design, because there were 128 different possibilities (economic use of resources (Gunst & Mason, 2009, p. 235)). With the use of the program Statistical Analysis System (SAS) the fractional factorial design was created and 16 (⅛th) alternatives instead of the originally 128 were generated (Appendix B – Rating sets). All levels of the attributes mentioned in 3.2 Attributes survey consist of an even number (two and four in this case), to make sure that a fractional factorial would represent the full factorial better (Rao, 2014). Up till 20 sets can be used without degradation in data quality, within the range 0-20 there is no evidence of increasing random error (Johnson & Orme, 1996). The task complexity (video) and respondent burden (duration of the survey) may lead to less valid responses (Hato & Timmermans, 2008). Therefore less than 16 sets per respondent would be advisable. However, ''doubling the number of tasks per respondent is about as effective in increasing precision as doubling the number of respondents'' (Johnson & Orme, 1996). Since for this study two separate samples were needed, a low(er) number of respondents was expected. Therefore the choice was made to let each respondent rate all 16 sets, with the remark that up till 20 sets can be used without degradation in data quality.

3.4 Virtual world

This section discusses the drawing package that was used, as well as how the 3D model was designed and why.

3.4.1 Drawing package

For the visualization of the neighborhood a drawing program of the Blender Foundation, which is a Dutch public-benefit corporation, was used. Blender is a free and open source 3D creation suite that is based upon a python script, which can be modified to suit the wishes of the designer (Blender Foundation, 2017). Blender version 2.78c was used. Blender has three types of drawing/render settings, which are Blender Render, Cycles Render and Blender game. Blender game was not used, because the purpose of this study was not to create a game. Furthermore this type is not used as often as the other two settings. Blender Render, also called Blender Internal, is the default setting. Blender Render was chosen to draw the neighborhood environment, because of two main reasons. The first is that Cycles Render is more complicated to work with, because it works with nodes and has more functionalities. Since the quality does not have to be a 1080p (full HD) video without glitches and taking into account time restrictions an easier type had the preference. The second reason is the render time, a model created in Cycles Render renders the ray traces in the end video differently, which results easily in a more than doubled render time.

3.4.2 The Blender model

Before the virtual world was created in Blender, a sketch was made of how the world should look. To make the designing process easier the choice was made to use a repetitive pattern in the virtual world. As a drawing guideline the ASVV was used (CROW, 2012). In this guideline minimum rules concerning road design are stated. The minimum road width with parking on/next to the street is 4.8 meters for traffic in both ways. For the design 5 meters was used due to practical reasons. The parking places alongside or on the road need to be at least 2 meters by 6 meters in order to be able to park a car, these dimensions were also used in the design. For the sidewalk the ASVV states that it needs to be at least 1 meter. Due to the fact that in some cases there needs to be green (trees, bushes or grass) on the sidewalk, a sidewalk of 1.5 meter was used. The parking places alongside the road could not be continuous and needed to be interrupted once in a while.

For the repetitive pattern a total length of 26 meters was chosen (Figure 5). This is equal to 4 parking places with a length of 6 meters each, plus on each end 1 meter space where parking is not possible. The road and sidewalk were drawn like earlier mentioned, 2.5 meter width for half of the road (5/2) and 1.5 meters for each sidewalk. The housing next to the road had the same length as the parking places, 24 meters in total. The other 2 meter were filled by a brick wall of 2 meter high with a width of 1 meter each to come to the total length of 26 meters. The block that represented the housing part was 8 meter high and has a depth of 8 meters. This allowed the block to have the dimensions of as well single houses as apartments. Also, each 26 meters a lamppost was positioned in the middle of the repetitive roadside of the sidewalk.

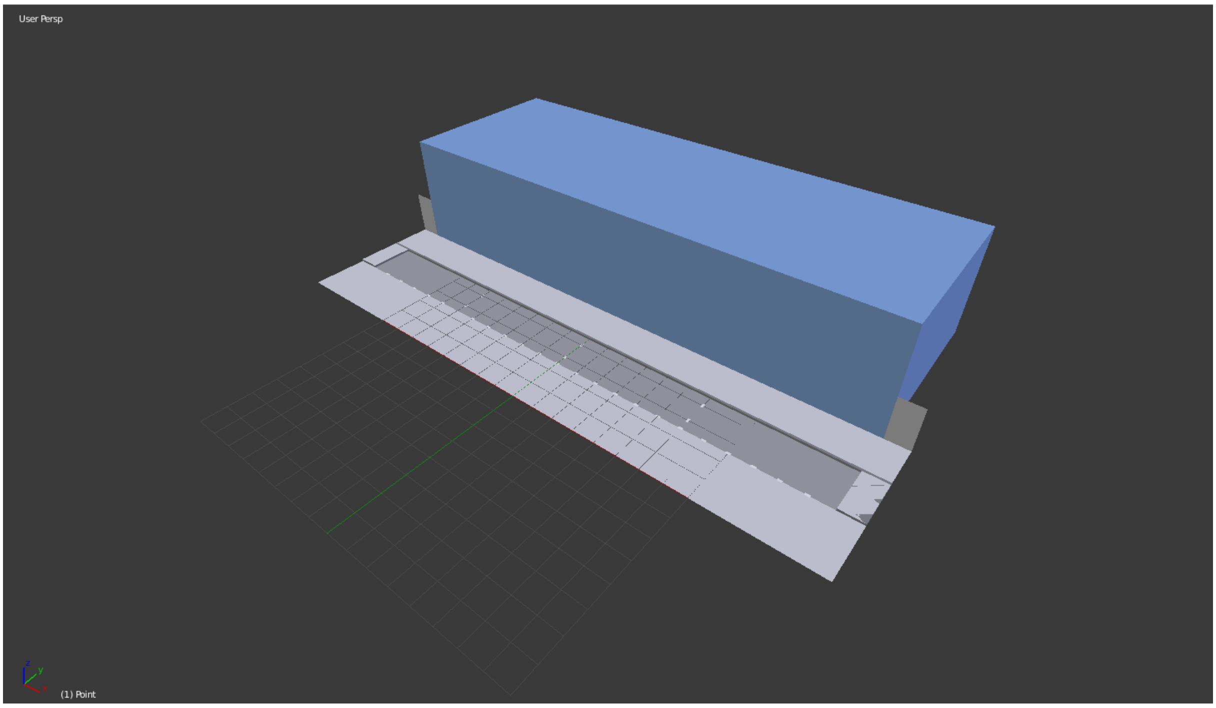

Figure 5. 26 meter block

The design (block) was duplicated and mirrored to create a road. To make the neighborhood more realistic, a straight road with no end was not an option, this is why a T-splitting was drawn and the repetitive road design continued in both ways of the T-splitting. Also, this street needed to end somewhere, which is why the total design was duplicated and pasted after making the right corner (Figure 6). For the pond as well as the playground one block of housing was removed and replaced with an empty space. The empty space was shown as a concrete open space. The reason for this was that the amount of housing as well as the depth people can see needed to be kept the same (Patterson, Darbani, Rezaei, & Zacharias, 2017). The amount of cars, benches etc. was equal in each model. In addition, the colors of all objects in the worlds, from tiles to cars to the blue sky, and the state of the sun was constant between all models.

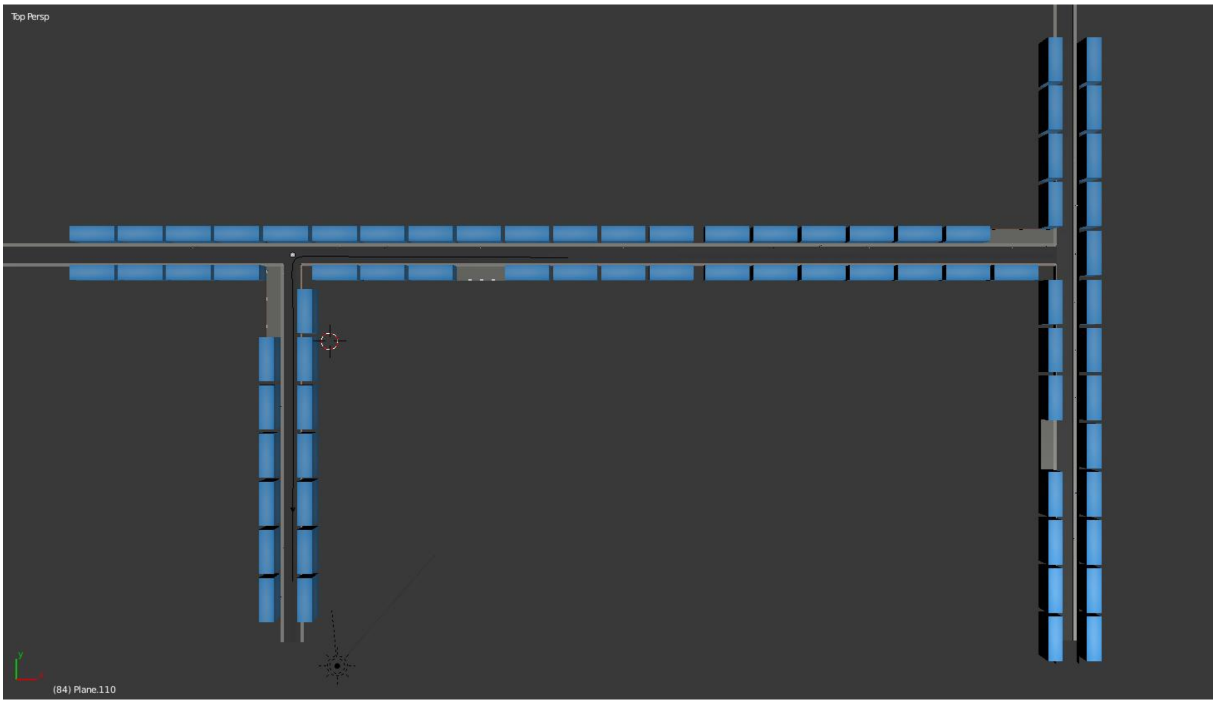

Figure 6. Top perspective neighborhood design

For the look of the model, seamless textures from the internet were used to texture for instance the road and the sidewalk (Figure 7). Some parts of the model were downloaded from the internet: the cars, lampposts, benches, bushes, trees and the playground. Sites used for this purpose were: cgtrader (CG Trader, 2017), Turbosquid (Turbosquid, 2017) and Free 3d (Free 3d, 2017).

Figure 7. Seamless concrete and sidewalk pavement

3.4.3 The base models

Four base models were designed, in these models the other attributes were added in different layers, which allowed to turn them on or off for each video. The four base models were chosen, because these layers could not be turned on or off and cause attributes or objects to move. The four base models contained the on street and off street parking as well as the road design (with or without separate cycle lane). The difference between the model with and without bicycle lane is the biggest, due to the fact that by incorporating the cycle lane also the houses, lampposts and other objects needed to be moved with the length of the cycle lane. Therefore a different design was necessary for both, as shown in Figure 9 and Figure 10. The color of the bicycle lane was red, which is commonly used in the Netherlands, to make the design more lifelike. To make clear that the red lane a bicycle lane, the sign of a bicycle lane (Figure 8) was placed in a repetitive manner upon the lane.

Figure 8. Bicycle lane

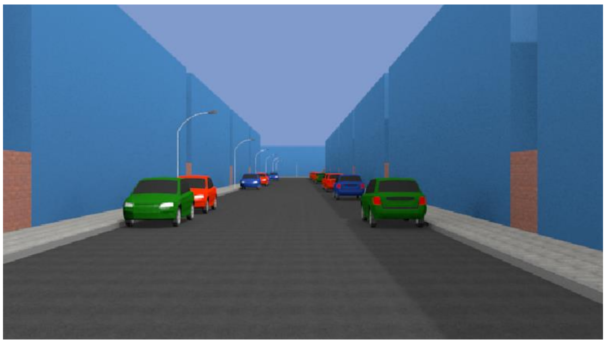

Figure 9. On street parking without bicycle lane

Figure 10. On street parking with bicycle lane

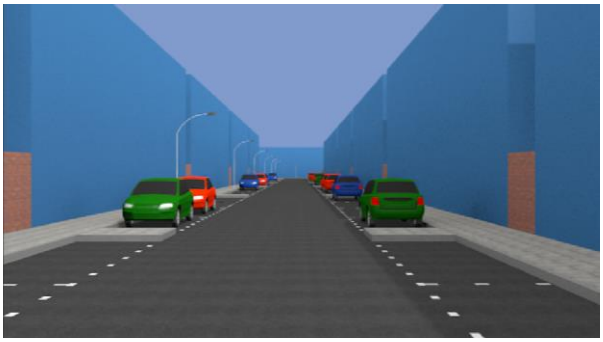

Figure 11. Designated parking spots

The difference in the attribute parking type was much smaller than the difference in the attribute street design. This was due to the fact that deliberately no cars were parked in the spot where no spot would be in the off street parking model. Only minor changes, like the lines and the addition of breaks between the parking places were the change as can be seen in Figure 9 and Figure 11.

Pond

A plane was used as starting point for drawing the pond, which was modified with an ocean modifier. By changing the amplitude of the waves (lower) and setting the total play time lower, a very slow and low ‘ocean’ was created, which represents the pond in this case (Figure 12).

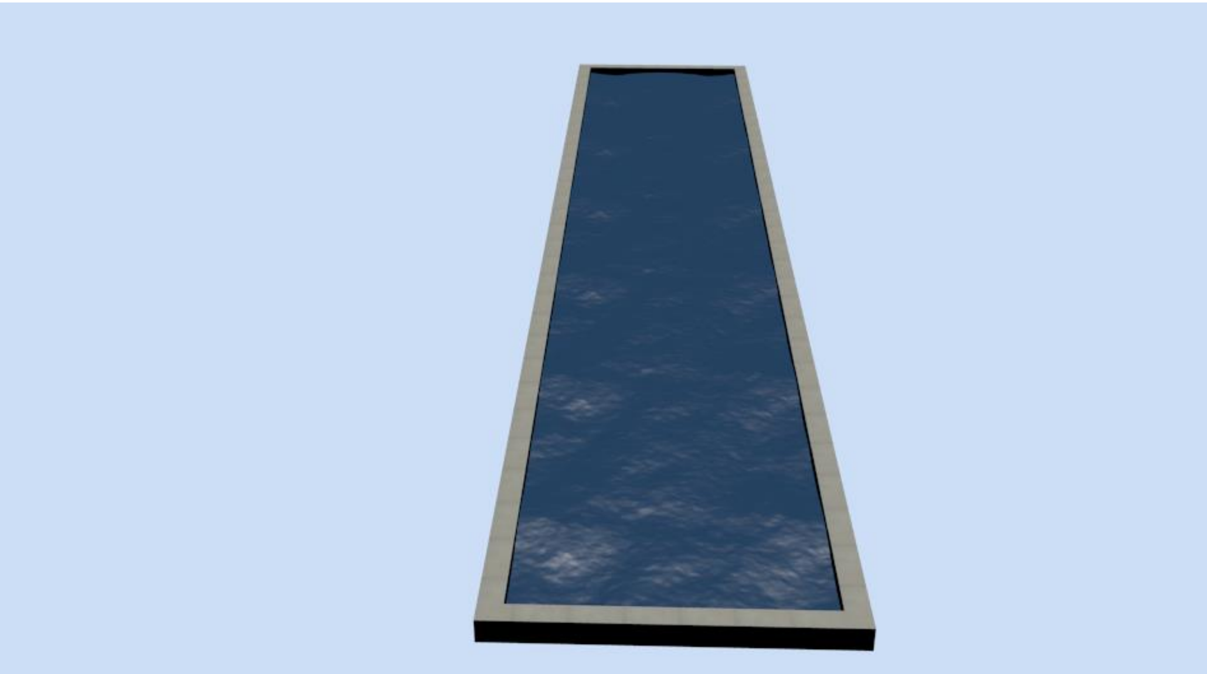

Figure 12. Pond

Playground

For the playground a plane with a sand texture was used as ground, due to the fact that a concrete underground would not be desirable for the safety of the playing children (Figure 13). The playground equipment was randomly placed upon the sand, but in such a way that all equipment could be seen in the video. The fence at the front of the playground was added in a later stadium. After sowing the videos to different people (panel), some suggested that the playground did not look safe in the environment, because there was no border between the road and the playground. By adding this fence the safety issue was taken into account.

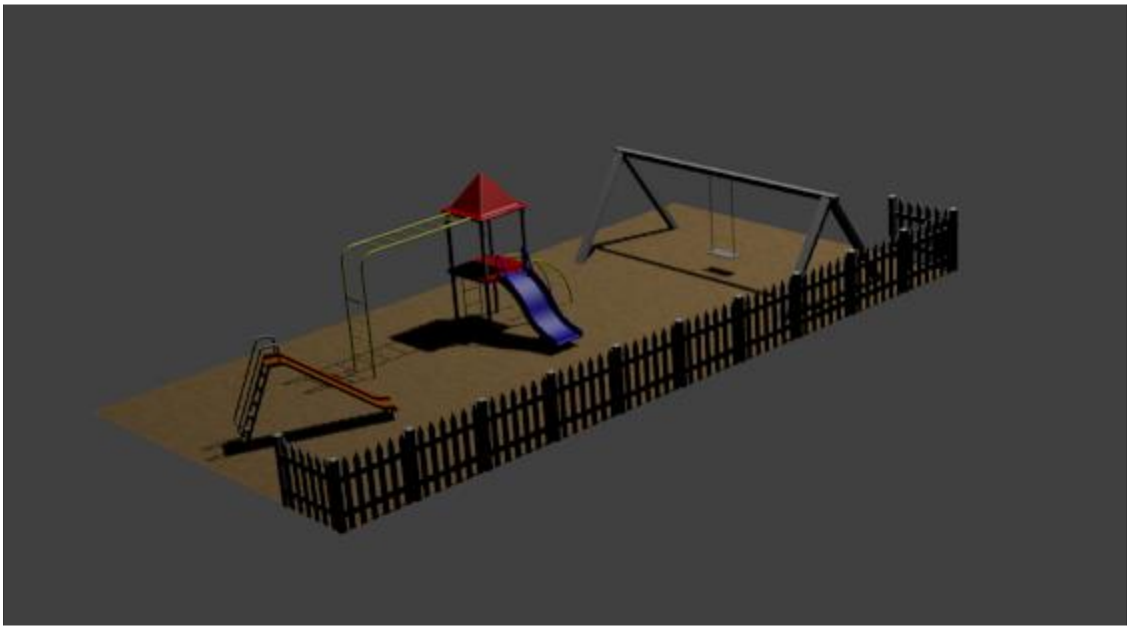

Figure 13. Playground

Speed slowing measures

As speed slowing measures, small and thin speedbumps were used (Figure 14) instead of the longer ones consisting of vowels. This was done because the technical design was more difficult, consisting of making the edges more rounded and giving the speedbumps a lifelike texture.

Figure 14. Speedbumps

Green

The last attribute in this study was the green type, which consisted of four levels. In the first level no green was present in the neighborhood, which can be seen in Figure 14. The three remaining levels of green type were designed in the same way but with the addition of 'pieces' of green (Figure 15, Figure 16 and Figure 17). The distance between each 'piece' of green is 26 meters (one each block) and the amount is therefore the same for all as well as the location(s).

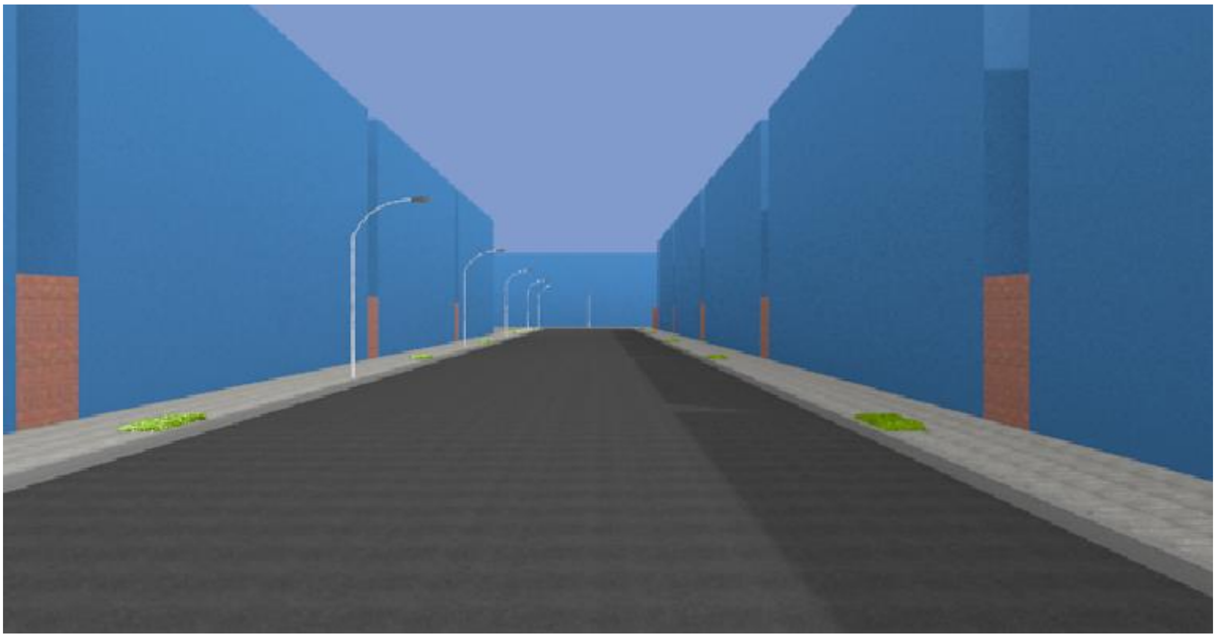

Figure 15. Low green type (grass)

Figure 16. Middle green type (bushes)

Figure 17. High green type (trees)

3.4.4 Camera settings

To make the video environment as realistic as possible, the camera needed to move through the environment just like a person would in a car, accordingly the height of the camera and the position on the street was chosen. The settings of the camera were: 720p, 840 frames length with a frame rate of 24 fps (frames per second). Also the standard setting for the depth the camera could see was changed. This was done because the initial setting would show 3 blocks of housing and thereafter blue sky was shown. So moving forward, parts of the environment after the (blue) blocks started loading. The human eye can see further and does need to load images that are further away from us. This is why the clipping settings were set higher to see to the end of the streets like a human would.

By making a video, the researcher is in control of what and how everything is shown. With this also some questions/problems did arise. One of these was what to do with the camera when seeing the pond and the playground or the empty spaces. One could opt for swinging the camera in that direction and therefore putting more focus on it, but this will also be done when the layer is off and 'nothing' is present in this spot. Also, a normal driver will be looking forward and not look for seconds to a side, because we already see parts of what's next to us due to peripheral vision of the human eye. Therefore, the choice was made to look straight ahead (from viewpoint of viewer), but to slow down the frame rate (more frames for the same distance) at the pond and the playground. This allowed people to see the attributes, but not put too much focus on these attributes.

The videos were 840 frames long, with a frame rate of 24 fps as earlier mentioned, which led to movies of 35 seconds each. Initially, the render time was approximately 28 hours per movie of 35 seconds, which was optimized by linking objects and using low poly cars to approximately 4-5 hours per movie of 35 seconds. This results in a total render time of 64 to 80 hours for the sixteen movies. The length of rendering was slowed down by ray trace building, because this could only be done on 1 core, instead over all of the computer cores.

The rendering itself went quickly, because all of the cores could be utilized. Each frame needed to be ray trace built and afterwards rendered. The ray trace building took approximately half a minute per frame, while rendering the frame itself took approximately one to two seconds.

3.5 Survey

The 'Berg enquete' system from the TU/E was used to perform the surveys. This is a web-based survey platform, where images and videos can be integrated. The 'Berg enquete' system allowed to have one main questionnaire (descriptive questions), with two separate sub-questionnaires (one containing video and one consisting of text-only). The descriptive questions (e.g. socio-demographic-, economic-, dwelling- and neighborhood characteristics) in the survey were based on the Dutch Woononderzoek, which is performed every four years by the Dutch government among inhabitants to derive residential information and market information (Rijksoverheid, 2012). When descriptive questions in the current study were based on other levels or surveys than the Woononderzoek, this is mentioned. Other research papers have also been used to come up with the important socio-demographic questions within neighborhood preference research (Patterson et al. 2017; Nijenstein et al. 2015; Vasanen 2012; Badland et al. 2012; Tian et al. 2015). For the online survey design chapter 9 (question and questionnaire design) from the handbook of survey research was followed (Krosnick & Presser, 2010). In this chapter best practices are shown, as to start with simple questions and to use simple words throughout the questionnaire.

The first page respondents saw was an introduction for the survey, on this page an explanation of the goal and the duration of the survey was provided. An overview of all the questions within the survey is shown in Appendix C – Online survey. After the first page the respondent was asked to fill in some demographics of him- or herself (e.g. gender, age, education level and ethnicity). The education levels were based on the Dutch bureau of statistics (CBS). The questions on the third page covered the health status of the respondent (e.g. health status and long-term illness). The fourth page of the survey covered questions regarding the household (e.g. household composition, household income and car ownership). The household income levels were based on the Dutch tax system (Belastingdienst, 2017), the option not to fill in the income was added to prevent respondents quitting the survey in an early stadium. When respondents answered the household question with one of the categories containing children, than two additional questions were presented. The first is how many children the household exists of. The second was in which age category these children are. This was done to make a distinction between families with younger children and older ones, which could allow to see if there are differences between these categories.

After these socio-demographic questions, an explanation page of the neighborhood sets follows. On this page the respondent was presented an overview of all attributes and their levels. Additionally it was mentioned that the experiment was only about the environment and not about the houses alongside the road. Because of this the houses were presented as (soft blue) blocks in the video experiment. After the experiment explanation, an example question was presented to make the respondent familiar with the look and scoring. The rating score for this example question was not included in further analyses. The actual sixteen sets (examples: Appendix D – Video part survey and Appendix E – Text only part survey) were randomly shown to the respondent, who rated each of them separately.

After the respondent rated the sixteen sets, another page with background questions about their current living situation was presented to them. This was done deliberately, because some respondents may quit the experiment in an earlier stage, when they were presented with a long list of questions at the start of the questionnaire. By starting with the most important questions (age, income etc.) and thereafter the neighborhood sets, the chance was higher that when a respondent quits, he or she quitted after the rating sets instead of during. When a respondent did not finish the sixteen neighborhoods, they were excluded from analysis.

At first, the respondent was asked to answer some questions about their current housing situation (e.g. property ownership, type of housing and building period). The respondent was given the opportunity to choose the option 'other', just as in the 'Woononderzoek'. Additionally, the respondent could fill in that they do not know the building year of the house/apartment to prevent guessing. Furthermore categories of the 'Woononderzoek' were bundled together to make the bandwidth of each level bigger from 10 to 20 years.

The pages thereafter were about their current neighborhood (e.g. urban density, type of parking, satisfaction living environment, attachment to neighborhood, satisfaction green, availability play facilities and proximity to a pond). On the last page the respondent was thanked for the participation and here they could fill in additional comments. Additionally they were asked to score if they enjoyed to fill in the survey on a 7 point Likert scale. In the handbook of survey research (2010) their review of scale length and adding a midpoint suggests that offering a midpoint is desirable and using a 7 point Likert scale is in most cases optimal (Krosnick & Presser, 2010). Additionally intended meanings (in words) of points were added (Appendix C – Online survey), which provided the respondent a with better understanding of the meaning of each of the points on the scale.

3.5.1 Embedding Video

The sixteen rendered Blender neighborhood videos needed to be incorporated in the survey, this was done by uploading all the videos onto YouTube and setting them hidden from being found. This allows only people to see it through a specific link for each video. YouTube allows videos to be easily embedded in for instance a survey and with a few clicks the embedding code can be retrieved from the website. The embed code can also be changed in order to make it fit the needs of the user. In this case a frame width of 640 and a height of 360 was chosen, which is lower as the rendering quality, but allows to play the movie without loading in between, also with a slower internet connection. The name of each movie was hidden for the respondents. Because the videos were presented in a random order, the numbering of the videos is not logical (1 to 16), which could confuse the respondents. Normally at the end of a YouTube video, after a few seconds, automatically another YouTube movie would start playing. This was blocked and therefore after watching the video, the respondent could replay the video and did not see other videos. The YouTube embed codes for each of the videos are shown in Appendix G – YouTube embed codes. A summary in text of the attributes was shown next to the video to make sure the respondent had a good picture of the neighborhood he or she was rating. This was done deliberately for two reasons, first because literature shows that including a summary in VR allows respondents to focus on all attributes (Patterson et al. 2017; Orzechowski et al. 2005). Second, the placing of the summary table was chosen deliberately, so that people do not have to go to a next screen or scroll each time, which could increase the chance that people quit in an early phase of the questionnaire. The code of the rating page for the video survey is shown in Appendix F – Code video rating page.

3.6 Rating scale

The scale that was be used as a rating scale for the neighborhoods required to be easy understandable for the respondents. In addition a sufficient amount of scale points needed to be shown to administer important differences. However, a scale with too many points would be too difficult to process, due to the fact that the respondent cannot place a good meaning (understand) on each of the points. Krosnick and Presser (2010) conclude that there appears to be no standard for the number of points on a rating scale, also common practice varies widely between studies (Krosnick & Presser, 2010). A ten point scale was chosen instead of an odd numbered scale. This was done to 'remove' the middle (neutral) option and, avoid respondents from selecting this option too easily. Additionally in real life people have to make a choice if they are willing to live there or not, however the preference may be slight. The 10 point scale therefore encompasses better with the reality, giving more data points.

3.7 Data collection

The data was collected through an internet survey. People were approached through different channels. In this research social media and e-mail were used to recruit respondents. The e-mails were spread within a few companies that were willing to corporate with the research. The companies were very diverse, from building companies to administrative companies to sport companies. The respondents could fill in either one of the online surveys (text-only or video).

3.7.1 Respondents

In total 565 respondents opened the two surveys, as indicated in Figure 18. From these respondents 234 opened the text-only survey (blue branch) and 331 respondents opened the video survey (dark yellow branch). Looking at the video survey, 225 respondents did not complete the survey, while only 106 respondents completed the survey of whom one was removed after inspection. This (removed) person rated all the profiles with the same grade and also noted a (very) short survey time. As earlier mentioned the survey was designed to have the (neighborhood) profiles in an earlier stadium and not at the end, which could result in more uncompleted surveys. This led to respondents who still completed all the profiles, but quitted in one of the end questions. For the video survey this was 1 person. After inspection, this person was added to the remaining completed surveys. This resulted in a total sample size of 106 people for the video experiment, producing 1.696 observations.

Looking at the text-only survey, 128 people out of 234 did not complete the total survey. 106 respondents completed the survey of whom none had to be removed after inspection. The survey design was the same as in the video experiment, which also resulted in uncompleted surveys, which could be used for the experiment (completion of all 16 choice sets). In this case 3 respondents could be added to the completed surveys, which resulted in a total sample size of 109 respondents for the text-only experiment, producing 1.744 observations.

The difference in numbers between the people that open the survey and the ones that actually participate is striking. This completion ratio number is quite different between both survey types. Where 45% of the people completed the text-only survey, only 32% completed the video survey. A part of this difference can be explained due to the fact that one company (approximately 50 mail addresses) had blocked the YouTube videos that were embedded in the video survey. Subsequently these people could not complete the survey, which resulted in a lower completion ratio. Also the length of the video survey was on average longer, which could lead to more people quitting the survey in an earlier stadium (3.7.2 Duration survey).

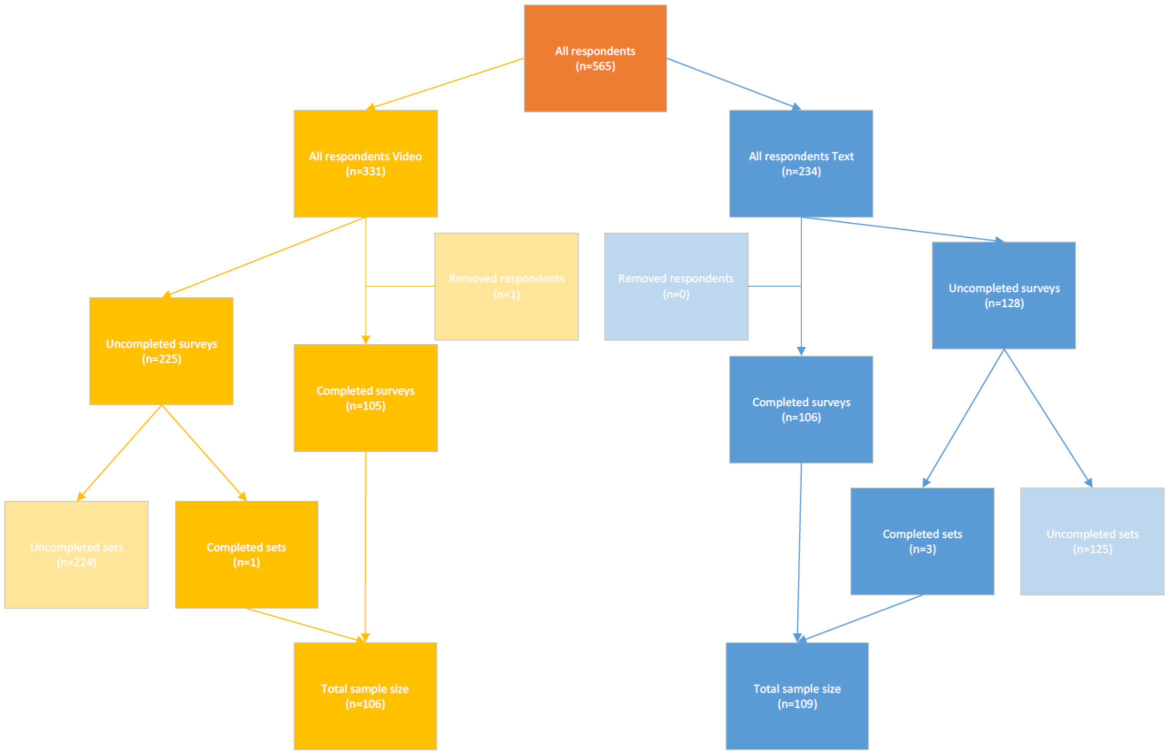

Figure 18. Respondent overview

3.7.2 Duration survey

The survey system collected not only the answers to the questions, but also the start and end time of each respondent. With this, the average duration of the survey per person could be calculated to have more information about the duration of the survey. A few surveys register a duration time of over an hour, which can probably be explained by the fact that people opened and/or started the survey and were interrupted (for instance on work) and therefore completed the survey later than average. These cases have been inspected and nothing irregular has been found, which is why these cases were not removed. For determining the average survey time these cases were not taken into account, because they strongly influence the average. The average time spent on the text-only survey was 7 minutes and 26 seconds (cases > 1 hour excluded), while the average time spent on video survey was 10 minutes and 13 seconds (cases > 1 hour excluded). A scatterplot of the survey times was added as Appendix H – Duration surveys, which showed that the distribution of duration did not include any outliers. The duration time of the video survey was higher compared to the text-only survey, as could be expected, due to the movie time(s).

3.8 Ordinal regression

An ordinal regression is commonly used in social sciences, especially when the scoring scale is ordinal, such as Likert scales and 10 point scales, which was the case in this study. The Ordinal Regression Model is "essentially sets of binary regressions that are estimated simultaneously with constraints on the parameters" (Long, 2012). These calculations were performed with the software package SPSS (version 23).

For a theoretical explanation of the ordinal regression model, the study of Long (2012) was followed. The ordinal model was derived from a regression with an unobserved and continuous variable y^*: $y_i^* = \beta_0 + \beta_i x_i + \varepsilon_i$

The ordinal logit model (OLM) assumes that ε is logistic with a mean of 0 and its variance $\pi^2/3$. The continuous y^* can be divided into observed, ordinal categories by using the thresholds τ_0 through τ_j, according to the research of long (2012): $y_i = j$ if $\tau_{j-1} \leq y_i^* < \tau_j$ for $j = 1$ to j, where $\tau_0 = -\infty$ and $\tau_j = \infty$. This means for this study with a 10 point scale that this would become the measurement model:

$$
y_i = \begin{cases} 1 \rightarrow \text{''not at all''} & \text{if } -\infty \leq y_i^* < \tau_1 \\ 2 \rightarrow & \text{if } \tau_1 \leq y_i^* < \tau_2 \\ 3 \rightarrow & \text{if } \tau_2 \leq y_i^* < \tau_3 \\ n \rightarrow & \text{if } \tau_{n-1} \leq y_i^* < \tau_n \\ 9 \rightarrow & \text{if } \tau_8 \leq y_i^* < \tau_9 \\ 10 \rightarrow \text{''very much''} & \text{if } \tau_9 \leq y_i^* < \infty \end{cases}
$$

3.8.1 Dummy coding

In order to analyze the 'design code' of each of the levels of the attributes as named in 3.2 Attributes survey the coding needed to be changed in SPSS. For this a dummy code was used, which is a binary coding method. This method was chosen because SPSS can recode the levels easily into dummy codes. The number of dummy codes needed per attribute is the number of levels -1. Membership in a particular level was coded with one and non-membership in the group on the other hand is coded with zero. One group (level) therefore receives only zeros on all dummy codes and becomes the reference category. The dummy coding for this study is shown in Table 6, where design code represents the original code. Based on expected results the lowest level of each attribute was coded as reference group.

Table 6. Dummy coding

Number of levels	Design code	Dummy coding			Explanation coding		
2	1	0			Lowest level		
	2	1			Highest level		
4	1	0	0	0	No low green	No middle green	No high green
	2	1	0	0	Yes low green	No middle green	No high green
	3	0	1	0	No low green	Yes middle green	No high green
	4	0	0	1	No low green	No middle green	Yes high green

The column ‘explanation code’ in Table 6 explains what the dummy coding actually means in words. Five attributes in this study consisted of two levels, the expected lowest utility level (primarily for cars, on street parking, no speed slowing measures, no playground and no pond) were coded as zero, while the expected highest utility levels (For cars/pedestrians and bicycles, designated parking places, speed slowing measures, playground and pond) were coded with one. Only one attribute consisted of four levels and required three dummy codes. The green type is a good example for the dummy coding (Table 6), because it shows that using three dummy codes all four levels are known. In this case no green as green type was coded as three times zero and was called the reference category.

3.9 Conclusion method

An online questionnaire was used, which was distributed through social media and via e-mail within a few companies that were willing to cooperate. The questionnaire was made with the ‘Berg enquete’ system of the TU/E. There were two survey types, namely the text-only and the video variant. Both consisted of the same six attributes, and the same corresponding levels. Due to the high amount of neighborhood possibilities a fractional factorial design was used, consisting of 16 neighborhoods. These neighborhoods were created with the drawing package Blender, which is an open source drawing package. Due to time restriction and processing power of the computer Blender Render was used instead of the other drawing types within Blender. All movies had the same duration. Additionally, in every movie the attributes that were not measured (for instance lamppost) had the same location, color and amount. This was done to make sure that these would not be measured in the survey. An ordinal regression was used to analyze the data, because of the 10 point rating scale that was used. In order to perform an ordinal regression the levels of each attribute were recoded as dummy variables. The average duration of the video survey was higher compared to the text-only survey, which could have resulted in a higher fallout rate.

4. Results

In this fourth chapter the results from the text-only and video survey were analyzed and will be discussed. and data was analyzed and will be discussed.

4.1 Descriptive statistics

In order to compare the results of both text based and video based groups it was important to look at the socio-demographics of the respondents. In Table 7 an overview of the socio-demographics of the respondents of both surveys is shown. Just as in the study performed by Patterson et al. (2017) there was a demographic match between both survey types with some minor differences, suggesting that the two sub-samples could be compared with each other. Because of this, the difference across representation modes (text-only vs video) may be primarily associated with different methods and not the difference between respondents of the two presentational methods (Patterson, Darbani, Rezaei, & Zacharias, 2017). The characteristics of the sample in this study had a Dutch ethnicity and most of the respondents lived in a house (74% and 77%) and owned one or multiple cars (92% and 86%). Additionally most respondents lived in low urban dense parts of the Netherlands and had a high level of education. This shows that some groups were overrepresented in comparison to the actual Dutch population, which typically happens with self-administrated questionnaires (Schwanen & Mokhtarian, 2004).

Table 7. Descriptive statistics data

	Text survey	***Video survey***
Gender		
Female	57%	51%
Male	43%	49%
Age		
<30	41%	33%
30-49	25%	29%
50+	34%	38%
Education level		
High	50%	56%
Middle-Low	51%	44%
Household composition		
No kids	69%	70%
one or more kids	31%	30%
Household income		
€ 0 -€ 33.790	44%	43%
> € 33.790	39%	42%
Unknown	17%	15%
Ethnicity		
Dutch	99%	100%
Other	1%	0%
Urban density		
Middle - High (20.000+)	47%	51%
Low (<20.000)	53%	49%

	Text survey	Video survey
Housing type		
House	74%	77%
Apartment	23%	19%
Other	3%	4%
Home Ownership		
Owner	65%	68%
Rented	35%	32%
Car ownership		
Yes, one	49%	43%
Yes, more than one	43%	43%
No car	8%	13%
Parking car		
On own property	58%	62%
On public/other ones property	42%	38%

4.2 Preference scores

Before the analysis could be performed on the importance of each attribute, preference scores were examined and compared between the two survey types. For each 'grade' the corresponding percentage of times that it was chosen can be derived from Figure 19. The preference scores were close to a normal distribution, in which more times neighborhoods were scored with a grade around the median and less times a score was given on the outer ends of the score bar (Figure 19). However the text-only answers appeared to be more normally distributed than the video answers, because 7 and 8 are less preferred, while 1, 2, 3 and 10 are clearly more preferred in the video answers than text-based (Figure 19). This could indicate that people who did the video survey overall tended to give lower grades compared to the text-only experiment.

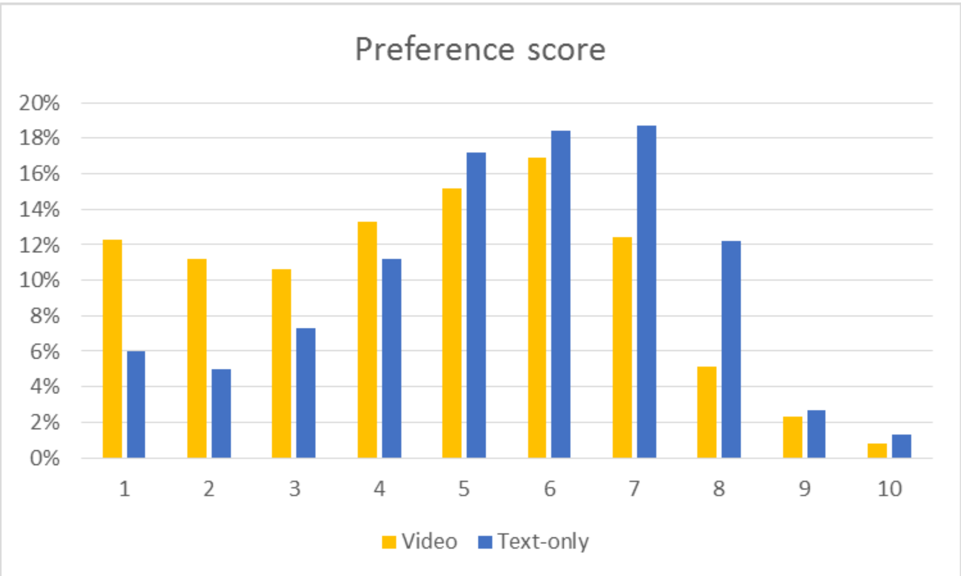

Figure 19. Preference scores survey types

After filtering on respondents that only give the score insufficient (≤5) from the data of the video experiment, eighteen respondents remained in the file. This means that 18 out of 105 respondents only scored a 5 or lower on all sixteen neighborhoods. When looking at what scores were given, mainly very low scores were given, the lower the score, the more often it was chosen (Figure 20). The same filtering was used on the text-only data in which only one respondent scored all 16 neighborhoods with a 5 or lower.

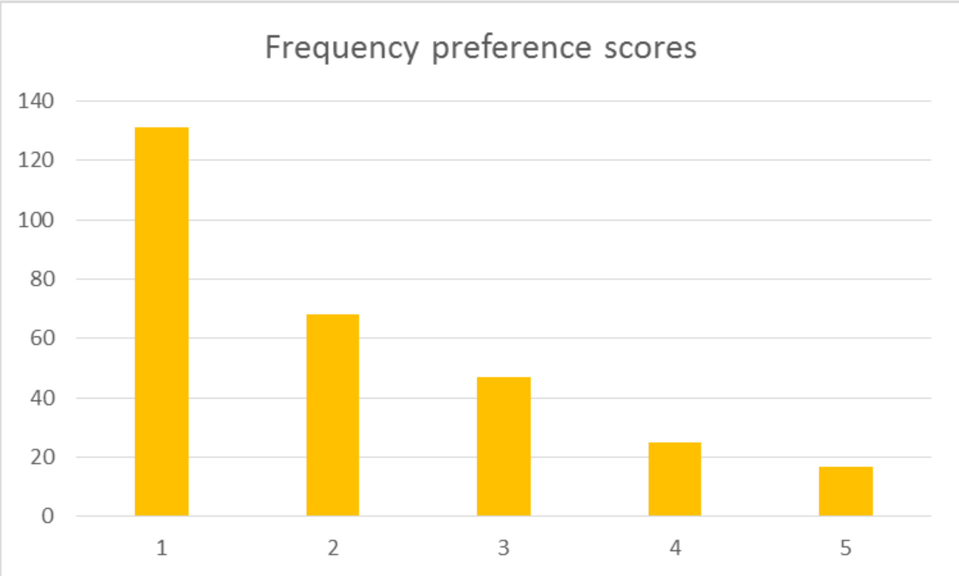

Figure 20. Scoring frequency video experiment

After discovering the low scoring of eighteen people in the video experiment, especially in comparison with the text-only data, it was interesting to find out what group of people was responsible for these low scores. When looking at the socio-demographics of the 18 respondents who only scored a 5 or lower it was striking that it was similar to the socio-demographics of the total sample. However the socio-demographic age deviated in comparison with the total sample. By expressing the age category of the 18 respondents who scored on all 16 sets a 5 or lower, as a percentage of the total respondent amount in that age category a good comparison could be made between the age categories. Only 6% of the respondents under 30 scored a 5 or lower on each neighborhood (Figure 21). 19% of the people in the age category 30-49 scored all neighborhoods with a 5 or lower, while even 25% of the respondents in the age category 50+ scored a 5 or lower on all neighborhood videos. Thus, between age categories a clear difference was observable in the relative respondent amount that scored a 5 or lower on all 16 videos. Especially the older respondents tended to be more negative in scoring within the video experiment. Also, the one person that scored a 5 or lower on all 16 neighborhoods in the text-only experiment was assigned to the 50+ age category. But compared with the total amount of respondents in the age category 50+, it was just a minor percentage.

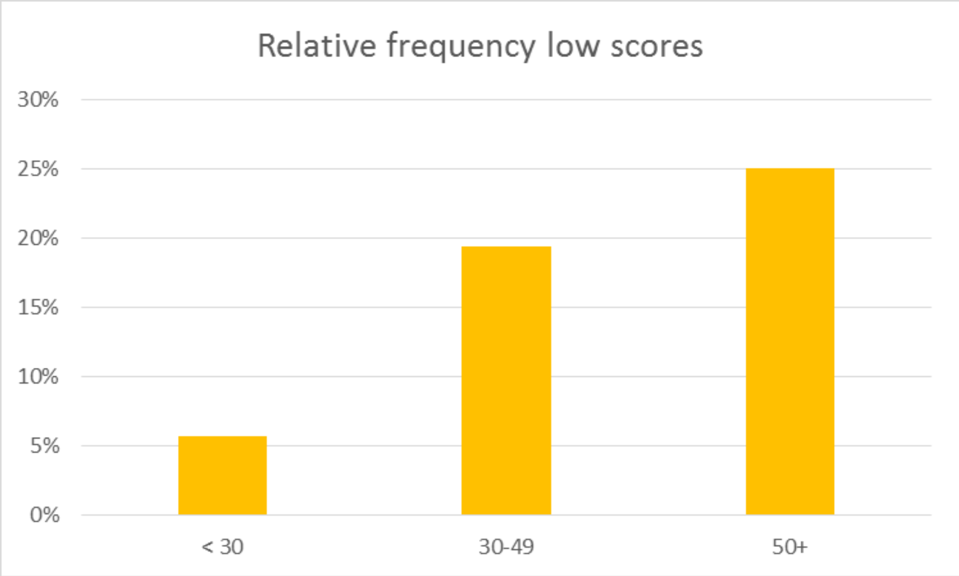

Figure 21. Relative frequency low scorers per age category

4.3 Estimation results

In this section the results for answering the first research question: What are the neighborhood preferences of people?, the second research question: Are there differences between the preferences of the video group and the text-only group? Will be answered in this section. The third research question: What is the added value of video based questionnaires? Will be discussed in the discussion and conclusion of this study.

4.3.1 Goodness of fit

Before answering the research questions of this research it was important to first examine the model fit of both experiment types. SPSS produces alongside the regression table extra information, these are added as Appendix K – Output ordinal regression Video experiment and Appendix L – Output ordinal regression Text-only experiment. One way of calculating the model fit is the McFadden R^2 (also referred to as likelihood ratio or pseudo R^2). This R^2 measures the amount of unpredictability in one variable that is shared by the other. The formula to calculate the R^2 was based upon the book best practices in quantitative methods written by Osborne (Osborne, 2008, p. 374):

$$R^2_{mf} = 1 - \frac{-2\text{LL}(\text{Final})}{-2\text{LL}(\text{Intercept})}$$

McFadden's R^2 shows if the model is able to reproduce (predict) the actual observed choices. The R^2 can vary from 0 to 1. If it is equal to 1, the decision makers' choice can be predicted perfectly (Hensher, Rose, & Greene, Applied choice analysis, 2015). Thus the R^2 shows how good the outcome model (utilities) can predict the actual ratings (choices) respondents made. According to Hensher, Rose, and Greene (2015), a value of at least 0,1 for a discrete choice model, represents a decent model. When the value of the R^2 is between 0,2 and 0,4 it means that the model has a good fit.

The -2 log likelihood for the video experiment is shown in Appendix K – Output ordinal regression Video experiment and these numbers were filled in the earlier mentioned formula:

$$\mathrm{R}^2 = 1 - \frac{622{,}914}{847{,}676} = 0{,}265$$

The R^2 was equal to 0,265 for the video experiment, which is considered a good fit by Hensher, Rose, and Greene (2015).

For the text-only experiment the same formula applied as for the video experiment. The -2 log likelihood for the text-only experiment is shown in Appendix L – Output ordinal regression Text-only experiment and these numbers were filled in the earlier mentioned formula:

$$\mathrm{R}^2 = 1 - \frac{629{,}030}{993{,}501} = 0{,}367$$

The pseudo R^2 is equal to 0,367, which is also considered a good fit according to Hensher, Rose, and Greene (2015). Remarkable was that the R^2 of the text-only experiment was higher than the one from the video experiment. This was mainly caused by the higher -2 Log Likelihood from the intercept, because in this number there is a relative 'big' difference (847,676 VS 993,501), while the -2 Log Likelihood final was approximately the same. Based on this can be concluded that the text-only survey had a better fit in this experiment compared with the video experiment, because a model with a higher R^2 is better at predicting the observed choices. It was expected that the video model would have a better model fit, because people see the environment and are not left to their imaginative capabilities. A possible explanation for the better model fit of the text-only experiment could be the limited amount of levels of the attributes, as well as the simplicity of the attributes (easy to imagine).

In the study performed by Patterson et al. (2017) the log-likelihood ratio of the VR study was slightly higher (0,243) than the ratio of the text-only study (0,229). The video experiment of this study scored slightly higher (0,265) compared to the VR survey of Patterson et al. (2017). In the research performed by Orzechowski et al. (2005), the text-only survey performed slightly better compared to the multimedia survey, which was also the case in this study. On the other hand Jansen et al. (2009) found that the tasks using multimedia had a better model fit compared to the text-only survey. The research of Orzechowski et al. (2005) and Jansen et al. (2009) report a R^2 between 0,08 and 0,14 for their models, which is a lot lower compared to the model fit of this study. However this can partially be explained due to the low amount of respondents in those studies (Table 3).

4.3.2 Influence low scoring respondents

In section 4.2 Preference scores, eighteen respondents that scored only insufficient on all neighborhoods in the video experiment were discussed. To test whether the 18 respondents had a big influence on the results, the likelihood ratio and the average survey perception grade had been calculated again, but then without these (low scoring) respondents. This resulted in a marginal change in the average grade people gave for the survey and the standard deviation did not change. Removing the respondents resulted in a slightly higher R^2, however the model fit was still less compared to the better performing text-only model. The part-worth utilities turned out higher in the overall model, but there was no change in order of importance (SPSS output Appendix I – Estimate ordinal regression Video experiment without low scorers). Thus, these 18 respondents had no serious influence on the overall model. Therefore, these 18 respondents were not removed from the sample.

4.3.3 Respondents' perception on text-only and video survey

Patterson et al. (2017) states that VR appears to have better attentive and focused respondents. This resulted in a better model performance of the VR model compared to the text survey. Another reason for this was that people are survey 'tired' and multimedia was a different approach that triggers people. In another research performed by Orzechowski et al. (2005) there was no significant difference between the two types, but results suggested that the reliability of the measurement was better for the VR experiment. Another research performed by Jansen et al. (2009) did a comparison between using images and using a text-only survey. They were unfavorably disposed towards using images in a conjoint measurement task about general housing preferences.

To test whether respondents were more triggered and interested in the video experiment, respondents were asked to rate on a seven point scale if they enjoyed filling in the survey. In Table 8 can be seen that the mean score of the text-only survey was slightly higher compared to the video survey. Also the standard deviation of the text-only experiment was smaller, which indicates that respondents slightly enjoyed the text-only survey more than the video experiment. One reason for this could be the duration of the survey, this was longer in the video experiment (3.7.2 Duration survey and Appendix H – Duration surveys), which could result in people liking the experiment less. To test whether there was a significant difference between the mean scores of the two experiment types an independent samples t-test was used. The experiment type was used as grouping variable and the perception score as test variable. The data of the study met the three underlying assumptions: assumption of independence(data (scores) are independent of each other), assumption of normality (test (dependent) variable is normally distributed in both experiment types) and the assumption of homogeneity of variance (The variances of the test (dependent) variable in the two populations are equal) (Northern Arizona University). The tests for these assumptions can be found in Appendix J – Respondents' perception on text-based and video-based questionnaire. The outcome of the independent sample t-test was that there was no significant difference ($p<0{,}05$)between the average perception score in the two experiment types the difference was not significant (Appendix J – Respondents' perception on text-based and video-based questionnaire).

Table 8. Score on 7 point Likert scale

Experiment type	N	minimum	maximum	Mean	Std. deviation
Video	105	2	7	4,93	1,049
Text-only	106	3	7	5,05	0,970

4.3.4 Attribute estimates

The parameter estimates for the video and text-only experiments are shown in Table 9. All other output that was generated with SPSS can be found in Appendix K – Output ordinal regression Video experiment and Appendix L – Output ordinal regression Text-only experiment. The thresholds and parameters are shown in Table 9 with the estimated value through the ordinal regression analysis. The values "0[a]" indicates that this attribute level was taken as the base or reference attribute, which results in a part-worth utility equal to 0. The part-worth utility value indicates the influence the attribute has on peoples' residential preference.

Table 9. Parameter estimates video and text-only experiment

		Video	Text-only
Threshold	[Preference_Score = 1]	-0,595***	-0,960***
	[Preference_Score = 2]	0,231*	-0,270**
	[Preference_Score = 3]	0,784***	0,382***
	[Preference_Score = 4]	1,382***	1,101***
	[Preference_Score = 5]	2,060***	1,972***
	[Preference_Score = 6]	2,980***	2,858***
	[Preference_Score = 7]	4,117***	3,993***
	[Preference_Score = 8]	5,168***	5,595***
	[Preference_Score = 9]	6,540***	6,783***
Parameter	[Street_Design= For cars/pedestrians and bicycles]	0,368***	0,092
	[Street_Design=Primarily for cars]	0[a]	0[a]
	[Parking_type= Designated parking places]	0,529***	0,454***
	[Parking_type= On street]	0[a]	0[a]
	[Speed_slowing_measures=yes, speedbumps]	0,166*	0,623***
	[Speed_slowing_measures=No]	0[a]	0[a]
	[Playground_neighborhood=Yes]	0,291***	0,699***
	[Playground_neighborhood=No]	0[a]	0[a]
	[Pond_neighborhood=Yes]	0,323***	0,203**
	[Pond_neighborhood=No]	0[a]	0[a]
	[Green=High green (trees)]	1,480***	1,671***
	[Green=Middle green (bushes)]	0,830***	1,569***
	[Green=Low green (grass)]	0,467***	1,132***
	[Green=No green]	0[a]	0[a]

****p < 0,01, **p < 0,05, *p < 0,1*

In the video experiment, five out of six attributes were significant based on a significance level of 0,05. The attribute speed slowing measures had a significance of 0,052 and was significant on a 0,10 significance level. In the text-only experiment one attribute was not significant (p<0,10), in this case the attribute street design, with a significance of 0,273. All other attributes in the text-only study were significant based on a 0,05 level. All utilities for both experiment types were positive and the utility level increased from low green to high green, which confirms the earlier expectations on which the dummy coding was based.

Besides the significance, the magnitude each level had on the total preference score is shown in Table 9 as an utility value. Table 9 shows that speedbumps had the lowest utility value in the video experiment, while in the text-only experiment the speedbumps had a relative high utility (0,623). The lowest utility value in the text-only experiment was from the attribute street design, which was insignificant (p<0,1). How the attributes interrelate to each other will be discussed further in the this sub-section, because it is better to compare them in terms of relative importance, instead of the actual utility values SPSS provides.

SPSS provides the intermediate (threshold) value (Table 9) between each of the ten scores (threshold), which means that “Preference_Score = 1” gives the value of the border point between “1 not at all” and “2”. “Preference_Score = 2” gives the next border point from “2” and “3”, and so on, as shown in Figure 22 for the video experiment. The overview in Figure 22 and Figure 23 gives perspective on the estimates of the attributes in Table 9 for the video and text-only experiment. The threshold values shown in Table 9 were used to distinguish ranges of values were the behavior predicted by the model varies in an important way, namely the border between each preference score.

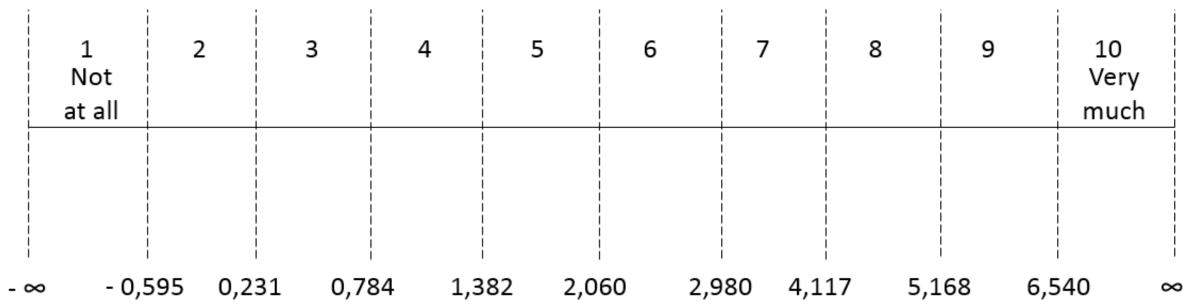

Figure 22. Threshold of ordinal regression video model

The different scales for both experiment types show that the utility estimates cannot be compared directly with each other in the way they are shown in Table 9.

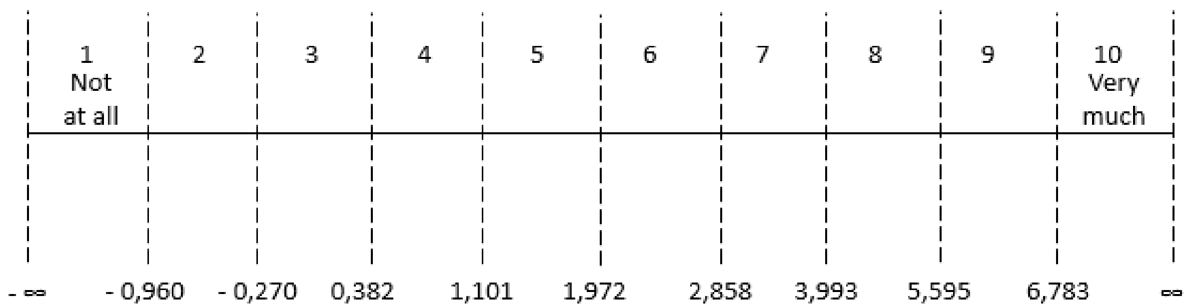

Figure 23. Threshold of ordinal regression text-only model

With the part-worth utilities from Table 9 the relative importance of each of the attributes can be calculated (Molin, Oppewal, & Timmermans, 1996). In the book Getting Started with Conjoint Analysis (2010) this calculation is explained (Orme B. K., 2010). This book was followed to calculate the relative importance of each of the attributes. The method is based on the idea of looking how much difference each attribute can make in the total utility of the neighborhood in this case. The maximum utility of all attributes combined that can be scored in this experiment add up to 100% according to Orme (2010). It is important to keep in mind when computing an attribute's importance, that it is relative to the other attributes defined in this study. This implies that the experiments using the same attributes and levels can be compared, but not with other studies using different attributes and/or levels.

The overview of the calculation is shown in Table 10 for the video experiment. In the last row of Table 10, the maximum utility that can be achieved in the video experiment is shown, this is calculated by adding the highest part-worth utility of each attribute. By calculating the difference between the highest and lowest value of the part-worth utilities, the utility range per attribute was defined. By calculating the utility range per attribute as a percentage of the maximum total utility the relative importance per attribute was defined, as shown in Table 10. The relative importance of the attributes is based upon the extremes of each attribute. Therefore this is not related to the part-worth utilities within an attribute. The relative importance of the attributes from the video experiment are shown as a pie chart in Figure 24 and the relative importance of the attributes of the text-only experiment are shown in Figure 25. These are based upon the same calculation as the video experiment, only with the part-worth utilities of the text-only experiment.

Table 10. Relative importance significant attributes

Attribute	Level	Part-worth utility	Utility range attribute	Attributes relative importance
Street design	For cars/pedestrians and bicycles	0,368	0,368-0,000 = 0,368	(0,368/3,157)*100% = 11,7%
	Primarily for cars	0,000		
Parking type	Designated parking places	0,529	0,529-0,000 = 0,529	(0,529/3,157)*100% = 16,8%
	On street	0,000		
Speed slowing measures	Yes, speedbumps	0,166	0,166-0,000 = 0,166	(0,166/3,157)*100% = 5,3%
	No	0,000		
Presence playground	Yes	0,291	0,291-0,000 = 0,291	(0,291/3,157)*100% = 9,2%
	No	0,000		
Presence pond	Yes	0,323	0,323-0,000 = 0,323	(0,323/3,157)*100% = 10,2%
	No	0,000		
Green type	High (trees)	1,480	1,480-0,000 = 1,480	(1,480/3,157)*100% = 46,9%
	Middle (bushes)	0,830		
	Low (grass)	0,467		
	No green	0,000		
Total utility range: 0,368+0,529+0,166+0,291+0,323+1,480 = 3,157				

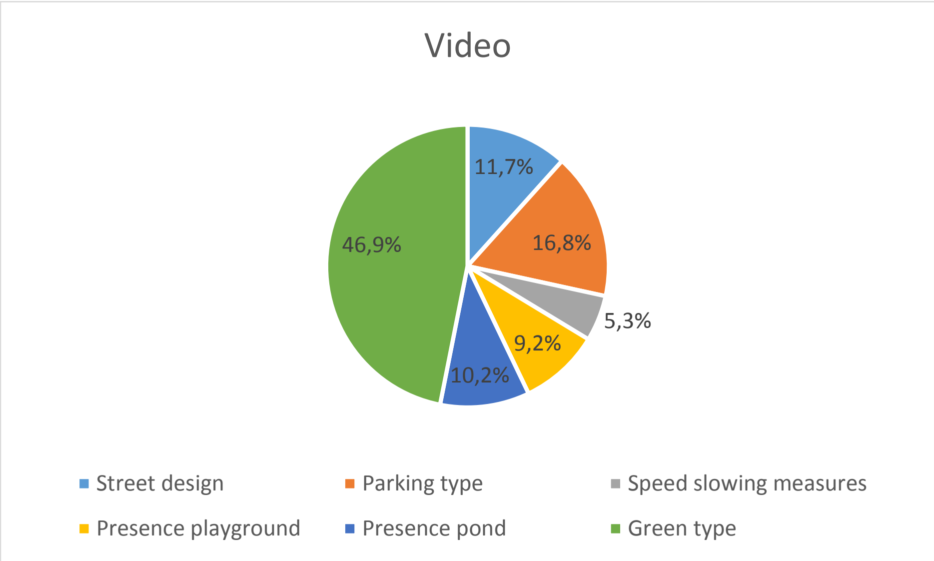

Figure 24. Relative importance attributes video experiment

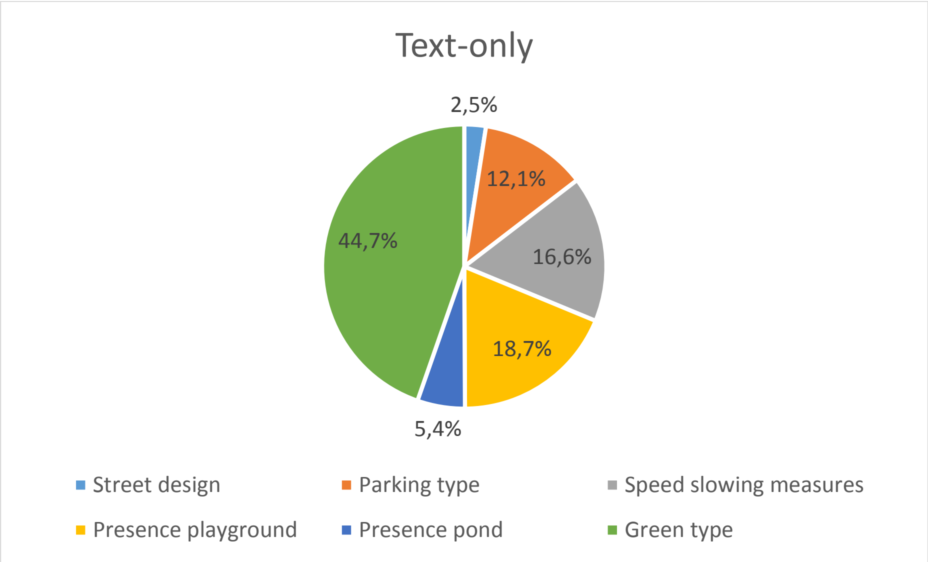

Figure 25. Relative importance attributes text-only experiment

The results are discussed per attribute and both experiment types' outcomes are compared, based on Figure 26. The relative importance of each attribute in Figure 26 is based on the part-worth values from Table 9.

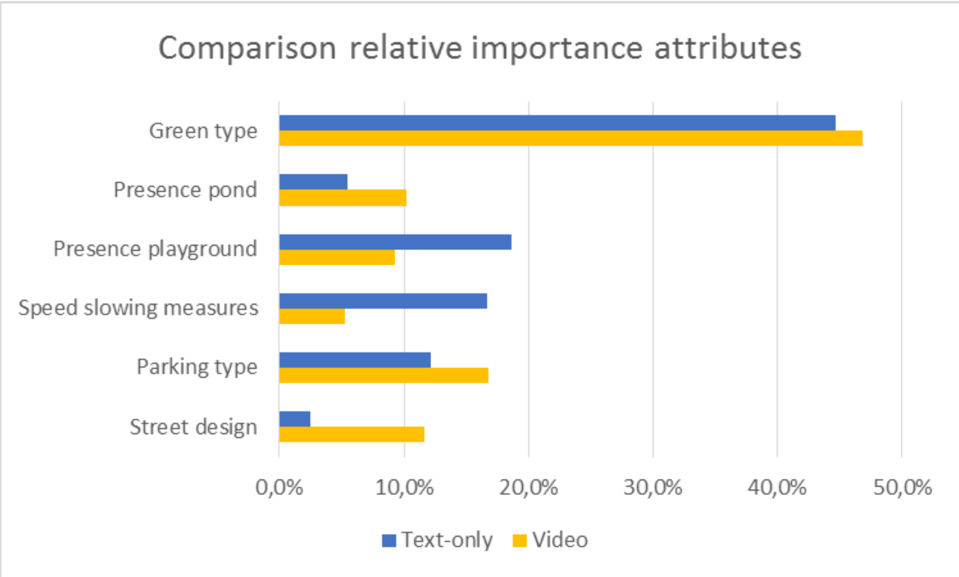

Figure 26. Comparison relative importance attributes

Street design

The first attribute in Table 9 is street design, with a part-worth utility value of 0,368 in the video experiment. Street design was also significant, with a p value of 0,000. The street design type 'primarily for cars' served as reference and was therefore 0. This means that people preferred the street design, which includes cars/pedestrians and bicycles usages over the street design that was primarily for cars. The part-worth utility from the text-only experiment had a much smaller value 0,092, which was not significant (p=0,273). When looking at Figure 24, the attribute street design had a relative importance of 11,7% in the video experiment, which was a big difference in comparison with the text-only (2,5%) experiment. As can be seen in Figure 26, street design was the third most important attribute in the video experiment, while it was the least important attribute in the text-only experiment. Liao et al. (2015) included street design in the same way as this study did. They found a significant difference between the two levels in the attribute street design, which supports the findings of the video experiment on this specific attribute. Probably two reasons are responsible for the low and insignificant result of the attribute street design in the text-only experiment. The first reason is that people could not imagine the difference between the two levels. The second reason can probably be found in the length of the text for this specific attribute. Because it is a very visual attribute, the levels cannot be explained in one or two words. This means that a description must be given of the level, which can lead to people not carefully reading the text or just ignoring it. These two reasons probably caused the low importance of street design in the text-only experiment. In the video experiment on the other hand people immediately see the difference resulting in a higher significant importance.

Parking type

The attribute parking type was significant in both experiment types. As expected, designated parking places had a higher part-worth utility value than parking on street for both experiment types. The part-worth utility value for designated parking places was 0,529 in the video experiment and was after the attribute green, the attribute with the highest part-worth utility. In the text-only experiment parking type had still a high relative importance (12,1%), but in this experiment the presence of a playground and speed slowing measures were more important attributes.

Speed slowing measures

The attribute speed slowing measures had the lowest part-worth utility value in the video experiment, which means that this attribute was the least important in peoples' preference. Because of the low value (low importance), the attribute had a significance of 0,052, which means that the p value was significant ($p<0,10$). It was expected that speed slowing measures would have a bigger influence, because speed slowing measures could give the feeling of a higher level of security. The text-only experiment had a higher relative importance, namely 16,6%. Regarding this attribute there was a clear difference notable in preference between the two experiments. It was expected that the speedbumps had a positive value, but the low relative importance (6^{th} attribute) in the video experiment was not expected. Especially compared to the relative high importance in the text-only experiment (3^{rd} attribute). One reason for this could be that people in the text-only take safety more into consideration. However in the video experiment, people are less considering and more visually oriented. In the research performed by Van Cauwenberg et al. (2016) pictures were used to retrieve older people's preference related to street characteristics. Their study included the attribute traffic calming device, which was the same as the speed slowing measures attribute in this study (also same levels). The attribute traffic calming measure had the lowest importance in their study, even a lower importance than the presence of benches and the presence of an obstacle on the sidewalk. This supports the idea that people process the two experiment types differently.

Playground neighborhood

In both experiment types the attribute playground within the neighborhood was significant ($p<0,05$). The part-worth utility had a part-worth value of 0,291 in the video experiment, which means that the presence of a playground gives a higher preference score. This was the same for the text-only experiment with a positive part-worth value. When comparing the relative attribute importance of the two experiment types a difference was notable. The relative attribute's importance in the Text-only experiment was much higher (18,7%) compared to the relative importance in the video experiment (9,2%). It was expected that the playground would have a positive value, but the low relative importance (5^{th} attribute) in the video experiment was not expected. Especially compared to the relative high importance in the text-only experiment (2^{nd} attribute). The low attribute importance of the playground in the video experiment could possibly be explained by the placement of the playground at the end of the video. Maybe respondents were not paying attention anymore at the end of the video.

Pond neighborhood

At the start of the experiment it was not clear whether the part-worth utility of the presence of the pond in the neighborhood would have a positive or a negative influence on the preference score. On the one hand one could argue that the presence of a pond would have a positive value, because of (more) nature. On the other hand the presence of a pond is could be seen as unsafe, for instance for kids, which could result in a negative part-worth utility. The utility value was positive in both experiment types (Table 9; 0,323 and 0,203). Therefore in general the presence of a pond results in a higher preference score. It was not expected that the pond would have a higher utility value than both the speed slowing measures and the playground, as is the outcome in the video experiment. The relative importance of the attribute presence pond in the video experiment is almost double compared to the text-only experiment, as shown in Figure 26.

Green type

The last attribute in this study is green type, which had a significant p-value of zero in both experiment types. The reference category was no green, with a utility of zero. In this study green type had the highest relative importance in both experiments and was therefore regarded as the most important attribute in peoples' residential preferences. It was expected that green would have a positive and important influence on peoples' residential preferences. The relative percentages of the two experiment methods were also close, namely 44,7% and 46,9%. Thus in both experiment types of this study, half of the total importance was determined by green type.

In both experiment types the utility value increases with a higher level of green type (Figure 27). When looking at the video experiment, the low green had a part-worth utility of 0,467, middle green of 0,830 and high green of 1,480. The text-only experiment had a part-worth utility of 1,132 for low green, 1,569 for middle green and 1,671 for high green. If these values are shown in a bar chart (Figure 27) it becomes clear that the utility value in the video experiment increases more over the levels of green type. On the other hand in the text-only there is a very steep increase between no green and low green. Also, middle green and high green were more similar looking at the utility values. This implies that a level change from no green to any type of green was very influential in the text-only experiment. While this was more dependent on the type of green in the video experiment.

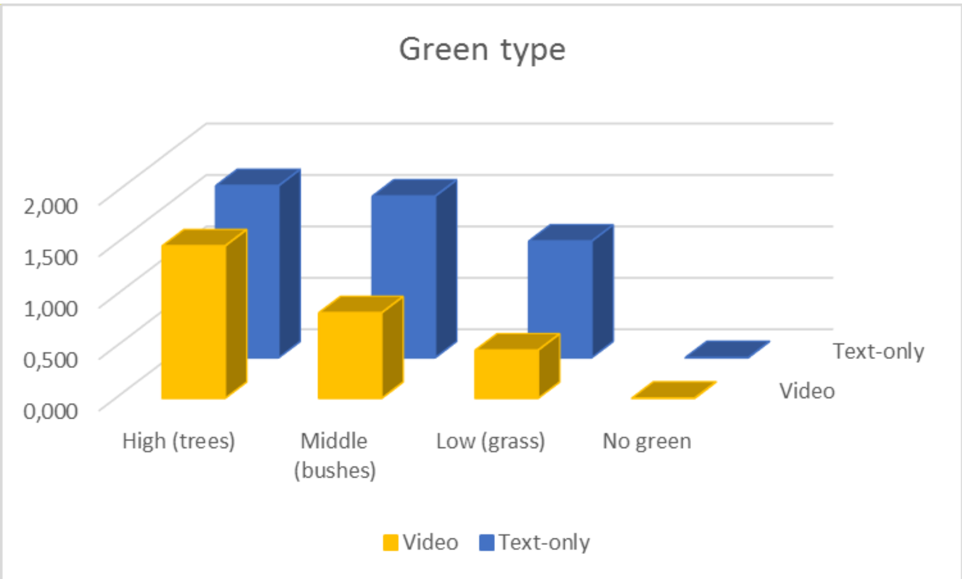

Figure 27. Comparison part-worth utilities green type

If there was high level of green (trees) in the neighborhood this alone resulted in a 5 on preference score (1,480 on scale Figure 22), while if there was no green in the neighborhood, but all the other attributes had the highest part-worth utility, the total neighborhood scores a 5 (1,677 on scale Figure 22) in the video experiment. This would suggest that if there was no green in a neighborhood and high green was added, this would have approximately the same effect (a 5 on a 10 point scale) as adding bicycle lanes, parking places, a playground, a pond and speedbumps altogether. Thus, without the presence of green in the neighborhood, the preference score of people was, in the most optimal situation, a slight preference to not live there (score 5 out of 10) for the video experiment. Without any green, the neighborhood could score a maximum of 6 (2,071 on scale Figure 23) in the text-only experiment. The level high green scores a 5 out of 10, which is the same as in the video experiment.

Overall

The most optimal neighborhood in this study was shaped by the highest total part-worth utility, that means a neighborhood with separate bicycle lanes, a pond, a playground, designated parking places and high green (Figure 28). The neighborhood that would score the least (lowest part-worth utility) consisted of no playground, no pond, street primarily made for cars, parking on street and no green. This was consisted between both experiment types. When comparing the maximum preference score on the 10 point scale, then can achieve a '7'. The video experiment on the lower side and the text-only experiment on the higher side of the seven (based on scales Figure 22 & Figure 23).

Figure 28. Highest preference neighborhood

The relative importance of speed slowing measures and a playground were more influential in the text-only survey compared to the video survey. The street design was not significant in the text-only experiment, while it was in the video experiment. The relative importance of all remaining four attributes was higher in the video experiment, especially the pond and the street design.

The text-only experiment yielded a better model fit, than the video experiment (McFadden R^2). Both have green type as the most important attribute. As can be seen in Table 11, the 2^{nd}-3^{rd} and 4^{th} most important attribute from the video experiment were the least important attributes in the text-only experiment. Therefore the two least important attributes in the video experiment became 2^{nd} and 3^{rd} in the text-only experiment.

Table 11. Attribute importance ranking

	Video experiment	Text-only-experiment
1	Green type	Green type
2	Parking type	Presence playground
3	Street design	Speed slowing measures
4	Presence pond	Parking type
5	Presence playground	Presence pond
6	Speed slowing measures	Street design

4.3.5 Estimation results of sub-groups

For the sub-groups McFadden's rule of thumb (1984) is followed, namely at least a sample size of thirty respondents per group (Hensher, Bus transport: Economics, policy and planning, 2007). In order to compare groups, sometimes recoding was necessary in order to achieve the thirty respondents per group. For each sub-group, a 3D bar chart is shown with the relative importance of all six attributes for both experiments. In this way the relative importance within the sub-group is presented, as well as the difference between the experiment types. No major observable differences were present in the sub-groups household income and urban density in terms of relative attribute importance. Therefore these sub-groups were not further discussed in this sub-section. The threshold values of each of the ordinal regressions were not included, but can be found in the appendix.

Gender

In the text-only experiment, female relatively score parking type higher than male, but in both cases it was the fourth attribute looking at its importance (Figure 29). This was not observed in the video experiment, where both were closer together, but also male scored relatively spoken higher than female, which was the opposite of the text-only experiment. The rest of the scores were in line with the overall scores of both experiments. Also the pseudo R^2 was higher in the text-only experiment compared to the video experiment, which was in line with the overall model (Table 12). The threshold values for the sub-group gender can be found in Appendix M – SPSS output ordinal regression sub-group gender.

Table 12. Utility overview sub-group gender

		Gender			
		Video		Text-only	
Attribute	**Level**	**male**	**female**	**male**	**female**
Street design	For cars/pedestrians and bicycles	0,389***	0,347***	0,107	0,085
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,581***	0,480***	0,274**	0,582***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,129	0,204*	0,653***	0,607***
	No	0	0	0	0
Presence playground	Yes	0,305**	0,281**	0,715***	0,690***
	No	0	0	0	0
Presence pond	Yes	0,350***	0,299**	0,230*	0,180
	No	0	0	0	0
Green type	High (trees)	1,476***	1,490***	1,690***	1,655***
	Middle (bushes)	0,776***	0,883***	1,531***	1,590***
	Low (grass)	0,450***	0,482***	1,101***	1,153***
	No green	0	0	0	0
Maximum utility		3,230	3,101	3,669	3,779
McFadden R^2		0,187	0,173	0,240	0,284

****p < 0,01, **p < 0,05, *p < 0,1*

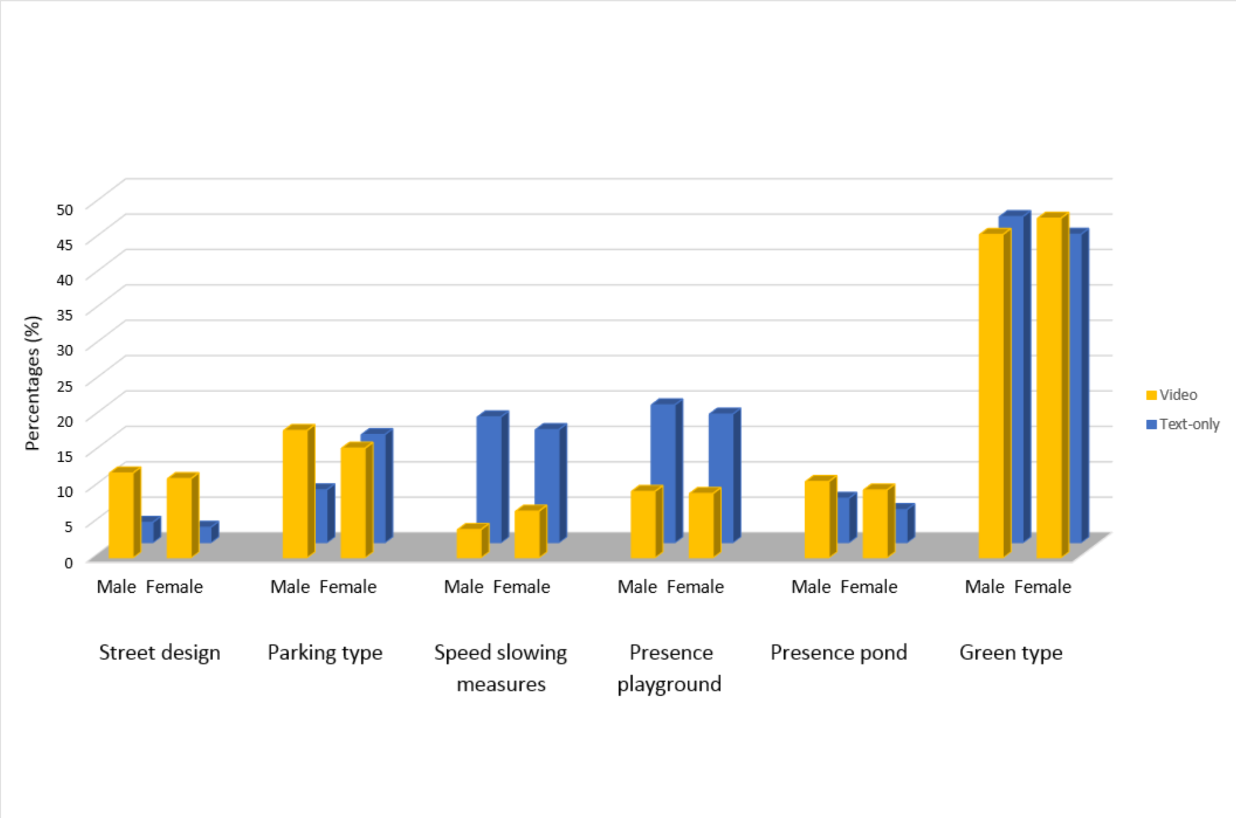

Figure 29. Relative attribute importance sub-group gender

Age

The sub-group age was recoded into three categories; <30, 30-49 and 50+. In both experiment types age category 30-49 scored relatively higher on green type in comparison with the other two categories. In the text-only experiment, speed slowing measures gained importance when people were older. Also the presence of the playground was more important in age category 30-49, which was as expected, because relatively spoken more people had children in this age category (Figure 30). This was not the case in the video experiment, where two age categories were not significant for the playground attribute. The attribute green in the video experiment was the perfect example that part-worth utilities could not be compared with other groups. On first sight one would comment that the importance of green (difference high green-no green) between the age category <30 and the other two categories is very different, namely 2,086 in comparison with 1,368 and 1,310 (Table 13). But when looking at Figure 30 the relative importance of green for the age category <30 (video experiment) was lower than the other two age groups.

Table 13. Utility overview sub-group age

		Age					
		Video			Text-only		
Attribute	**Level**	**<30**	**30-49**	**50+**	**<30**	**30-49**	**50+**
Street design	For cars/pedestrians and bicycles	0,489***	0,302*	0,365***	0,196	-0,149	0,158
	Primarily for cars	0	0	0	0	0	0
Parking type	Designated parking places	0,907***	0,363**	0,402***	0,587***	0,311*	0,399***
	On street	0	0	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,202	0,055	0,244*	0,514***	0,668***	0,776***
	No	0	0	0	0	0	0
Presence playground	Yes	0,480***	0,241	0,224	0,666***	1,183***	0,404***
	No	0	0	0	0	0	0
Presence pond	Yes	0,442***	0,262*	0,288**	0,318**	0,16	0,113
	No	0	0	0	0	0	0
Green type	High (trees)	2,086***	1,368***	1,310***	1,834***	1,833***	1,468***
	Middle (bushes)	1,063***	0,759***	0,817***	1,643***	1,841***	1,377***
	Low (grass)	0,557***	0,462**	0,461**	1,040***	1,412***	1,138***
	No green	0	0	0	0	0	0
Maximum utility		4,606	2,591	2,833	4,115	4,304	3,318
McFadden R^2		0,242	0,111	0,125	0,252	0,245	0,199

****p < 0,01, **p < 0,05, *p < 0,1*

The maximum utility for each sub-group as shown in Table 13 showed some peculiar values, especially in the video experiment. The first age group had a very high maximum utility (4,606) in comparison with the other two age groups (2,591 and 2,833). When these maximum utility values are placed on their preference score scale (Appendix N – SPSS output ordinal regression sub-group age), the age category <30 could score a maximum of an 8 (out of 10), while the other two age categories could in the most optimal situation score a 6 (out of 10). This difference could be explained by the high amount of respondents that rated all 16 neighborhoods with insufficient scores.

In section 4.2 Preference scores was explained that the age categories 30-49 and 50+ contained a large number of low scoring respondents in the video survey. This influenced the average preference score that could be achieved in these age categories. Also in the text-only, the 50+ age category scored a lower maximum utility compared to the other two age categories. On the preference scale the 50+ group could achieve at highest a 7, while the other two age categories could score an 8 out of 10. This could imply that in this experiment people older than 50 give on average lower scores compared to the other age groups. The model fit of the video model differed between the different age groups (Table 13). This was mainly caused by the group of people who only scored insufficient on the sets as earlier explained in this section, in section 4.2 Preference scores and in sub-section 4.3.3 Respondents' perception on text-only and video survey.

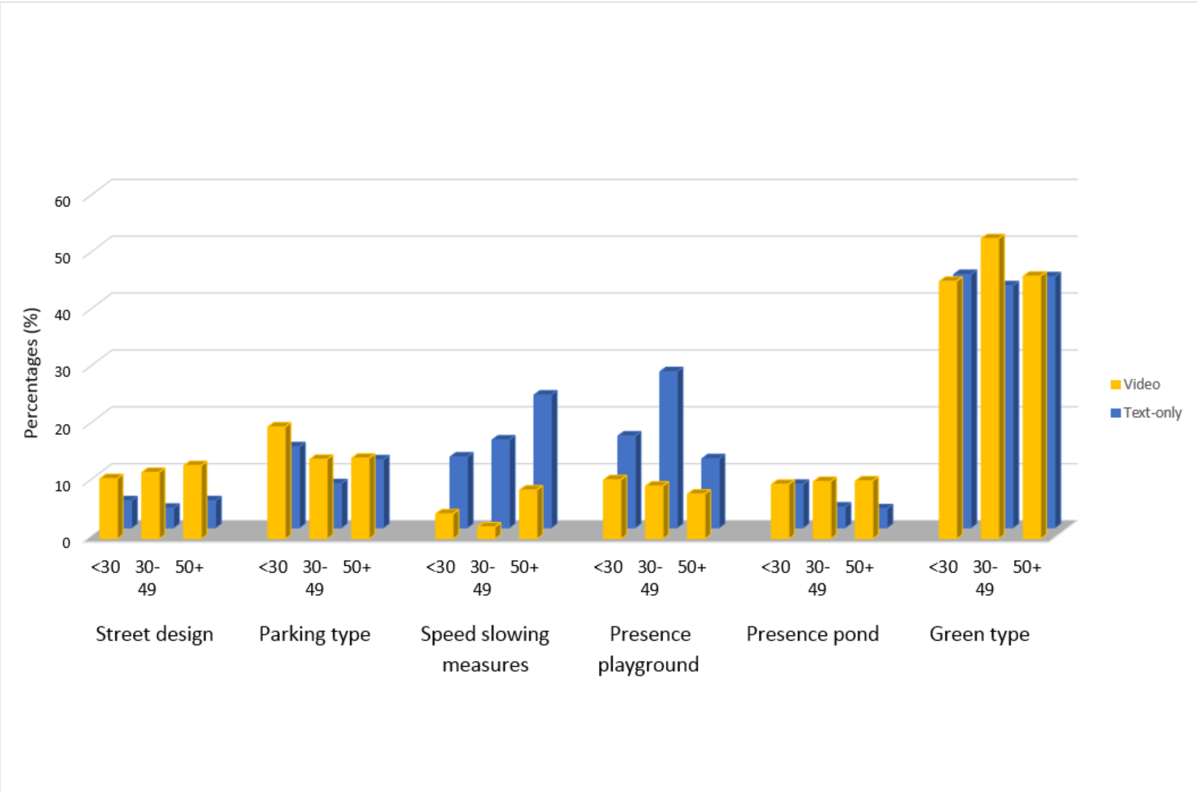

Figure 30. Relative attribute importance sub-group age

Education level

The sub-group education level was recoded into two categories based on the standards of the Dutch CBS. These were: high (Universiteit and HBO) and middle-low (remaining). In both experiment types, middle-low educated people find parking type relatively more important than high educated people (Figure 31). Also green type was more important to high educated people in comparison to middle-low educated people, this was demonstrated by both experiment types. The total maximum utility was higher for the higher educated people in comparison with the middle-low group in both experiments. Furthermore, when the maximum utility was scored on the 1 to 10 preference scale, it was clear that in both experiments higher educated people score higher in comparison with the middle-low educated people (1 point higher in both cases). This would imply that higher educated people were more satisfied with the same attribute compared to the middle-low educated group.

In each experiment type the sample sizes of the sub-groups in education level were in balance (Table 7), which made the difference in model fit stand out (Table 14). A low(er) model fit could be caused by a low(er) number of respondents per sub-group, however this was not the case. In both experiment types the model fit of the group with a middle-low education level was worse than the group with a high education level.

Table 14. Utility overview sub-group education level

		Education level			
		Video		**Text-only**	
Attribute	**Level**	**High**	**Middle-Low**	**High**	**Middle-Low**
Street design	For cars/pedestrians and bicycles	0,380***	0,349***	0,135	0,064
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,551***	0,507***	0,412***	0,511***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,115	0,237*	0,747***	0,514***
	No	0	0	0	0
Presence playground	Yes	0,406***	0,168	0,695***	0,688***
	No	0	0	0	0
Presence pond	Yes	0,366***	0,266**	0,241**	0,178
	No	0	0	0	0
Green type	High (trees)	1,822***	1,119***	2,093***	1,295***
	Middle (bushes)	0,884***	0,769***	1,882***	1,288***
	Low (grass)	0,428***	0,529***	1,150***	1,132***
	No green	0	0	0	0
Maximum utility		3,640	2,646	4,323	3,250
McFadden R^2		0,257	0,114	0,319	0,217

****p < 0,01, **p < 0,05, *p < 0,1*

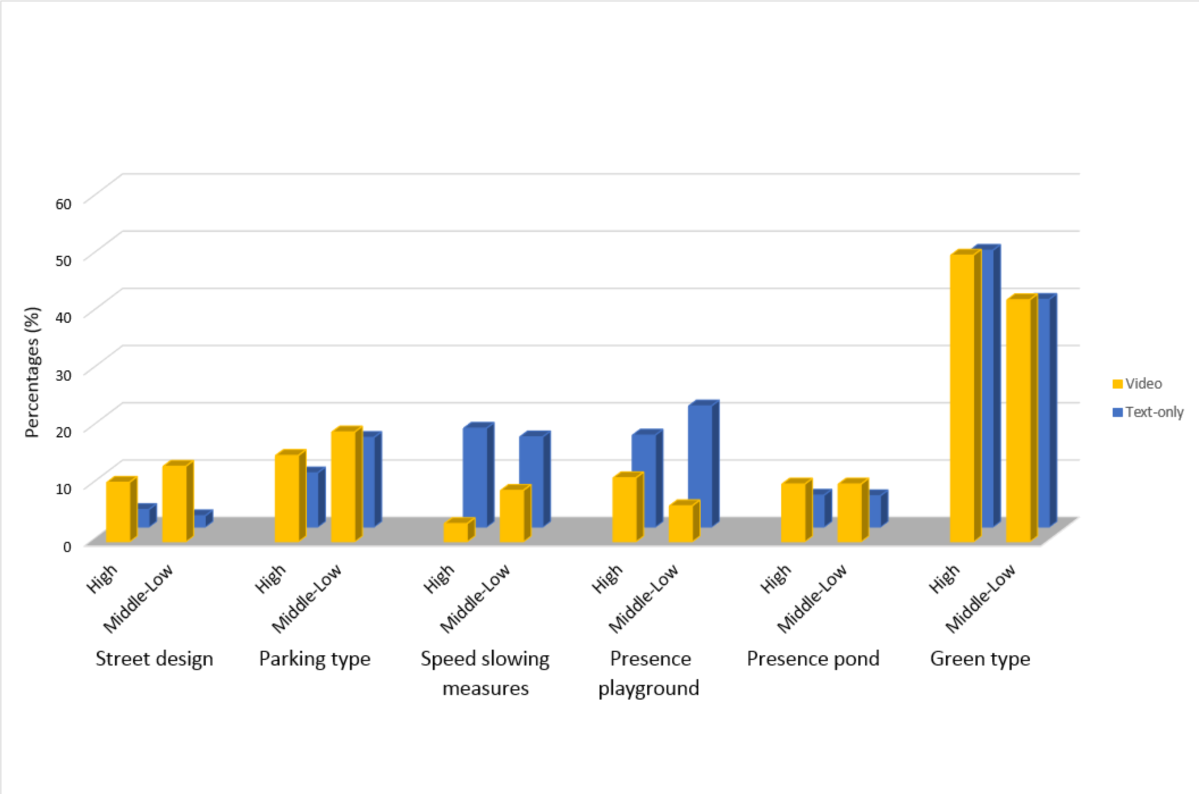

Figure 31. Relative attribute importance sub-group education level

Presence of kids

Speed slowing measures scored higher when people have kids, however this was not significant in the video experiment (Table 15). Striking was the low relative importance of green for people with kids in the video experiment (37,3%) as can be seen in Figure 32. This was mainly caused by the attribute parking type, which scored a lot higher as in the group with no kids. Also speed slowing measures, the pond and the playground score higher in the group with kids. In both experiments when people had children in their household. So people with children valued safety higher and therefore off street parking and speed slowing measures gained preference. As expected the group respondents with kids valued the attribute playground higher.

Table 15. Utility overview sub-group presence of kids

		Presence of kids			
		Video		Text-only	
Attribute	**Level**	**No kids**	**Kids**	**No kids**	**Kids**
Street design	For cars/pedestrians and bicycles	0,418***	0,257*	0,157	-0,034
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,478***	0,670***	0,526***	0,335**
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,146	0,217	0,557***	0,791***
	No	0	0	0	0
Presence playground	Yes	0,283***	0,328**	0,595***	0,941***
	No	0	0	0	0
Presence pond	Yes	0,318***	0,365**	0,262**	0,088
	No	0	0	0	0
Green type	High (trees)	1,645***	1,095***	1,623***	1,850***
	Middle (bushes)	0,961***	0,516**	1,584***	1,632***
	Low (grass)	0,500***	0,393*	1,114***	1,252***
	No green	0	0	0	0
Maximum utility		3,288	2,932	3,72	4,039
McFadden R^2		0,237	0,111	0,296	0,247

****p < 0,01, **p < 0,05, *p < 0,1*

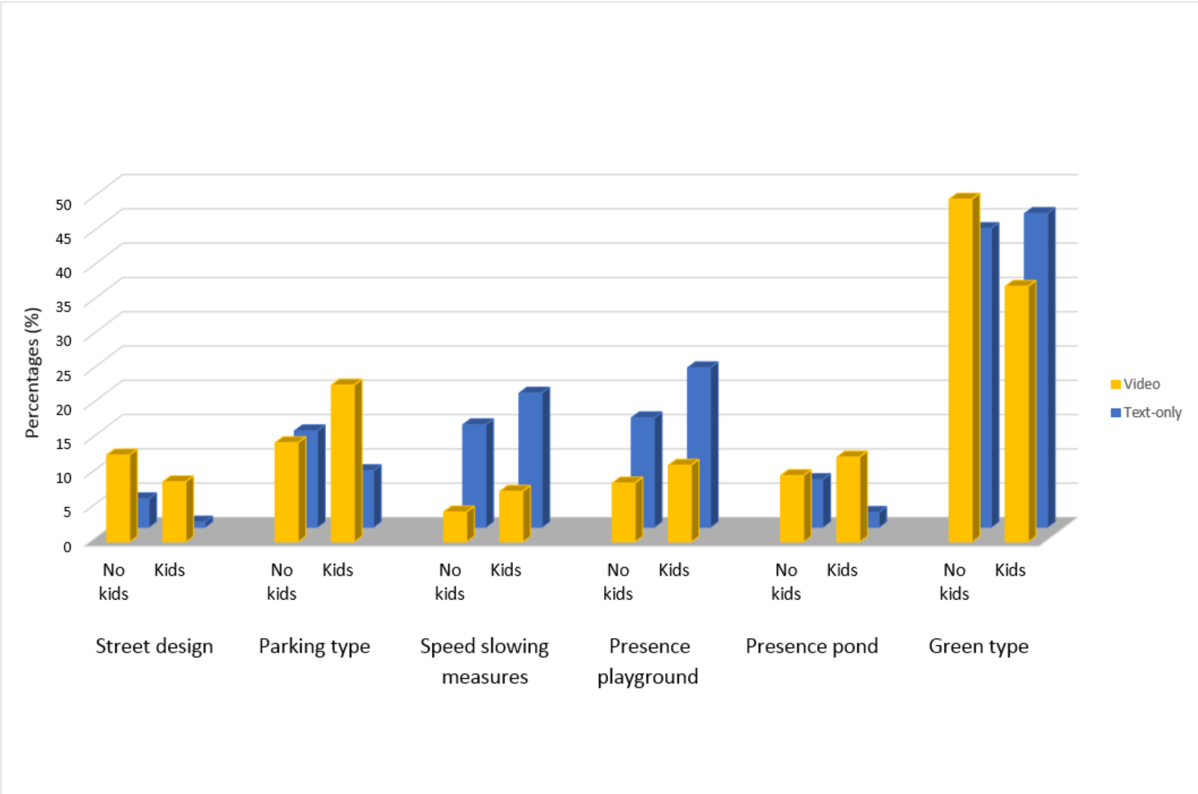

Figure 32. Relative attribute importance sub-group presence of kids

Building year current home

To meet McFadden's rule of thumb, building year was recoded into three categories; newer (1981 – 2017), older (1980 or earlier) and unknown. Two categories (older and newer) were used in this sub-group, because the third category (unknown) could not be used. In the video experiment (Figure 33) can clearly be seen that the attribute parking type was relatively more important for people living in newer homes (12,9% vs 20,4%). In the text-only experiment this was not observed, even the opposite was true, however small. Also the attribute presence of playground leads to opposite findings between the two experiment types. In the video experiment the respondents living in newer homes give more relative importance to the playground, while in the text-only experiment the opposite was true. The most important attribute in both experiments was also in this sub-group the green type. The green type attribute's relative importance showed, just as the other attributes in this sub-group, opposite results. The respondents living in older homes in the text-only survey (Table 16) preferred bushes (middle green) over trees (high green), as was opposite to other findings in this study until now.

Table 16. Utility overview sub-group building year current home

		Building year current home			
		Video		**Text-only**	
Attribute	**Level**	**Older**	**Newer**	**Older**	**Newer**
Street design	For cars/pedestrians and bicycles	0,436***	0,293*	0,046	0,126
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,424***	0,625***	0,426***	0,339***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,205*	0,122	0,626***	0,642***
	No	0	0	0	0
Presence playground	Yes	0,258**	0,368**	0,831***	0,650***
	No	0	0	0	0
Presence pond	Yes	0,349***	0,276*	0,250*	0,076
	No	0	0	0	0
Green type	High (trees)	1,611***	1,380***	1,541***	1,953***
	Middle (bushes)	0,904***	0,764***	1,572***	1,780***
	Low (grass)	0,523***	0,407*	1,219***	1,247***
	No green	0	0	0	0
Maximum utility		3,283	3,064	3,720	3,786
McFadden R^2		0,218	0,131	0,248	0,262

****p < 0,01, **p < 0,05, *p < 0,1*

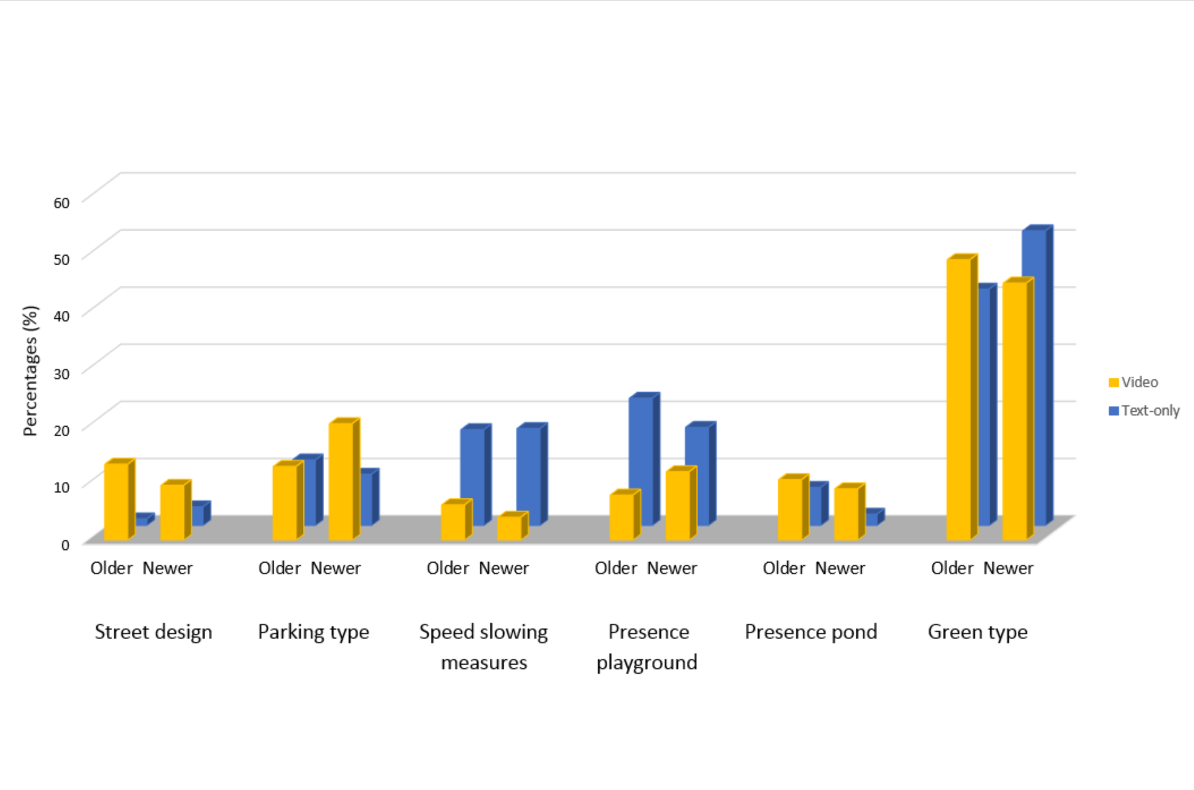

Figure 33. Relative attribute importance sub-group building year current home

Home ownership

The group home ownership did not need recoding, therefore the same two categories were used. For the first time street design was significant in the text-only experiment, this was the case for the sub group of respondents who lived rented (Table 17). When looking at the relative importance it was clear that respondents who lived rented valued the attribute street design more than the respondents who owned their home (Figure 34). In the video experiment, parking type was relatively more important for home owners compared to people who rented their home. This finding was not observed in the text-only experiment. The relative importance of speed slowing measures in the neighborhood was more valued in the rented group compared to the owner group in the text-only experiment. In both experiment types the owner attributed more importance to the playground in comparison with the rented group. Green type showed again (also in building year home) mixed results between the two experiment types. While in the video experiment evidently the rented group values the green very much, this was the other way around in the text-only experiment.

Table 17. Utility overview sub-group home ownership

		Home ownership			
		Video		**Text-only**	
Attribute	**Level**	**Owner**	**Rented**	**Owner**	**Rented**
Street design	For cars/pedestrians and bicycles	0,333***	0,466***	-0,014	0,293**
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,635***	0,351**	0,381***	0,584***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,179*	0,163	0,503***	0,886***
	No	0	0	0	0
Presence playground	Yes	0,386***	0,103	0,771***	0,582***
	No	0	0	0	0
Presence pond	Yes	0,374***	0,233	0,193*	0,210
	No	0	0	0	0
Green type	High (trees)	1,401***	1,73***	1,694***	1,671***
	Middle (bushes)	0,827***	0,867***	1,667***	1,418***
	Low (grass)	0,469***	0,472**	1,174***	1,102***
	No green	0	0	0	0
Maximum utility		3,308	3,046	3,556	4,226
McFadden R^2		0,232	0,145	0,294	0,241

****p < 0,01, **p < 0,05, *p < 0,1*

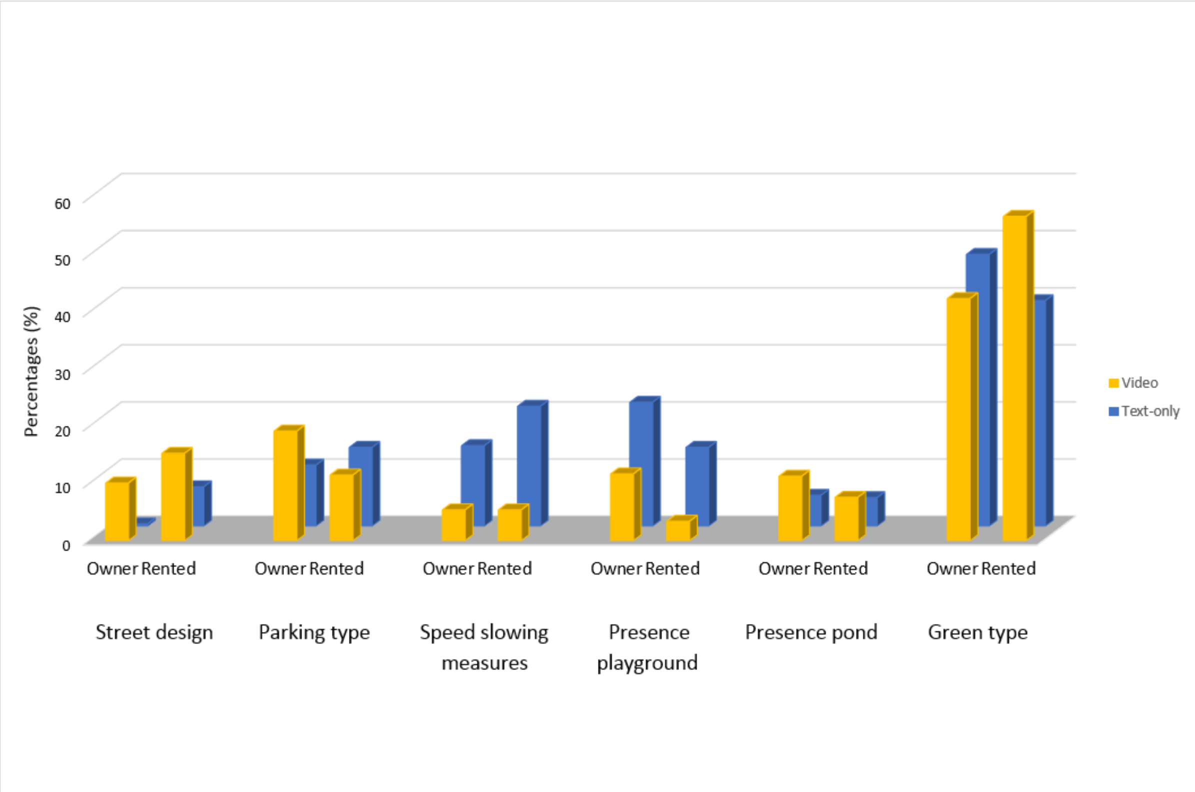

Figure 34. Relative attribute importance sub-group home ownership

Car ownership

Looking at the maximum utility of each sub-group in Table 18 there were quite some differences notable, which raised the question if one of the sub groups had a different maximum preference score. After comparing the maximum utility with the scale (preference 1 to 10) all maximum utilities score the same within each experiment type. This showed again the importance of not comparing the part-worth utilities directly with each other, but as relative importance. What immediately stands out in Figure 35 was the high relative importance of green type in the video experiment within the group that owned one car. This was caused by the low(er) scores on parking type, speed slowing measures and the presence of a playground. The relative importance of the playground increased in both experiments when comparing the one car group with respondents who own multiple cars. This can partially be caused by the fact that the percentage with kids among the respondents with multiple cars was in both experiments significantly higher compared to the group of respondents who own just one car.

Table 18. Utility overview sub-group car ownership

		Car ownership			
		Video		Text-only	
Attribute	**Level**	**One car**	**Multiple cars**	**One car**	**Multiple cars**
Street design	For cars/pedestrians and bicycles	0,352***	0,336**	0,162	-0,032
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,328**	0,733***	0,492***	0,407***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,056	0,275**	0,738***	0,478***
	No	0	0	0	0
Presence playground	Yes	0,082	0,471***	0,419***	1,028***
	No	0	0	0	0
Presence pond	Yes	0,197	0,390***	0,110	0,223*
	No	0	0	0	0
Green type	High (trees)	1,515***	1,331***	1,475***	1,798***
	Middle (bushes)	0,800***	0,795***	1,466***	1,633***
	Low (grass)	0,447**	0,462**	0,938***	1,238***
	No green	0	0	0	0
Maximum utility		2,530	3,536	3,396	3,966
McFadden R^2		0,139	0,189	0,239	0,276

****p < 0,01, **p < 0,05, *p < 0,1*

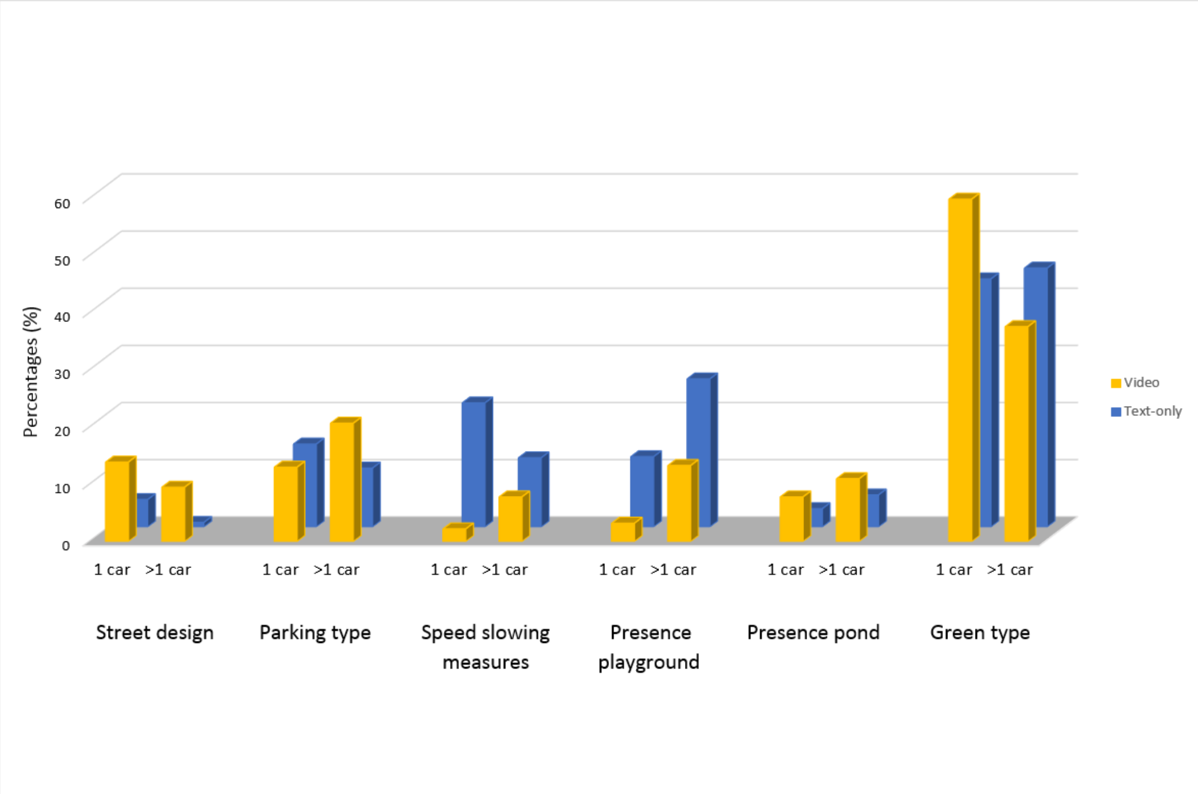

Figure 35. Relative attribute importance sub-group car ownership

Parking on property type (current situation)
As in the other sub-groups also in the parking on property type group there was a difference between the average maximum preference scores (Table 19). The people who could park their car only on public property could achieve a higher preference score, a 7 in the video experiment and an 8 in the text-only experiment, against a 6 in video experiment and a 7 in text-only experiment. People who have to park their car on public property found the parking type in their neighborhood more important than the people who park on their own property (Figure 36). This is a logical result, because for the people who can park their car on own property it matters less if there is on or off street parking. While the people who have to park in public parking spaces find it more important that they can in designated parking spots instead of on the street.

Table 19. Utility overview sub-group parking on property type

		Parking on property type			
		Video		Text-only	
Attribute	**Level**	**Own property**	**Public property**	**Own property**	**Public property**
Street design	For cars/pedestrians and bicycles	0,306***	0,477***	0,056	0,123
	Primarily for cars	0	0	0	0
Parking type	Designated parking places	0,501***	0,630***	0,398***	0,518***
	On street	0	0	0	0
Speed slowing measures	Yes, speedbumps	0,181*	0,15	0,518***	0,767***
	No	0	0	0	0
Presence playground	Yes	0,375***	0,143	0,667***	0,745***
	No	0	0	0	0
Presence pond	Yes	0,284***	0,409***	0,181	0,226*
	No	0	0	0	0
Green type	High (trees)	1,420***	1,705***	1,603***	1,783***
	Middle (bushes)	0,780***	0,986***	1,579***	1,567***
	Low (grass)	0,394**	0,617***	1,098***	1,193***
	No green	0	0	0	0
Maximum utility		3,067	3,514	3,423	4,162
McFadden R^2		0,209	0,179	0,269	0,268

****p < 0,01, **p < 0,05, *p < 0,1*

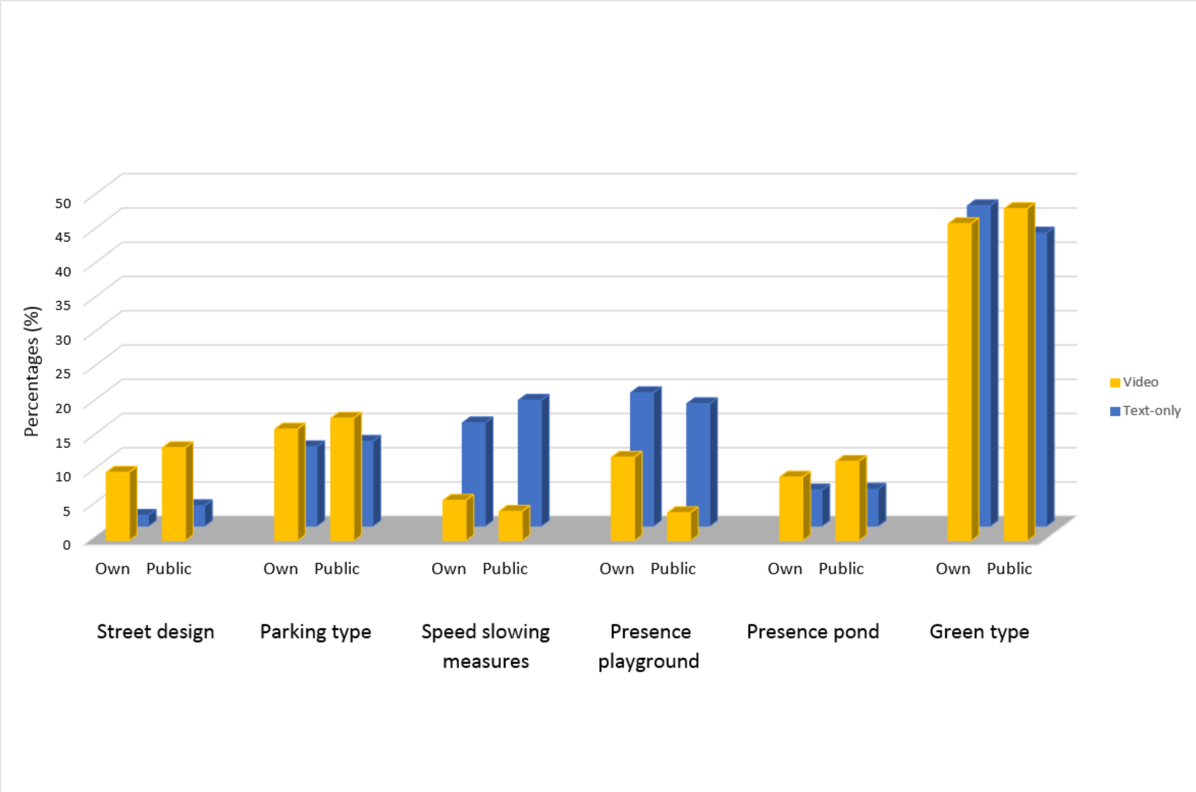

Figure 36. Relative attribute importance sub-group parking on property type

4.4 Discussion

One of the most interesting findings of this research was the difference in outcome between the two experiment types (text-only and video). Previous studies about the residential environment (Orzechowski et al. 2005; Jansen et al. 2009) found that visually presented variables have a tendency to take on more importance, compared to variables that were presented in text format. Even outside the residential environmental research studies have been done regarding the added value of using multimedia in SP studies, Vriens et al. (Vriens, Loosschilder, Rosbergen, & Wittink, 1998) found the same results as in the research performed by Orzechowski et al. (2005) and Jansen et al. (2009). Patterson et al. (2017) was the first to perform a study with more respondents and found that the text-only and VR model were quite similar. However, this study also included more respondents but found differences between the two presentation methods. The most important one was that attributes that cannot be explained in a few words, seem to lose importance in a text study. In this study a clear example of this concept was the attribute 'street design'. A higher utility value in the video model was supported by research of Liao et al. (2015) for the attribute 'street design'. Therefore it is better to represent attributes that cannot be described in a few words through multimedia. On the other hand care should be taken in using any form of multimedia, because the location of the attribute can devaluate its importance. This happened with the playground in this study, which lost importance because it was located close to the end of the video. Yet it is not clear if different representations of attributes will lead to different preferences, therefore more research has to be done about the optimal way to design a video/VR study.

Patterson et al. (2017) conclude that their VR experiment leads to a better focus among respondents. Although this study implies the opposite, because of two reasons. Respondents in the text-only study enjoyed participating in the survey more than the respondents that participated in the video experiment. Second the McFadden R^2 of the text-only model was higher and therefore had a better model fit compared to the video experiment, which leads to an opposite finding of Patterson et al. (2017). When comparing the pseudo R^2 with the relevant research (Patterson et al. (2017); Orzechowski et al. (2005); Jansen et al. (2009)) the pseudo R^2 in this study was rather higher, especially in the text-only experiment. This could be caused by the limited amount of attributes and their levels and that the attributes were quite simple to imagine. Another reason of the higher R^2 compared to other research is that most research into the differences between text and multimedia had a low amount of respondents per experiment type.

The attribute green type was the most important attribute in this study. In every model green type was the most important for each group. Relatively spoken the utility values of the levels of green type increase quite even (in terms of utility). The text-only experiment showed no linear increase in utility over the levels of green type. There was a steep increase in utility between 'no green' and 'low green'. Moreover, the 'middle green' and the 'high green' were relatively close to each other in all groups. So not only in attribute importance there was a difference between the two experiment types, but also in the levels of an attribute. The other five attributes consisted of only two levels, therefore no comparison could be made between the different levels. Both experiment types agreed on which level was more important in an attribute than another (in overall model), which made these findings robust.

On sub-group level there were less observations per group, because each experiment type was divided in 2 or more sub-groups. This led to a lower significance on the attributes and their levels, as well as results that were inconclusive in this research (different findings in video and text-only on sub-group level). Findings that were supported by both of the experiment types were considered to be robust. However in most sub-groups contradictory results were found on attribute level between the two experiment types. The main reason for this was the low amount of respondents per group, which led to a decrease of power. The difference in results is likely to occur because of hat the two samples that were not exactly the same (other demographics) on sub-group level. One good (robust finding) example was the presence of kids in a household, which led as expected, to a higher importance of both the playground and speed slowing measures (safety). Additionally, speed slowing measures were also more important in the age category 50+ compared to the other (younger) age categories.

It is unclear why a group of respondents in the video experiment scored insufficient on all neighborhoods, because there was no connection between them. What could be concluded from the socio-demographics of these respondents is that most of them were older. This could indicate that 'older' people were more averse against a video/VR study, or could not focus on the attributes. However this group of respondents had no significant influence on the conclusions that were drawn from the results.

5. Conclusion

In this final chapter the research questions will be answered, as well the societal and scientific relevance of this study will be explained. At last some recommendations will be given for follow-up research.

5.1 Answering research question(s)

In each chapter of this report a short conclusion per chapter was given. Based on the results the research question(s) can be answered. The first research question of this report:

1 What are the neighborhood preferences of people and are there differences observable between sub-groups?

In this study the overall neighborhood preferences have been investigated (Table 20), as well as the preferences within socio-demographic groups. In both experiment types the attribute green type had the highest relative importance (almost 50%) in the overall model. Also in all the sub-groups the attribute green was the most important attribute. This finding supports the study performed by Heins (2004) that showed that greenness is one of the most important residential attributes. When observing the levels of the attribute green type, a higher level of green type (grass-bushes-trees) resulted in a higher part-worth utility in both experiment types (Table 9). Except for the attribute green type, the importance of the other attributes differed between the two experiments. Therefore these attributes will not be discussed further in this research question, but in research question 2. The most optimal neighborhood was the same in both experiment types. This neighborhood consisted of a street that was designed for cars, with a separate bicycle- and pedestrian lane, off street parking, a playground, a pond, speed slowing measures and high green (trees).

For the sub-groups only the most important findings on which both experiment types agree on are discussed. When the municipality (or any other organization) wants to attract high educated people, than the attribute green (especially high green) needs to be considered, because it was by far the most important attribute, especially when compared to the middle-low educated group. Households who have children, showed that the inclusion of a playground raised their utility level more compared to households without kids. Additionally, the attribute speed slowing measures showed a higher importance when a household included children. This could probably be explained by the fact that speedbumps provide a safer environment for children, which explains why it was less important for households without children. Additionally, speed slowing measures were also more important in the age category 50+ compared to the other (younger) age categories.

The second research question in this study:

2 Are there differences between the preferences of the VR group and the text-only group?

Differences were found between the two methods. One unexpected outcome was that the text-only experiment had a better R^2 (model fit) compared with the video experiment. As can be seen in Table 20 the order of the relative importance of the attributes was different between the two experiments. The low relative importance of the street design in the text-only experiment was unexpected. This can probably be explained by two reasons. The first reason is that people find it difficult to imagine this attribute and therefore do not take it into account (both levels had an utility of zero or close to zero). The second reason could be that street design was not explainable in one or two words, therefore more text was included on this attribute. This could have led to people not reading it accurately and therefore attached no importance to it.

Table 20 Attribute relative importance

Attribute importance	Video experiment		Text-only-experiment	
1	Green type	46,9%	Green type	44,7%
2	Parking type	16,8%	Presence playground	18,7%
3	Street design	11,7%	Speed slowing measures	16,6%
4	Presence pond	10,2%	Parking type	12,1%
5	Presence playground	9,2%	Presence pond	5,4%
6	Speed slowing measures	5,3%	Street design	2,5%

The third research question in this study:

3 What is the added value of video based SP questionnaires?

In the video experiment, street design was the third most important attribute, which suggests that an attribute that needs to be described can be represented better using multimedia. The lower importance of the playground compared to the pond in the video experiment was also not expected, but can probably be explained by the location of the attribute in the movie. The playground was shown close to the end of the movie, while the pond was located earlier in the movie. This may have led to people already answering the question before the end of the movie, or people to lose attention at the end of the movie. After comparing both experiment types, it can be concluded that when a text-only SP survey is used people think and consider what attributes they value and choose based on this. While in a video experiment they choose more on what they see instead of rationally thinking and taking into consideration what they find important.

The added value of using multimedia lies with the attributes that cannot be explained in 1 or 2 words, as can clearly be seen from the attribute street design. However using multimedia in every neighborhood study can be risky, due to the fact that the attributes and their levels can be presented in many ways. Therefore thorough evaluation should take place regarding the presentation and if this encompasses reality. Additionally, the location of the attributes needs to be taken into account. In the video experiment the playground scored a lower importance, probably due to the location near the end of the video.

5.2 Scientific relevance

At first this study contributes to the literature on residential preferences, especially in neighborhood preferences. In most studies the neighborhood attributes are combined with other residential attributes, while this study only focused on the neighborhood. The second contribution of this research is providing more information whether using video/multimedia in neighborhood SP surveys has added value compared to the traditional text-only survey. In this study only visual attributes were used instead of a combination between text and a virtual world as done in other research.

This research shows the advantages of using a video, namely difficult to imagine attributes become understandable. Furthermore it was observed that people rate more on how it visually looks, instead of asking themselves which attributes they find important. One of the points that need to be taken into account before using a video is that it needs to have added value in measuring people's preference. When a video is used it is important to make sure that the attributes are shown in the same manner (same angle of view, color, amount etc.). Moreover, other attributes which are not included in the experiment should be depicted the same and not influence the choice of the respondent to produce unbiased data.

5.3 Societal relevance

Approximately ten years ago the Dutch government (Ministry of Housing, Spatial Planning and the Environment) published a list of 40 neighborhoods, which had a low(er) quality of the living environment, caused by an accumulation of problems (Ministerie van VROM, 2007). Not only the Netherlands, but all countries have neighborhoods with a low(er) quality of living environment, with overrepresented socio-economic groups. Complex social problems like school failures, a living environment with few possibilities for social contacts, high (youth) unemployment, flawed integration of newcomers, high crime, feelings of insecurity and the lack of relevant social networks and contacts, arise frequently in these neighborhoods (Ministerie van VROM, 2007).

The Dutch Social and Cultural Bureau mentions that these earlier discussed problems with certain 'problem' neighborhoods could be solved by changing the urban layout of the public space to reduce the opportunity for unwanted behaviors and the emergence of feelings of insecurity (Wittebrood & Dijk, 2007). Additionally, the Bureau mentions in a report that diversity in the socio-economic position of residents should reduce the risk of a culture of poverty among neighborhood residents and a poor image of the neighborhoods (Kullberg & Permentier, 2013). Therefore, this study provides municipalities, housing associations and market parties with more information about neighborhood preferences of people and contributes to increase social cohesion and improve quality of life within neighborhoods.

As earlier mentioned, this research solely focused on how people would like to live, which gives this study from an inhabitants view more important compared to the studies involving monetary values. However, neighborhood designers can now make the calculation what adding an attribute into a neighborhood yields in terms of preference increase per euro. For instance by calculating what it costs to go from low green (grass) to high green (trees) or just adding a playground, what would yield more utility per euro in that specific case.

5.4 Limitations

One of the most influential limitations in this study was the limited amount of respondents. For the overall model the amount of respondents per experiment was seen as sufficient, however this cannot be said for the sub-groups. The low(er) amount of respondents led to a lower goodness of fit for the models, which could be improved with more respondents. Also multiple attributes became insignificant due to the low amount of respondents per sub-group.

Because the study was self-administered, the sample distribution did not fit the Dutch population. The distribution was not diverse enough in terms of age for instance. Almost 100% of the sample had the Dutch ethnicity, which is not an accurate representation of the Dutch population. Also respondents from a lower (urban) dene area with a higher education level and people living in a house were overrepresented. This was especially a problem for the outcomes of the sub-groups, were a minimum of 30 respondents was necessary per group. Therefore the chance that the group is normally distributed as the Dutch population is very low, which led to opposite results between the experiment types in most sub-groups.

Furthermore, the amount of attributes was limited with only six. Also the levels within each attribute (five times two levels) led to less diversity per attribute. However increasing the number of levels and attributes in combination with the low amount of respondents, would have led to more attributes being insignificant. By increasing the amount of levels per attribute (more than two) more diversity would be added to the virtual world.

5.5 Recommendations

In this section several recommendations are given for further research into neighborhood preference research as well SP surveys using video/multimedia. Additionally recommendations for public authorities are given.

In order to obtain more accurate results it is important to use larger sample sizes, especially for estimates on sub-groups. This study focused solely on neighborhood attributes, therefore it is important to do more research with more attributes in order to examine how these attributes relate to residential attributes. At the moment a few studies (Patterson et al. 2017; Jansen et al. 2009; Nasar 1984; Orzechowski et al. 2005) have been done to compare text-only surveys with a level of multimedia (pictures, movies or VR). Instead of comparing text with multimedia it would be interesting to study how differences in VR or any other level of multimedia influence people's preferences. The influence of different representations for a certain attribute or level on preference scores should be studied. For instance speedbumps can be shown in multiple ways, as well as almost all neighborhood attributes. From this an uniform drawing standard should be developed. This would provide guidelines for researchers developing surveys with a virtual world (e.g. VR or video).

Public authorities can use this study to gain more insight in the overall neighborhood preferences. Also more knowledge is available on neighborhood preferences for different sub-groups of people. However only robust findings should be considered. As earlier mentioned, more research with larger sample sizes is needed to gain insight in the preferences of sub-groups. Additionally this study can be used as a guideline for public authorities who are thinking about doing a SP survey. Not only the added value of using a video, but also the pitfalls are shown in this study. In all cases the attribute green (especially high green) adds the most preference value, which makes this a powerful intervention in each neighborhood.

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Appendices

Appendix A – Frequently stated preferences

Most frequently stated preferences and their weighted totals (%) (Heins, 2004)

	%	% Reject-inducing	% Trade-off	% Relative preference	Weighted total %
Garden/balcony	98	82	15	4	95
Location	95	66	28	6	89
Presence of greenness	96	65	25	9	86
Number of rooms	95	80	11	9	86
Type of dwelling	92	47	47	7	86
Public safety	91	88	3	9	83
Peace and quiet	90	88	4	8	83
Density	90	70	22	8	83
Proximity of shops	87	90	5	5	83
Type of location	88	63	31	6	83
Type of buildings	92	56	33	11	82
Size of dwelling	84	75	15	11	76
Type of landscape	89	47	37	16	75
Road safety	83	76	10	14	71
Outbuildings	89	58	22	20	71
Architecture of buildings	84	71	12	17	70
Atmosphere	90	69	7	24	68
Open space	86	71	8	21	68
Proximity of nature	87	47	23	30	61
Architecture of dwelling	71	71	13	17	60
Population	77	62	14	24	59
Size of plot	68	71	15	15	58
Age of buildings	62	48	26	26	46
Proximity of water	77	27	24	49	39
Presence of animals	65	38	8	53	30

Weighted total % = (% * (% reject-inducing + % trade-off attributes)/100).
Only aspects stated by more than 60% of the respondents are considered.
$N = 112$.

Appendix B – Rating sets

Obs	Block	Run	x1	x2	x3	x4	x5	x6
1	1	1	1	2	1	2	2	4
2	1	2	1	1	2	2	1	4
3	1	3	2	2	2	1	1	3
4	1	4	1	2	1	1	2	1
5	1	5	2	2	2	2	1	2
6	1	6	2	1	1	2	1	1
7	1	7	1	1	2	1	2	2
8	1	8	2	1	1	1	2	3
9	2	1	1	1	2	2	2	3
10	2	2	2	1	1	2	2	2
11	2	3	1	2	1	2	1	3
12	2	4	2	2	2	1	2	4
13	2	5	2	2	2	2	2	1
14	2	6	1	1	2	1	1	1
15	2	7	1	2	1	1	1	2
16	2	8	2	1	1	1	1	4

Appendix C – Online survey

Technische Universiteit
Eindhoven
University of Technology

(Readonly)

Allereerst wil ik u hartelijk danken voor uw deelname aan dit onderzoek.

Voor mijn afstuderen aan de Technische universiteit Eindhoven doe ik onderzoek naar voorkeuren in de directe woonomgeving van mensen.
Het doel van mijn onderzoek is om inzicht te krijgen in de voorkeuren van mensen in hun directe woonomgeving, om zo te achterhalen hoe de 'perfecte' woonomgeving eruitziet.

Het onderzoek zal ongeveer 15-20 minuten van uw tijd in beslag nemen.
Er zal vertrouwelijk met uw gegevens worden omgegaan en de resultaten worden automatisch geheel anoniem verwerkt.
Tevens wordt er een bol.com waardebon van 10 euro verloot onder de deelnemers.

Volgende

Technische Universiteit
Eindhoven
University of Technology

(Readonly)

Wat is uw geslacht?

- Man
- Vrouw

Wat is uw leeftijd (in jaren)?

Wat is uw hoogst genoten opleiding?

- Universiteit
- HBO
- MBO 2 t/m 4
- MBO 1
- VWO
- HAVO
- VMBO
- Basisonderwijs

Tot welke etnische groepering rekent u zich?

- Nederlands
- Westers (anders dan Nederlands)
- Niet westers

Vorige Volgende

TU/e Technische Universiteit Eindhoven University of Technology

(Readonly)

De volgende vragen gaan over uw gezondheid

Hoe is uw gezondheid?

	Slecht	Soms goed, soms slecht	Gaat wel	Goed	Zeer goed
	○	○	○	○	○

Heeft u last van een of meer langdurige ziekten, aandoeningen of handicaps?

- ○ Ja
- ○ Nee

Vorige | Volgende

TU/e Technische Universiteit Eindhoven University of Technology

(Readonly)

De volgende vragen gaan over uw huishouden

Wat is de samenstelling van uw huishouden?

- ○ Alleenstaand
- ○ Samenwonend
- ○ Alleenstaand met kinderen
- ○ Samenwonend met kinderen
- ○ Inwonend bij ouders
- ○ Inwonend bij ouders met kinderen
- ○ Overig

Wat is uw jaarlijks bruto huishoudinkomen?

- ○ € 0 t/m € 19.981
- ○ € 19.982 t/m € 33.790
- ○ € 33.791 t/m 67.071
- ○ € 67.072 of meer
- ○ Niet bekend/ wil niet zeggen

Bezit uw huishouden één of meerdere auto's?

- ○ Ja, één
- ○ Ja, meerdere
- ○ Nee, geen auto

Vorige | Volgende

Technische Universiteit Eindhoven University of Technology

(Readonly)

Uitleg experiment

Stel u voor dat u wil gaan verhuizen en mogelijke wijken/buurten gaat bekijken.
U krijgt op de volgende pagina's 16 verschillende woonomgevingen te zien door middel van een filmpje, elk filmpje duurt 35 seconden
Naast het filmpje is een tabel weergegeven, die als samenvatting dient van alles wat u in het filmpje gezien heeft.

Bij elke woonomgeving wordt u gevraagd om aan te geven of u in deze wijk/buurt zou willen wonen door middel van een score (schaal 1 t/m 10).
Het cijfer 1 geeft aan dat u helemaal niet graag in deze woonomgeving woont, het cijfer 10 geeft aan dat u heel graag in deze woonomgeving woont.

De woningen zijn in elk filmpje weergegeven door middel van blauwe blokken, omdat het puur om de keuze ten aanzien van de woonomgeving gaat.
Op de volgende pagina is een voorbeeldvraag weergegeven.

Hieronder is een overzicht weergegeven uit welke onderdelen de wijk kan bestaan.
De linker kolom geeft de onderdelen waaruit de woonomgeving kan bestaan weer, welke verschillende levels bevatten.
Deze levels zijn weergegeven in de rechterkolom

Attribute	Levels
Straat design	[1] Gericht op auto's, met voetpad [2] Voor auto's, met separaat voet- en fietspad
Parkeersoort	[1] Op straat parkeren [2] Langsparkeren in parkeervakken
Snelheidsremmende maatregelen	[1] Niet aanwezig [2] Aanwezig (drempels)
Speelvoorzieningen	[1] Niet aanwezig [2] Aanwezig (speeltuin)
Vijver	[1] Niet aanwezig [2] Aanwezig
Groen	[1] Niet aanwezig [2] Laag groen (gras) [3] middelhoog groen (struiken) [4] Hoog groen (bomen)

Vorige Volgende

Technische Universiteit Eindhoven University of Technology

(Readonly)

De volgende vragen gaan over uw huidige woning

Is de woning waarin u woont een koop- of huurwoning?

- ◯ Koopwoning
- ◯ Huurwoning

In wat voor type woning woont u?

- ◯ een rijtjeshuis, hoekwoning, vrijstaand, twee onder een kap, villa, bungalow, landhuis
- ◯ een flat, etagewoning, appartement, maisonnette, bovenwoning, benedenwoning,
- ◯ een wooneenheid met gezamenlijk gebruik van keuken en/of toilet?
- ◯ geen van deze

Kunt u aangeven in welke periode uw woning is gebouwd?

- ◯ 1945 of eerder
- ◯ 1946 t/m 1959
- ◯ 1960 t/m 1980
- ◯ 1981 t/m 2000
- ◯ 2001 of later
- ◯ Niet bekend

Vorige | Volgende

Technische Universiteit Eindhoven University of Technology

(Readonly)

De volgende vragen gaan over uw huidige woonomgeving

Hoe stedelijk is de plaats waar u woont?

- ◯ Hoog (>100.000 inwoners)
- ◯ Gemiddeld (100.000 - 20.000 inwoners)
- ◯ Laag (<20.000 inwoners)

Waar heeft u de mogelijkheid om een auto te parkeren? (u kunt slechts een mogelijkheid kiezen)

- ◯ Op eigen terrein
- ◯ Op straat
- ◯ In een parkeervak op/naast de straat
- ◯ Parkeerplaats

Hoe tevreden bent u met uw huidige woonomgeving?

	Zeer ontevreden	Ontevreden	Niet tevreden, maar ook niet ontevreden	Tevreden	Zeer tevreden
	◯	◯	◯	◯	◯

Ik ben gehecht aan deze buurt?

	Helemaal oneens	Oneens	Niet mee eens, maar ook niet mee oneens	Mee eens	Helemaal mee eens
	◯	◯	◯	◯	◯

Hoe tevreden bent u met het groen bij u in de buurt?

	Zeer ontevreden	Ontevreden	Niet tevreden, maar ook niet ontevreden	Tevreden	Zeer tevreden
	○	○	○	○	○

Zijn er speelvoorzieningen in uw woonomgeving?

- ○ Ja
- ○ Nee

Is er een vijver in uw woonomgeving?

- ○ Ja
- ○ Nee

Vorige | Volgende

TU/e Technische Universiteit Eindhoven University of Technology

(Readonly)

Vond u het leuk om deze vragenlijst in te vullen?

Zeer vervelend		Vervelend		Leuk		Zeer leuk
○ 1	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7

Vul hieronder uw e-mail adres in als u kans wil maken op de bol.com cadeaukaart

example@example.com

Hieronder kunt u nog eventuele opmerkingen achterlaten

Bedankt voor het invullen van de enquete.

Klik hieronder op versturen om deze enquete af te sluiten.

Vorige | Versturen

Appendix D – Video part survey

TU/e Technische Universiteit Eindhoven University of Technology

(Readonly)

Voorbeeld keuze situatie: (deze vraag telt NIET mee voor het onderzoek)

Attribute	Levels
Straat design	*Gericht op auto's, met voetpad*
Parkeersoort	*Langsparkeren in parkeervakken*
Verkeersremmende maatregelen	*Niet aanwezig*
Speelvoorzieningen	*Speeltuin*
Vijver	*Aanwezig*
Groen	*Hoog groen (bomen)*

Geef aan of u in deze wijk wil wonen

	Helemaal niet graag									Heel graag
	1	2	3	4	5	6	7	8	9	10
	○	○	○	○	○	○	○	○	○	○

Hierna volgen 16 keuze situaties.

Vorige Volgende

Appendix E – Text only part survey

TU/e Technische Universiteit Eindhoven University of Technology

(Readonly)

Voorbeeld keuze situatie: (deze vraag telt NIET mee voor het onderzoek)

Attribute	Levels
Straat design	*Gericht op auto's, met voetpad*
Parkeersoort	*Op straat parkeren*
Verkeersremmende maatregelen	*Aanwezig (drempels)*
Speelvoorzieningen	*Speeltuin*
Vijver	*Niet aanwezig*
Groen	*Hoog groen (bomen)*

Geef aan of u in deze wijk wil wonen

Helemaal niet graag									Heel graag
1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○

Hierna volgen 16 keuze situaties.

Vorige Volgende

Appendix F – Code video rating page

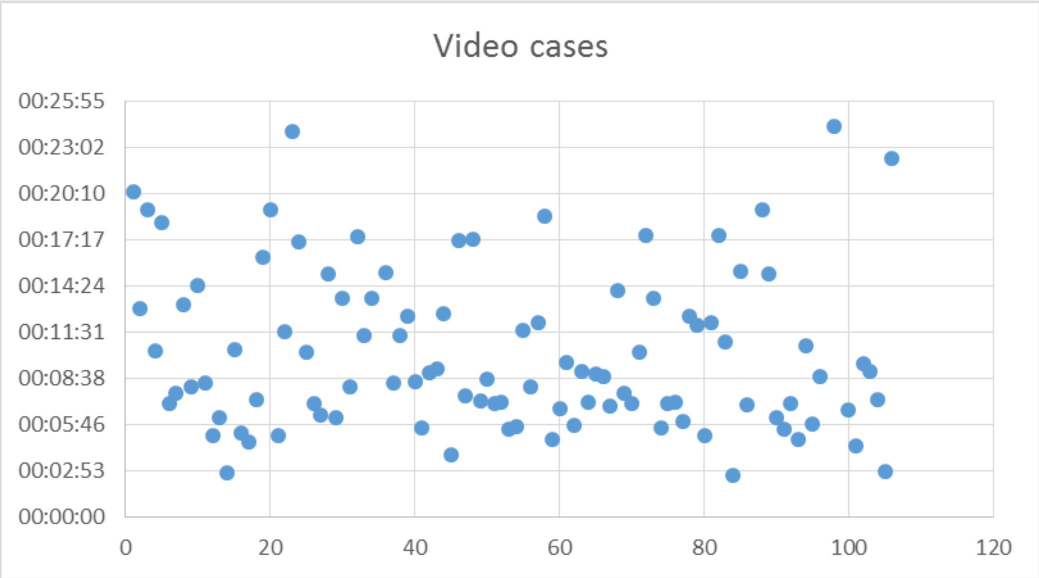
```
<p>
<div class="disable-autofocus"></div>
<table class="table table-bordered" >
<tr>
  <span>
  <th   rowspan="7"><iframe   width="640"   height="360"   frameborder="0"   allowfullscreen
src="<%= prop['Youtube'] %>"></iframe></th>
  <th class="info">Attribute</th>
  <th class="info">Levels</th>
  </span>
  </tr>
  <tr>
    <td>Straat design</td><td><i><%= prop['Straat_design'] %></i></td>
  </tr>
<tr>
  <td>Parkeersoort</td><td><i><%= prop['Parkeersoort'] %></i></td>
  </tr>
<tr>
  <td>Verkeersremmende                                              maatregelen</td><td><i><%=
prop['Snelheidsremmende_maatregelen'] %></i></td>
  </tr>
<tr>
  <td>Speelvoorzieningen</td><td><i><%= prop['Speelvoorzieningen'] %></i></td>
  </tr>
<tr>
  <td>Vijver</td><td><i><%= prop['Vijver'] %></i></td>
  </tr>
  <tr>
    <td>Groen</td><td><i><%= prop['Groen'] %></i></td>
  </tr>
   <tr>
</table>
```

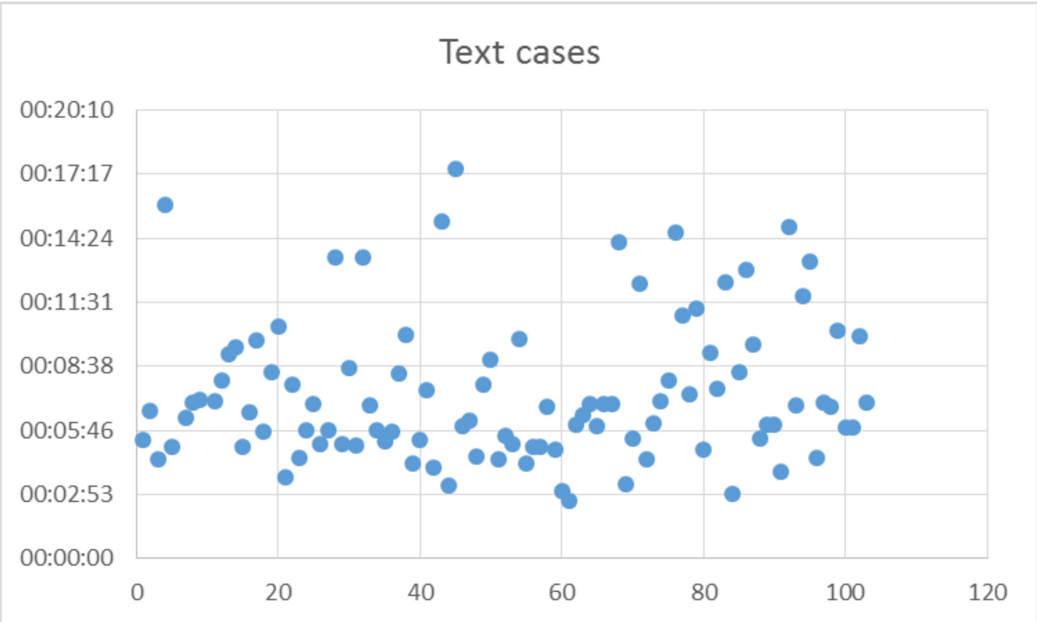
Appendix G – YouTube embed codes

1	<iframe width="640" height="360" src="https://www.youtube.com/embed/ArgVthUt3d8?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
2	<iframe width="640" height="360" src="https://www.youtube.com/embed/43MDckkh1eM?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
3	<iframe width="640" height="360" src="https://www.youtube.com/embed/a27n4Pr_WDs?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
4	<iframe width="640" height="360" src="https://www.youtube.com/embed/eApHirmqOjU?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
5	<iframe width="640" height="360" src="https://www.youtube.com/embed/7RnvSAcask8?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
6	<iframe width="640" height="360" src="https://www.youtube.com/embed/IirzxFaYSKY?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
7	<iframe width="640" height="360" src="https://www.youtube.com/embed/LNFKTD5gGKY?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
8	<iframe width="640" height="360" src="https://www.youtube.com/embed/AKwY9HIpxBk?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
9	<iframe width="640" height="360" src="https://www.youtube.com/embed/EH1-Tbzcsfs?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
10	<iframe width="640" height="360" src="https://www.youtube.com/embed/nDSdYk9narA?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
11	<iframe width="640" height="360" src="https://www.youtube.com/embed/xlt0eDybTZw?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
12	<iframe width="640" height="360" src="https://www.youtube.com/embed/VlECDbomtaY?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
13	<iframe width="640" height="360" src="https://www.youtube.com/embed/-VuKQqX6GE8?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
14	<iframe width="640" height="360" src="https://www.youtube.com/embed/JzVcl4XP3wU?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>

15	<iframe width="640" height="360" src="https://www.youtube.com/embed/s3wtHlysqr4?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>
16	<iframe width="640" height="360" src="https://www.youtube.com/embed/QjM2k7P2bjE?rel=0&controls=0&showinfo=0" frameborder="0" allowfullscreen></iframe>

Appendix H – Duration surveys





Appendix I – Estimate ordinal regression Video experiment without low scorers

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Eindvraag	1392	2	7	5,03	1,045
Valid N (listwise)	1392				

Case Processing Summary

		N	Marginal Percentage
Preference_Score	1 Not at all	77	5,5%
	2	122	8,7%
	3	133	9,4%
	4	201	14,3%
	5	240	17,0%
	6	286	20,3%
	7	210	14,9%
	8	86	6,1%
	9	39	2,8%
	10 Very much	14	1,0%
prop.Straat_design=Gericht op auto's met voetpad	For cars/pedestrians and bicycles	704	50,0%
	Primarily for cars	704	50,0%
prop.Parkeersoort=Op straat parkeren	Designated parking places	704	50,0%
	On street	704	50,0%
prop.Snelheidsremmende_maatregelen=Niet aanwezig	Yes (speedbumps)	704	50,0%
	No	704	50,0%
prop.Speelvoorzieningen=Niet aanwezig	Yes	704	50,0%
	No	704	50,0%
prop.Vijver=Niet aanwezig	Yes	704	50,0%
	No	704	50,0%
prop.Groen=Hoog groen (bomen)	Yes (trees)	352	25,0%
	No high green	1056	75,0%
prop.Groen=Middelhoog groen (struiken)	Yes (bushes)	352	25,0%
	No middle green	1056	75,0%
prop.Groen=Laag groen (gras)	Yes (grass)	352	25,0%
	No low green	1056	75,0%
Valid		1408	100,0%
Missing		0	
Total		1408	

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	835,407			
Final	562,161	273,247	8	,000

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,230	,167	54,427	1	,000	-1,556	-,903
	[Preference_Score = 2]	-,128	,146	,767	1	,381	-,415	,159
	[Preference_Score = 3]	,548	,144	14,418	1	,000	,265	,831
	[Preference_Score = 4]	1,305	,147	78,591	1	,000	1,017	1,594
	[Preference_Score = 5]	2,101	,153	188,125	1	,000	1,801	2,402
	[Preference_Score = 6]	3,151	,164	370,247	1	,000	2,830	3,472
	[Preference_Score = 7]	4,365	,182	574,083	1	,000	4,008	4,722
	[Preference_Score = 8]	5,445	,214	646,083	1	,000	5,025	5,865
	[Preference_Score = 9]	6,831	,315	470,479	1	,000	6,214	7,449
Location	[Street_Design=0]	,434	,094	21,207	1	,000	,249	,619
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,695	,095	53,370	1	,000	,508	,881
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,209	,094	4,980	1	,026	,025	,393
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,359	,094	14,542	1	,000	,175	,544
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,393	,094	17,438	1	,000	,209	,578
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,798	,139	166,739	1	,000	1,525	2,071
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,036	,135	58,949	1	,000	,771	1,300
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,595	,133	19,967	1	,000	,334	,856
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Appendix J – Respondents' perception on text-based and video-based questionnaire

Group Statistics

	Experiment_type	N	Mean	Std. Deviation	Std. Error Mean
Eindvraag	Video	105	4,93	1,049	,102
	Text-only	106	5,05	,970	,094

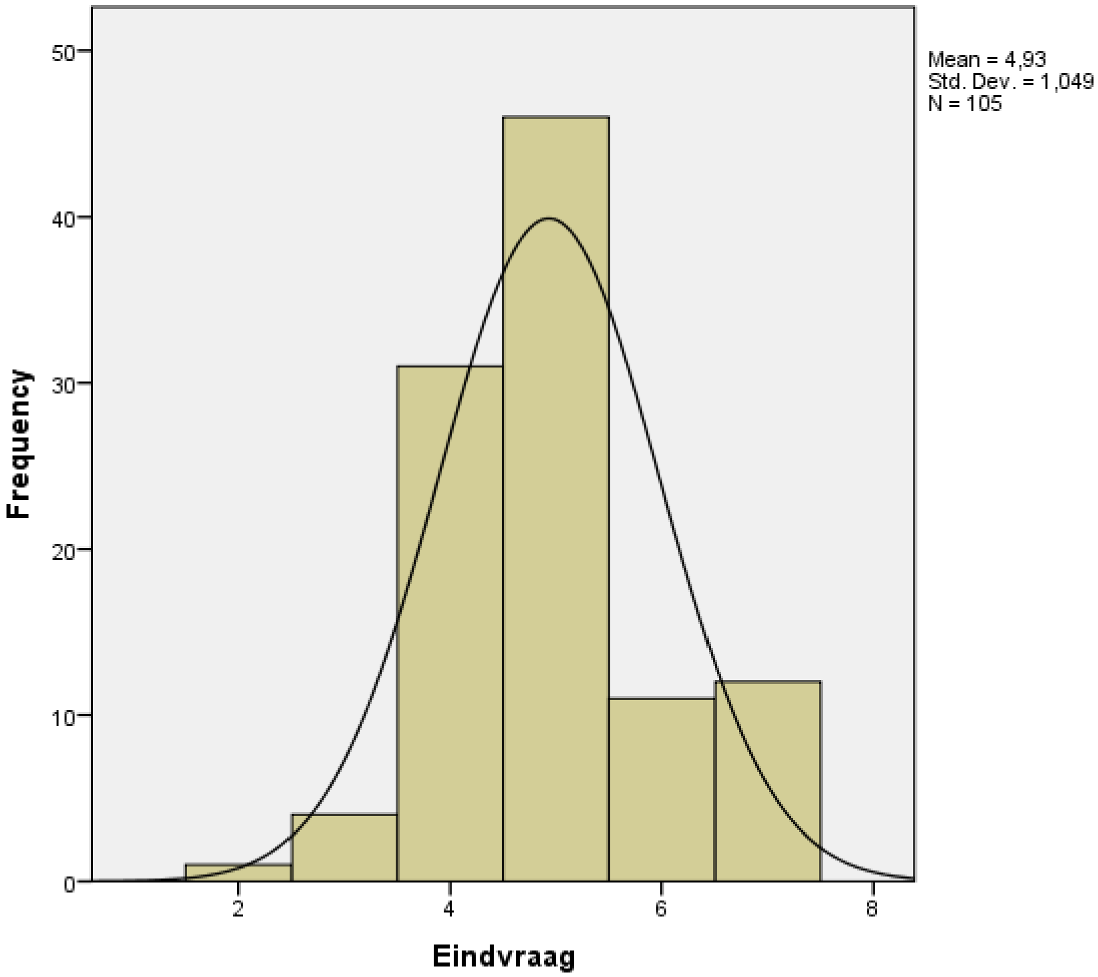
Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Eindvraag	Equal variances assumed	,673	,413	-,818	209	,414	-,114	,139	-,388	,160
	Equal variances not assumed			-,818	207,387	,414	-,114	,139	-,388	,160

Video

Descriptive Statistics

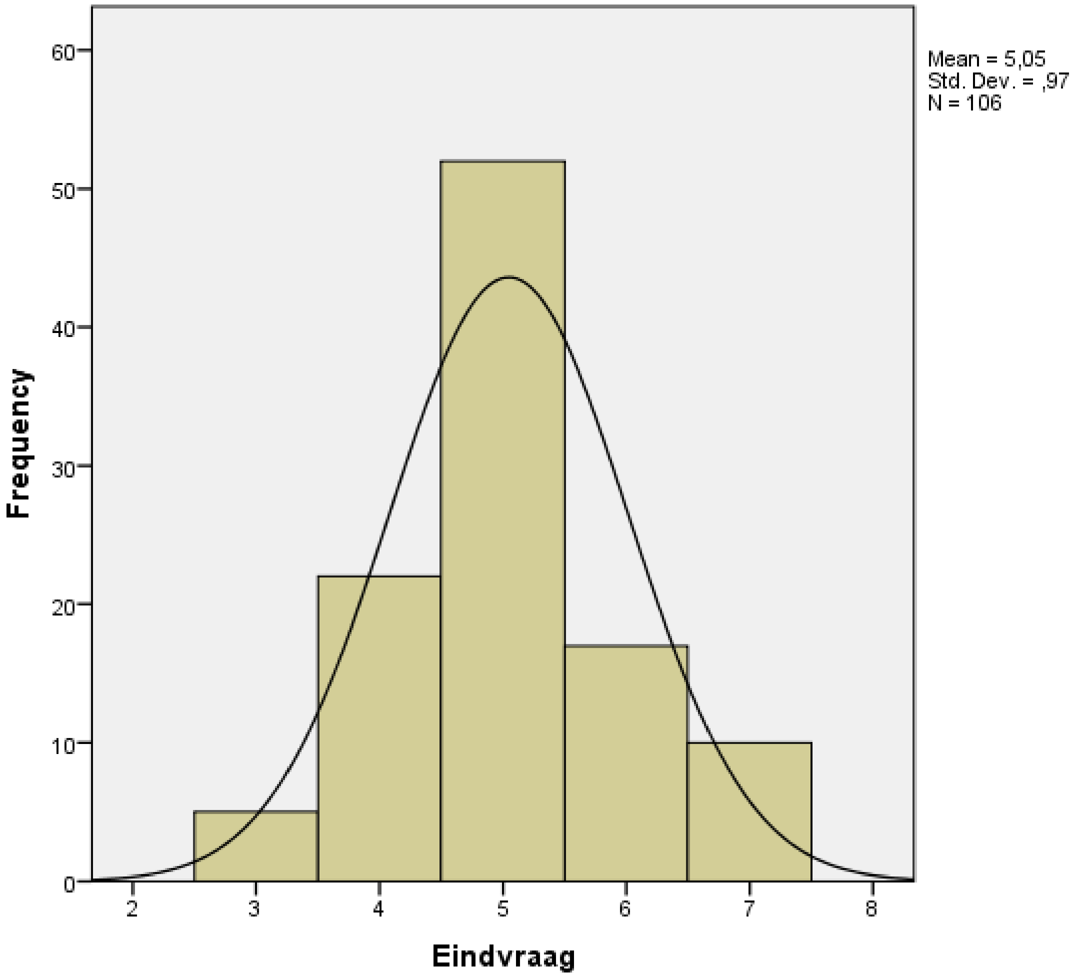
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Eindvraag	105	2	7	4,93	1,049	,339	,236	,158	,467
Valid N (listwise)	105								



Text-Only

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Eindvraag	106	3	7	5,05	,970	,224	,235	,032	,465
Valid N (listwise)	106								



Appendix K – Output ordinal regression Video experiment

Case Processing Summary

		N	Marginal Percentage
Preference_Score	1 Not at all	208	12,3%
	2	190	11,2%
	3	180	10,6%
	4	226	13,3%
	5	257	15,2%
	6	286	16,9%
	7	210	12,4%
	8	86	5,1%
	9	39	2,3%
	10 Very much	14	0,8%
prop.Straat_design=Gericht op auto's met	For cars/pedestrians and bicycles	848	50,0%
voetpad	Primarily for cars	848	50,0%
prop.Parkeersoort=Op straat parkeren	Designated parking places	848	50,0%
	On street	848	50,0%
prop.Snelheidsremmende_maatregelen=Niet	Yes (speedbumps)	848	50,0%
aanwezig	No	848	50,0%
prop.Speelvoorzieningen=Niet aanwezig	Yes	848	50,0%
	No	848	50,0%
prop.Vijver=Niet aanwezig	Yes	848	50,0%
	No	848	50,0%
prop.Groen=Hoog groen (bomen)	Yes (trees)	424	25,0%
	No high green	1272	75,0%
prop.Groen=Middelhoog groen (struiken)	Yes (bushes)	424	25,0%
	No middle green	1272	75,0%
prop.Groen=Laag groen (gras)	Yes (grass)	424	25,0%
	No low green	1272	75,0%
Valid		1696	100,0%
Missing		0	
Total		1696	

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	120,246	127	,652
Deviance	131,187	127	,381

Link function: Logit.

Pseudo R-Square

Cox and Snell	,124
Nagelkerke	,126
McFadden	,031

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,595	,135	19,320	1	,000	-,860	-,329
	[Preference_Score = 2]	,231	,131	3,126	1	,077	-,025	,488
	[Preference_Score = 3]	,784	,132	35,481	1	,000	,526	1,042
	[Preference_Score = 4]	1,382	,134	105,854	1	,000	1,119	1,646
	[Preference_Score = 5]	2,060	,139	219,776	1	,000	1,788	2,333
	[Preference_Score = 6]	2,980	,147	408,773	1	,000	2,691	3,269
	[Preference_Score = 7]	4,117	,165	625,966	1	,000	3,794	4,440
	[Preference_Score = 8]	5,168	,198	680,916	1	,000	4,780	5,556
	[Preference_Score = 9]	6,540	,303	464,475	1	,000	5,945	7,135
Location	[Street_Design= For cars/pedestrians and bicycles]	,368	,085	18,571	1	,000	,201	,536
	[Street_Design=Primarily for cars]	0[a]	.	.	0	.	.	.
	[Parking_type= Designated parking places]	,529	,086	38,012	1	,000	,361	,697
	[Parking_type= On street]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=yes, speedbumps]	,166	,085	3,788	1	,052	-,001	,333
	[Speed_slowing_measures=No]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=Yes]	,291	,085	11,640	1	,001	,124	,459
	[Playground_neighborhood=No]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=Yes]	,323	,085	14,338	1	,000	,156	,491
	[Pond_neighborhood=No]	0[a]	.	.	0	.	.	.
	[Green=High green (trees)]	1,480	,125	141,035	1	,000	1,235	1,724
	[Green=Middle green (bushes)]	,830	,122	46,472	1	,000	,591	1,069
	[Green=Low green (grass)]	,467	,121	14,955	1	,000	,230	,704
	[Green=No green]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	847,676			
Final	622,914	224,763	8	,000

Link function: Logit.

Appendix L – Output ordinal regression Text-only experiment

Case Processing Summary

		N	Marginal Percentage
Preference_Score	1 Not at all	105	6,0%
	2	87	5,0%
	3	128	7,3%
	4	196	11,2%
	5	300	17,2%
	6	321	18,4%
	7	326	18,7%
	8	212	12,2%
	9	47	2,7%
	10 Very much	22	1,3%
prop.Straat_design=Gericht op auto's met	For cars/pedestrians and bicycles	872	50,0%
voetpad	Primarily for cars	872	50,0%
prop.Parkeersoort=Op straat parkeren	Designated parking places	872	50,0%
	On street	872	50,0%
prop.Snelheidsremmende_maatregelen=Niet	Yes (speedbumps)	872	50,0%
aanwezig	No	872	50,0%
prop.Speelvoorzieningen=Niet aanwezig	Yes	872	50,0%
	No	872	50,0%
prop.Vijver=Niet aanwezig	Yes	872	50,0%
	No	872	50,0%
prop.Groen=Hoog groen (bomen)	Yes (trees)	436	25,0%
	No high green	1308	75,0%
prop.Groen=Middelhoog groen (struiken)	Yes (bushes)	436	25,0%
	No middle green	1308	75,0%
prop.Groen=Laag groen (gras)	Yes (grass)	436	25,0%
	No low green	1308	75,0%
Valid		1744	100,0%
Missing		0	
Total		1744	

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	135,438	127	,288
Deviance	147,757	127	,100

Link function: Logit.

Pseudo R-Square

Cox and Snell	,189
Nagelkerke	,192
McFadden	,050

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,960	,146	42,944	1	,000	-1,247	-,673
	[Preference_Score = 2]	-,270	,134	4,089	1	,043	-,532	-,008
	[Preference_Score = 3]	,382	,130	8,678	1	,003	,128	,636
	[Preference_Score = 4]	1,101	,131	70,291	1	,000	,843	1,358
	[Preference_Score = 5]	1,972	,138	205,352	1	,000	1,702	2,241
	[Preference_Score = 6]	2,858	,145	386,452	1	,000	2,573	3,143
	[Preference_Score = 7]	3,993	,157	649,619	1	,000	3,686	4,300
	[Preference_Score = 8]	5,595	,191	862,163	1	,000	5,222	5,969
	[Preference_Score = 9]	6,783	,260	680,561	1	,000	6,273	7,292
Location	[Street_Design=0]	,092	,084	1,199	1	,273	-,073	,258
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,454	,085	28,620	1	,000	,287	,620
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,623	,085	53,309	1	,000	,456	,790
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,699	,086	66,635	1	,000	,531	,866
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,203	,084	5,787	1	,016	,038	,368
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,671	,124	180,044	1	,000	1,427	1,915
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,569	,124	160,154	1	,000	1,326	1,812
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,132	,122	86,656	1	,000	,894	1,371
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	993,501			
Final	629,030	364,471	8	,000

Link function: Logit.

Appendix M – SPSS output ordinal regression sub-group gender

VIDEO - Male

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,504	,192	6,854	1	,009	-,881	-,127
	[Preference_Score = 2]	,244	,187	1,701	1	,192	-,123	,611
	[Preference_Score = 3]	,802	,188	18,159	1	,000	,433	1,171
	[Preference_Score = 4]	1,457	,193	57,211	1	,000	1,080	1,835
	[Preference_Score = 5]	2,121	,199	113,296	1	,000	1,730	2,512
	[Preference_Score = 6]	3,156	,214	218,371	1	,000	2,737	3,574
	[Preference_Score = 7]	4,400	,244	324,385	1	,000	3,921	4,879
	[Preference_Score = 8]	5,578	,312	319,082	1	,000	4,966	6,190
	[Preference_Score = 9]	7,117	,541	173,084	1	,000	6,057	8,177
Location	[Street_Design=0]	,389	,122	10,102	1	,001	,149	,628
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,581	,123	22,318	1	,000	,340	,822
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,129	,122	1,128	1	,288	-,109	,368
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,305	,122	6,252	1	,012	,066	,544
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,350	,122	8,227	1	,004	,111	,590
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,476	,178	68,697	1	,000	1,127	1,825
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,776	,174	19,924	1	,000	,435	1,116
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,450	,173	6,799	1	,009	,112	,789
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	611,442			
Final	497,159	114,283	8	,000

Link function: Logit.

VIDEO - Female

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,687	,191	12,971	1	,000	-1,060	-,313
	[Preference_Score = 2]	,221	,183	1,463	1	,226	-,137	,580
	[Preference_Score = 3]	,769	,184	17,451	1	,000	,408	1,130
	[Preference_Score = 4]	1,314	,188	49,065	1	,000	,946	1,682
	[Preference_Score = 5]	2,006	,194	106,881	1	,000	1,626	2,386
	[Preference_Score = 6]	2,827	,204	191,890	1	,000	2,427	3,227
	[Preference_Score = 7]	3,894	,224	301,316	1	,000	3,454	4,333
	[Preference_Score = 8]	4,875	,261	348,972	1	,000	4,364	5,387
	[Preference_Score = 9]	6,175	,374	272,169	1	,000	5,441	6,908
Location	[Street_Design=0]	,347	,120	8,410	1	,004	,112	,581
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,480	,120	15,986	1	,000	,245	,715
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,204	,119	2,914	1	,088	-,030	,438
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,281	,119	5,550	1	,018	,047	,516
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,299	,119	6,269	1	,012	,065	,533
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,490	,174	72,915	1	,000	1,148	1,832
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,883	,171	26,725	1	,000	,548	1,217
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,482	,169	8,124	1	,004	,151	,814
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	646,931			
Final	534,909	112,022	8	,000

Link function: Logit.

TEXT-ONLY - Male

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,289	,236	29,743	1	,000	-1,752	-,826
	[Preference_Score = 2]	-,385	,205	3,534	1	,060	-,787	,016
	[Preference_Score = 3]	,200	,198	1,016	1	,313	-,188	,587
	[Preference_Score = 4]	1,018	,200	26,033	1	,000	,627	1,410
	[Preference_Score = 5]	1,922	,209	84,331	1	,000	1,512	2,332
	[Preference_Score = 6]	2,859	,222	166,439	1	,000	2,425	3,294
	[Preference_Score = 7]	4,137	,242	293,005	1	,000	3,664	4,611
	[Preference_Score = 8]	5,723	,301	361,777	1	,000	5,133	6,313
	[Preference_Score = 9]	7,034	,441	254,002	1	,000	6,169	7,899
Location	[Street_Design=0]	,107	,129	,688	1	,407	-,146	,359
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,274	,129	4,518	1	,034	,021	,526
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,653	,130	25,083	1	,000	,397	,908
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,715	,131	29,958	1	,000	,459	,971
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,230	,129	3,187	1	,074	-,022	,482
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,690	,190	79,039	1	,000	1,317	2,063
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,531	,189	65,844	1	,000	1,161	1,901
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,101	,185	35,283	1	,000	,737	1,464
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	633,598			
Final	481,578	152,020	8	,000

Link function: Logit.

TEXT-ONLY - Female

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,752	,189	15,932	1	,000	-1,122	-,383
	[Preference_Score = 2]	-,190	,176	1,157	1	,282	-,536	,156
	[Preference_Score = 3]	,508	,172	8,752	1	,003	,172	,845
	[Preference_Score = 4]	1,158	,174	44,123	1	,000	,816	1,500
	[Preference_Score = 5]	2,007	,183	120,736	1	,000	1,649	2,365
	[Preference_Score = 6]	2,858	,193	219,931	1	,000	2,480	3,236
	[Preference_Score = 7]	3,901	,206	357,796	1	,000	3,497	4,306
	[Preference_Score = 8]	5,521	,248	497,447	1	,000	5,036	6,006
	[Preference_Score = 9]	6,646	,325	418,265	1	,000	6,009	7,283
Location	[Street_Design=0]	,085	,112	,586	1	,444	-,133	,304
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,582	,113	26,643	1	,000	,361	,804
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,607	,113	28,863	1	,000	,386	,829
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,690	,113	37,040	1	,000	,468	,912
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,180	,112	2,584	1	,108	-,039	,399
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,655	,165	100,862	1	,000	1,332	1,978
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,590	,164	93,557	1	,000	1,268	1,912
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,153	,161	51,075	1	,000	,837	1,469
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	759,050			
Final	543,253	215,797	8	,000

Link function: Logit.

Appendix N – SPSS output ordinal regression sub-group age

VIDEO - Category 1 (<30 years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,986	,260	14,348	1	,000	-1,497	-,476
	[Preference_Score = 2]	,025	,233	,011	1	,915	-,432	,481
	[Preference_Score = 3]	,769	,230	11,146	1	,001	,318	1,221
	[Preference_Score = 4]	1,412	,235	36,134	1	,000	,951	1,872
	[Preference_Score = 5]	2,150	,244	77,724	1	,000	1,672	2,627
	[Preference_Score = 6]	3,236	,262	153,155	1	,000	2,724	3,749
	[Preference_Score = 7]	4,470	,290	237,758	1	,000	3,902	5,038
	[Preference_Score = 8]	5,858	,350	280,882	1	,000	5,173	6,543
	[Preference_Score = 9]	7,186	,494	211,823	1	,000	6,219	8,154
Location	[Street_Design=0]	,489	,150	10,631	1	,001	,195	,783
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,907	,153	35,342	1	,000	,608	1,206
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,202	,149	1,832	1	,176	-,090	,494
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,480	,150	10,249	1	,001	,186	,774
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,442	,150	8,703	1	,003	,148	,735
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	2,086	,225	86,256	1	,000	1,646	2,526
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,063	,214	24,565	1	,000	,643	1,483
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,557	,211	6,949	1	,008	,143	,971
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	599,190			
Final	453,920	145,270	8	,000

Link function: Logit.

VIDEO - Category 2 (30-49 years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,914	,253	13,055	1	,000	-1,410	-,418
	[Preference_Score = 2]	-,266	,243	1,199	1	,273	-,742	,210
	[Preference_Score = 3]	,491	,242	4,124	1	,042	,017	,965
	[Preference_Score = 4]	1,222	,247	24,476	1	,000	,738	1,706
	[Preference_Score = 5]	1,960	,256	58,820	1	,000	1,459	2,461
	[Preference_Score = 6]	2,830	,270	109,827	1	,000	2,301	3,359
	[Preference_Score = 7]	4,306	,322	178,831	1	,000	3,675	4,937
	[Preference_Score = 8]	5,826	,483	145,495	1	,000	4,880	6,773
Location	[Street_Design=0]	,302	,158	3,667	1	,056	-,007	,612
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,363	,158	5,280	1	,022	,053	,673
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,055	,157	,124	1	,725	-,253	,364
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,241	,158	2,328	1	,127	-,069	,550
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,262	,158	2,757	1	,097	-,047	,571
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,368	,229	35,550	1	,000	,918	1,818
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,759	,225	11,405	1	,001	,319	1,200
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,462	,223	4,276	1	,039	,024	,900
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	459,855			
Final	408,960	50,895	8	,000

Link function: Logit.

VIDEO - Category 3 (50+ years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,168	,215	,606	1	,436	-,589	,254
	[Preference_Score = 2]	,754	,215	12,278	1	,000	,332	1,176
	[Preference_Score = 3]	1,132	,218	27,070	1	,000	,706	1,559
	[Preference_Score = 4]	1,658	,223	55,484	1	,000	1,222	2,095
	[Preference_Score = 5]	2,317	,231	100,884	1	,000	1,865	2,769
	[Preference_Score = 6]	3,225	,246	171,783	1	,000	2,743	3,708
	[Preference_Score = 7]	4,126	,272	230,007	1	,000	3,593	4,659
	[Preference_Score = 8]	4,720	,301	245,344	1	,000	4,130	5,311
	[Preference_Score = 9]	5,943	,422	198,536	1	,000	5,116	6,770
Location	[Street_Design=0]	,365	,139	6,873	1	,009	,092	,639
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,402	,140	8,311	1	,004	,129	,676
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,244	,139	3,081	1	,079	-,028	,517
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,224	,139	2,591	1	,107	-,049	,497
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,288	,139	4,295	1	,038	,016	,561
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,310	,202	42,118	1	,000	,914	1,705
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,817	,199	16,876	1	,000	,427	1,207
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,461	,198	5,438	1	,020	,074	,849
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	535,872			
Final	468,735	67,137	8	,000

Link function: Logit.

TEXT-ONLY - Category 1 (<30 years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Preference_Score = 1]	-,929	,230	16,255	1	,000	-1,381	-,477
	[Preference_Score = 2]	-,276	,210	1,727	1	,189	-,687	,136
	[Preference_Score = 3]	,315	,203	2,405	1	,121	-,083	,712
	[Preference_Score = 4]	,901	,203	19,668	1	,000	,503	1,299
	[Preference_Score = 5]	1,748	,211	68,395	1	,000	1,334	2,162
	[Preference_Score = 6]	2,745	,225	148,649	1	,000	2,304	3,187
	[Preference_Score = 7]	3,890	,242	257,446	1	,000	3,415	4,365
	[Preference_Score = 8]	5,132	,272	357,001	1	,000	4,599	5,664
	[Preference_Score = 9]	6,199	,328	356,055	1	,000	5,555	6,842
Location	[Street_Design=0]	,196	,132	2,228	1	,136	-,061	,454
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,587	,133	19,541	1	,000	,327	,847
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,514	,133	15,018	1	,000	,254	,773
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,666	,133	24,985	1	,000	,405	,927
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,318	,132	5,819	1	,016	,060	,576
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,834	,196	87,909	1	,000	1,451	2,217
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,643	,194	71,731	1	,000	1,263	2,024
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,040	,189	30,262	1	,000	,669	1,410
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	654,108			
Final	489,498	164,611	8	,000

Link function: Logit.

TEXT-ONLY - Category 2 (30-49 years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,380	,274	1,921	1	,166	-,917	,157
	[Preference_Score = 2]	,278	,262	1,123	1	,289	-,236	,792
	[Preference_Score = 3]	,766	,262	8,563	1	,003	,253	1,280
	[Preference_Score = 4]	1,559	,271	33,116	1	,000	1,028	2,090
	[Preference_Score = 5]	2,426	,287	71,628	1	,000	1,865	2,988
	[Preference_Score = 6]	3,307	,303	118,870	1	,000	2,713	3,902
	[Preference_Score = 7]	4,288	,323	176,312	1	,000	3,655	4,921
	[Preference_Score = 8]	6,909	,489	199,655	1	,000	5,951	7,867
	[Preference_Score = 9]	8,881	1,051	71,446	1	,000	6,822	10,940
Location	[Street_Design=0]	-,149	,170	,762	1	,383	-,483	,185
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,311	,170	3,342	1	,068	-,022	,645
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,668	,172	15,083	1	,000	,331	1,005
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	1,183	,177	44,717	1	,000	,836	1,530
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,160	,170	,892	1	,345	-,172	,493
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,833	,253	52,720	1	,000	1,339	2,328
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,841	,253	53,075	1	,000	1,345	2,336
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,412	,248	32,500	1	,000	,926	1,897
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	527,714			
Final	398,563	129,150	8	,000

Link function: Logit.

TEXT-ONLY - Category 3 (50+ years)

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,486	,274	29,370	1	,000	-2,024	-,949
	[Preference_Score = 2]	-,661	,236	7,828	1	,005	-1,125	-,198
	[Preference_Score = 3]	,238	,223	1,143	1	,285	-,198	,674
	[Preference_Score = 4]	1,073	,225	22,731	1	,000	,632	1,515
	[Preference_Score = 5]	2,033	,237	73,885	1	,000	1,570	2,497
	[Preference_Score = 6]	2,858	,249	132,116	1	,000	2,371	3,346
	[Preference_Score = 7]	4,183	,275	231,569	1	,000	3,645	4,722
	[Preference_Score = 8]	6,129	,392	244,626	1	,000	5,361	6,897
	[Preference_Score = 9]	7,857	,751	109,450	1	,000	6,385	9,329
Location	[Street_Design=0]	,158	,145	1,197	1	,274	-,125	,442
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,399	,145	7,512	1	,006	,114	,684
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,776	,148	27,644	1	,000	,487	1,065
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,404	,146	7,702	1	,006	,119	,689
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,113	,145	,610	1	,435	-,171	,397
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,468	,212	48,010	1	,000	1,053	1,883
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,377	,211	42,575	1	,000	,964	1,791
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,138	,209	29,615	1	,000	,728	1,547
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	514,051			
Final	411,553	102,498	8	,000

Link function: Logit.

Appendix O – SPSS output ordinal regression sub-group education level

VIDEO - High

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,470	,181	6,737	1	,009	-,825	-,115
	[Preference_Score = 2]	,269	,176	2,327	1	,127	-,077	,614
	[Preference_Score = 3]	,897	,178	25,512	1	,000	,549	1,245
	[Preference_Score = 4]	1,442	,181	63,353	1	,000	1,087	1,798
	[Preference_Score = 5]	2,135	,188	129,377	1	,000	1,767	2,502
	[Preference_Score = 6]	3,145	,200	246,456	1	,000	2,752	3,538
	[Preference_Score = 7]	4,565	,231	389,147	1	,000	4,112	5,019
	[Preference_Score = 8]	5,941	,308	372,545	1	,000	5,337	6,544
	[Preference_Score = 9]	6,913	,428	261,448	1	,000	6,075	7,751
Location	[Street_Design=0]	,380	,115	10,931	1	,001	,155	,605
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,551	,115	22,754	1	,000	,324	,777
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,115	,114	1,009	1	,315	-,109	,339
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,406	,115	12,486	1	,000	,181	,632
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,366	,115	10,155	1	,001	,141	,591
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,822	,170	114,424	1	,000	1,488	2,156
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,884	,164	29,143	1	,000	,563	1,205
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,428	,162	6,973	1	,008	,110	,746
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	674,729			
Final	501,040	173,688	8	,000

Link function: Logit.

VIDEO - Middle-Low

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,744	,204	13,318	1	,000	-1,144	-,345
	[Preference_Score = 2]	,188	,196	,927	1	,336	-,195	,572
	[Preference_Score = 3]	,656	,196	11,158	1	,001	,271	1,041
	[Preference_Score = 4]	1,325	,201	43,517	1	,000	,931	1,718
	[Preference_Score = 5]	1,994	,208	92,311	1	,000	1,587	2,400
	[Preference_Score = 6]	2,816	,219	165,874	1	,000	2,388	3,245
	[Preference_Score = 7]	3,671	,237	240,841	1	,000	3,207	4,134
	[Preference_Score = 8]	4,508	,268	282,663	1	,000	3,983	5,034
	[Preference_Score = 9]	6,173	,432	204,256	1	,000	5,327	7,020
Location	[Street_Design=0]	,349	,128	7,406	1	,007	,098	,600
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,507	,129	15,506	1	,000	,254	,759
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,237	,128	3,447	1	,063	-,013	,488
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,168	,128	1,721	1	,190	-,083	,418
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,266	,128	4,320	1	,038	,015	,516
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,119	,184	36,919	1	,000	,758	1,480
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,769	,182	17,771	1	,000	,411	1,126
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,529	,181	8,504	1	,004	,174	,885
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	598,200			
Final	530,020	68,179	8	,000

Link function: Logit.

TEXT-ONLY - High

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Preference_Score = 1]	-,764	,206	13,769	1	,000	-1,168	-,361
	[Preference_Score = 2]	-,070	,189	,137	1	,711	-,441	,301
	[Preference_Score = 3]	,498	,185	7,253	1	,007	,136	,861
	[Preference_Score = 4]	1,257	,188	44,581	1	,000	,888	1,626
	[Preference_Score = 5]	2,024	,197	105,743	1	,000	1,638	2,410
	[Preference_Score = 6]	3,086	,211	213,560	1	,000	2,672	3,500
	[Preference_Score = 7]	4,321	,229	356,273	1	,000	3,872	4,770
	[Preference_Score = 8]	5,746	,267	463,932	1	,000	5,223	6,269
	[Preference_Score = 9]	7,061	,363	377,935	1	,000	6,349	7,773
Location	[Street_Design=0]	,135	,120	1,258	1	,262	-,101	,371
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,412	,121	11,642	1	,001	,175	,648
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,747	,122	37,348	1	,000	,507	,986
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,695	,122	32,504	1	,000	,456	,934
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,241	,120	4,024	1	,045	,006	,477
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	2,093	,182	132,922	1	,000	1,737	2,449
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,882	,180	109,788	1	,000	1,530	2,234
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,150	,173	43,959	1	,000	,810	1,490
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	744,052			
Final	507,064	236,988	8	,000

Link function: Logit.

TEXT-ONLY - Middle-Low

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,146	,209	30,176	1	,000	-1,555	-,737
	[Preference_Score = 2]	-,457	,189	5,838	1	,016	-,827	-,086
	[Preference_Score = 3]	,277	,182	2,317	1	,128	-,080	,634
	[Preference_Score = 4]	,968	,184	27,772	1	,000	,608	1,328
	[Preference_Score = 5]	1,943	,193	101,397	1	,000	1,565	2,321
	[Preference_Score = 6]	2,685	,202	177,437	1	,000	2,290	3,081
	[Preference_Score = 7]	3,741	,216	298,942	1	,000	3,317	4,165
	[Preference_Score = 8]	5,579	,280	397,297	1	,000	5,031	6,128
	[Preference_Score = 9]	6,601	,376	307,515	1	,000	5,863	7,339
Location	[Street_Design=0]	,064	,119	,294	1	,588	-,168	,297
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,511	,119	18,265	1	,000	,276	,745
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,514	,120	18,461	1	,000	,279	,748
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,688	,120	32,711	1	,000	,452	,924
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,178	,119	2,247	1	,134	-,055	,410
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,295	,172	56,622	1	,000	,958	1,633
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,288	,172	55,975	1	,000	,951	1,625
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,132	,171	43,779	1	,000	,797	1,468
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	668,416			
Final	523,362	145,054	8	,000

Link function: Logit.

Appendix p – SPSS output ordinal regression sub-group presence of kids

VIDEO - No kids

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,507	,161	9,890	1	,002	-,823	-,191
	[Preference_Score = 2]	,400	,157	6,502	1	,011	,093	,708
	[Preference_Score = 3]	,892	,158	31,760	1	,000	,582	1,203
	[Preference_Score = 4]	1,450	,162	80,370	1	,000	1,133	1,767
	[Preference_Score = 5]	2,092	,167	156,957	1	,000	1,765	2,419
	[Preference_Score = 6]	3,016	,177	290,683	1	,000	2,670	3,363
	[Preference_Score = 7]	4,114	,196	441,324	1	,000	3,730	4,498
	[Preference_Score = 8]	5,206	,235	490,287	1	,000	4,745	5,666
	[Preference_Score = 9]	6,344	,327	376,354	1	,000	5,704	6,985
Location	[Street_Design=0]	,418	,102	16,682	1	,000	,218	,619
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,478	,103	21,710	1	,000	,277	,679
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,146	,102	2,056	1	,152	-,054	,346
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,283	,102	7,658	1	,006	,083	,483
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,318	,102	9,691	1	,002	,118	,519
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,645	,150	119,768	1	,000	1,351	1,940
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,961	,146	43,101	1	,000	,674	1,248
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,500	,145	11,911	1	,001	,216	,784
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	752,224			
Final	574,015	178,210	8	,000

Link function: Logit.

VIDEO - Kids

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,790	,249	10,037	1	,002	-1,279	-,301
	[Preference_Score = 2]	-,163	,239	,465	1	,495	-,632	,306
	[Preference_Score = 3]	,558	,238	5,500	1	,019	,092	1,024
	[Preference_Score = 4]	1,260	,243	26,957	1	,000	,784	1,735
	[Preference_Score = 5]	2,026	,252	64,599	1	,000	1,532	2,520
	[Preference_Score = 6]	2,945	,268	120,678	1	,000	2,419	3,470
	[Preference_Score = 7]	4,206	,307	187,512	1	,000	3,604	4,808
	[Preference_Score = 8]	5,154	,371	193,345	1	,000	4,427	5,880
	[Preference_Score = 9]	7,835	1,033	57,497	1	,000	5,810	9,861
Location	[Street_Design=0]	,257	,155	2,731	1	,098	-,048	,561
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,670	,157	18,157	1	,000	,362	,978
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,217	,155	1,950	1	,163	-,088	,521
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,328	,156	4,449	1	,035	,023	,633
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,365	,156	5,493	1	,019	,060	,670
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,095	,223	24,000	1	,000	,657	1,532
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,516	,220	5,494	1	,019	,085	,947
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,393	,220	3,197	1	,074	-,038	,823
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	490,828			
Final	436,503	54,325	8	,000

Link function: Logit.

TEXT-ONLY - No kids

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,200	,186	41,754	1	,000	-1,564	-,836
	[Preference_Score = 2]	-,554	,166	11,096	1	,001	-,879	-,228
	[Preference_Score = 3]	,120	,158	,577	1	,448	-,189	,428
	[Preference_Score = 4]	,912	,157	33,584	1	,000	,604	1,221
	[Preference_Score = 5]	1,898	,165	131,680	1	,000	1,574	2,222
	[Preference_Score = 6]	2,777	,175	253,226	1	,000	2,435	3,119
	[Preference_Score = 7]	3,993	,189	445,785	1	,000	3,622	4,363
	[Preference_Score = 8]	5,461	,225	589,939	1	,000	5,020	5,902
	[Preference_Score = 9]	6,533	,291	503,857	1	,000	5,962	7,103
Location	[Street_Design=0]	,157	,102	2,369	1	,124	-,043	,356
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,526	,103	26,281	1	,000	,325	,727
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,557	,103	29,371	1	,000	,356	,759
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,595	,103	33,398	1	,000	,393	,797
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,262	,102	6,603	1	,010	,062	,462
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,623	,150	117,046	1	,000	1,329	1,917
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,584	,150	111,737	1	,000	1,290	1,878
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,114	,147	57,477	1	,000	,826	1,401
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	803,576			
Final	565,376	238,200	8	,000

Link function: Logit.

TEXT-ONLY - Kids

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,484	,246	3,880	1	,049	-,966	-,002
	[Preference_Score = 2]	,295	,233	1,608	1	,205	-,161	,752
	[Preference_Score = 3]	,961	,234	16,874	1	,000	,502	1,419
	[Preference_Score = 4]	1,597	,241	43,925	1	,000	1,125	2,069
	[Preference_Score = 5]	2,264	,251	81,223	1	,000	1,771	2,756
	[Preference_Score = 6]	3,188	,267	142,867	1	,000	2,665	3,710
	[Preference_Score = 7]	4,150	,284	213,415	1	,000	3,593	4,707
	[Preference_Score = 8]	6,114	,368	275,804	1	,000	5,392	6,836
	[Preference_Score = 9]	7,831	,640	149,809	1	,000	6,577	9,085
Location	[Street_Design=0]	-,034	,151	,049	1	,824	-,330	,262
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,335	,151	4,887	1	,027	,038	,631
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,791	,154	26,498	1	,000	,490	1,092
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,941	,155	36,901	1	,000	,637	1,245
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,088	,151	,337	1	,561	-,208	,383
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,850	,225	67,818	1	,000	1,410	2,291
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,632	,222	53,911	1	,000	1,196	2,067
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,252	,219	32,800	1	,000	,823	1,680
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	575,289			
Final	433,408	141,881	8	,000

Link function: Logit.

Appendix Q – SPSS output ordinal regression sub-group building year home

VIDEO - Older

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,728	,174	17,544	1	,000	-1,069	-,388
	[Preference_Score = 2]	,221	,166	1,778	1	,182	-,104	,546
	[Preference_Score = 3]	,854	,167	26,065	1	,000	,526	1,181
	[Preference_Score = 4]	1,483	,171	74,985	1	,000	1,147	1,818
	[Preference_Score = 5]	2,197	,178	153,016	1	,000	1,849	2,545
	[Preference_Score = 6]	3,175	,189	280,840	1	,000	2,803	3,546
	[Preference_Score = 7]	4,360	,214	414,258	1	,000	3,941	4,780
	[Preference_Score = 8]	5,317	,256	431,488	1	,000	4,815	5,818
	[Preference_Score = 9]	6,387	,353	327,468	1	,000	5,695	7,078
Location	[Street_Design=0]	,436	,109	16,139	1	,000	,223	,649
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,424	,109	15,277	1	,000	,211	,637
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,205	,108	3,593	1	,058	-,007	,417
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,258	,108	5,682	1	,017	,046	,470
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,349	,108	10,396	1	,001	,137	,561
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,611	,159	102,729	1	,000	1,299	1,922
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,904	,155	34,177	1	,000	,601	1,208
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,523	,153	11,613	1	,001	,222	,823
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	692,533			
Final	541,538	150,995	8	,000

Link function: Logit.

VIDEO - Newer

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,199	,234	,725	1	,395	-,658	,260
	[Preference_Score = 2]	,505	,232	4,721	1	,030	,049	,960
	[Preference_Score = 3]	,937	,234	15,978	1	,000	,477	1,396
	[Preference_Score = 4]	1,490	,239	38,759	1	,000	1,021	1,959
	[Preference_Score = 5]	2,163	,248	76,197	1	,000	1,678	2,649
	[Preference_Score = 6]	3,012	,262	132,144	1	,000	2,499	3,526
	[Preference_Score = 7]	4,145	,294	199,116	1	,000	3,569	4,720
	[Preference_Score = 8]	5,306	,367	209,163	1	,000	4,587	6,025
	[Preference_Score = 9]	6,887	,631	119,053	1	,000	5,650	8,124
Location	[Street_Design=0]	,293	,151	3,757	1	,053	-,003	,588
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,625	,152	16,828	1	,000	,326	,923
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,122	,151	,653	1	,419	-,173	,417
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,368	,151	5,913	1	,015	,071	,664
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,276	,151	3,352	1	,067	-,019	,572
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,380	,219	39,559	1	,000	,950	1,810
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,764	,215	12,595	1	,000	,342	1,185
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,407	,214	3,618	1	,057	-,012	,827
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	538,537			
Final	468,133	70,404	8	,000

Link function: Logit.

TEXT-ONLY - Older

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,766	,219	12,215	1	,000	-1,195	-,336
	[Preference_Score = 2]	-,061	,203	,090	1	,764	-,458	,336
	[Preference_Score = 3]	,690	,200	11,955	1	,001	,299	1,081
	[Preference_Score = 4]	1,445	,205	49,559	1	,000	1,043	1,847
	[Preference_Score = 5]	2,227	,215	107,195	1	,000	1,806	2,649
	[Preference_Score = 6]	3,006	,226	177,195	1	,000	2,563	3,448
	[Preference_Score = 7]	3,867	,239	262,706	1	,000	3,399	4,335
	[Preference_Score = 8]	5,766	,301	367,573	1	,000	5,176	6,355
	[Preference_Score = 9]	6,758	,391	299,276	1	,000	5,993	7,524
Location	[Street_Design=0]	,046	,130	,125	1	,724	-,208	,300
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,426	,130	10,725	1	,001	,171	,682
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,626	,131	22,824	1	,000	,369	,883
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,831	,132	39,476	1	,000	,572	1,090
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,250	,130	3,713	1	,054	-,004	,504
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,541	,190	65,713	1	,000	1,168	1,914
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,572	,190	68,105	1	,000	1,198	1,945
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,219	,188	42,196	1	,000	,851	1,586
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	647,787			
Final	486,837	160,950	8	,000

Link function: Logit.

TEXT-ONLY - Newer

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,033	,225	20,983	1	,000	-1,475	-,591
	[Preference_Score = 2]	-,355	,205	2,993	1	,084	-,757	,047
	[Preference_Score = 3]	,169	,199	,722	1	,395	-,221	,559
	[Preference_Score = 4]	,868	,199	18,965	1	,000	,477	1,259
	[Preference_Score = 5]	1,875	,210	79,917	1	,000	1,464	2,286
	[Preference_Score = 6]	2,884	,223	167,193	1	,000	2,447	3,321
	[Preference_Score = 7]	4,393	,247	315,870	1	,000	3,908	4,877
	[Preference_Score = 8]	5,898	,306	371,419	1	,000	5,298	6,498
	[Preference_Score = 9]	7,507	,504	221,824	1	,000	6,519	8,495
Location	[Street_Design=0]	,126	,129	,952	1	,329	-,127	,380
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,339	,130	6,829	1	,009	,085	,592
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,642	,131	24,114	1	,000	,386	,898
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,650	,131	24,695	1	,000	,394	,906
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,076	,129	,345	1	,557	-,177	,329
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,953	,194	101,694	1	,000	1,573	2,332
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,780	,192	86,014	1	,000	1,404	2,156
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,247	,187	44,446	1	,000	,880	1,613
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	666,159			
Final	491,815	174,344	8	,000

Link function: Logit.

Appendix R – SPSS output ordinal regression sub-group home ownership

VIDEO - Owner

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,519	,164	10,003	1	,002	-,841	-,198
	[Preference_Score = 2]	,337	,159	4,487	1	,034	,025	,648
	[Preference_Score = 3]	,940	,160	34,287	1	,000	,625	1,254
	[Preference_Score = 4]	1,604	,165	94,700	1	,000	1,281	1,927
	[Preference_Score = 5]	2,311	,171	182,098	1	,000	1,975	2,646
	[Preference_Score = 6]	3,307	,183	324,961	1	,000	2,947	3,666
	[Preference_Score = 7]	4,467	,208	461,075	1	,000	4,059	4,875
	[Preference_Score = 8]	5,498	,255	463,615	1	,000	4,998	5,999
	[Preference_Score = 9]	7,804	,604	166,991	1	,000	6,621	8,988
Location	[Street_Design=0]	,333	,104	10,304	1	,001	,130	,536
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,635	,105	36,847	1	,000	,430	,840
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,179	,103	3,002	1	,083	-,024	,382
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,386	,104	13,797	1	,000	,182	,589
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,374	,104	12,979	1	,000	,170	,577
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,401	,151	86,366	1	,000	1,105	1,696
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,827	,148	31,253	1	,000	,537	1,117
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,469	,147	10,218	1	,001	,182	,757
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	687,791			
Final	528,033	159,759	8	,000

Link function: Logit.

VIDEO - Rented

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,700	,239	8,582	1	,003	-1,168	-,232
	[Preference_Score = 2]	,067	,231	,085	1	,770	-,385	,520
	[Preference_Score = 3]	,517	,231	5,008	1	,025	,064	,970
	[Preference_Score = 4]	,987	,234	17,805	1	,000	,528	1,445
	[Preference_Score = 5]	1,629	,240	46,068	1	,000	1,159	2,100
	[Preference_Score = 6]	2,457	,251	95,637	1	,000	1,965	2,949
	[Preference_Score = 7]	3,617	,276	172,065	1	,000	3,076	4,157
	[Preference_Score = 8]	4,726	,323	214,428	1	,000	4,094	5,359
	[Preference_Score = 9]	5,556	,393	199,737	1	,000	4,785	6,326
Location	[Street_Design=0]	,466	,151	9,484	1	,002	,169	,762
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,351	,151	5,422	1	,020	,056	,647
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,163	,150	1,174	1	,278	-,132	,458
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,103	,150	,470	1	,493	-,192	,398
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,233	,151	2,393	1	,122	-,062	,528
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,730	,223	60,292	1	,000	1,293	2,167
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,867	,215	16,261	1	,000	,446	1,289
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,472	,213	4,909	1	,027	,054	,890
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	551,363			
Final	471,678	79,686	8	,000

Link function: Logit.

TEXT-ONLY - Owner

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,849	,176	23,350	1	,000	-1,193	-,504
	[Preference_Score = 2]	-,171	,163	1,093	1	,296	-,491	,149
	[Preference_Score = 3]	,470	,160	8,573	1	,003	,155	,784
	[Preference_Score = 4]	1,220	,164	55,430	1	,000	,899	1,541
	[Preference_Score = 5]	2,051	,172	142,862	1	,000	1,714	2,387
	[Preference_Score = 6]	2,905	,181	258,886	1	,000	2,552	3,259
	[Preference_Score = 7]	4,043	,195	431,443	1	,000	3,662	4,425
	[Preference_Score = 8]	5,851	,252	540,152	1	,000	5,357	6,344
	[Preference_Score = 9]	7,076	,365	374,836	1	,000	6,360	7,793
Location	[Street_Design=0]	-,014	,104	,019	1	,891	-,219	,190
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,381	,105	13,192	1	,000	,175	,586
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,503	,105	22,838	1	,000	,297	,709
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,771	,106	52,583	1	,000	,562	,979
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,193	,104	3,411	1	,065	-,012	,398
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,694	,154	120,425	1	,000	1,391	1,996
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,667	,154	116,854	1	,000	1,365	1,969
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,174	,151	60,564	1	,000	,879	1,470
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	815,794			
Final	575,815	239,979	8	,000

Link function: Logit.

TEXT-ONLY - Rented

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,252	,275	20,766	1	,000	-1,791	-,714
	[Preference_Score = 2]	-,510	,238	4,603	1	,032	-,976	-,044
	[Preference_Score = 3]	,194	,223	,756	1	,384	-,243	,630
	[Preference_Score = 4]	,870	,221	15,525	1	,000	,437	1,303
	[Preference_Score = 5]	1,868	,231	65,384	1	,000	1,415	2,321
	[Preference_Score = 6]	2,840	,246	132,869	1	,000	2,357	3,323
	[Preference_Score = 7]	3,997	,267	224,293	1	,000	3,474	4,521
	[Preference_Score = 8]	5,383	,306	308,999	1	,000	4,783	5,984
	[Preference_Score = 9]	6,559	,388	285,527	1	,000	5,798	7,320
Location	[Street_Design=0]	,293	,143	4,179	1	,041	,012	,574
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,584	,145	16,306	1	,000	,301	,868
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,886	,147	36,464	1	,000	,599	1,174
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,582	,145	16,166	1	,000	,298	,866
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,210	,143	2,155	1	,142	-,070	,491
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,671	,211	62,451	1	,000	1,256	2,085
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,418	,209	45,972	1	,000	1,008	1,828
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,102	,206	28,538	1	,000	,698	1,507
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	581,563			
Final	441,365	140,198	8	,000

Link function: Logit.

Appendix S – SPSS output ordinal regression sub-group car ownership

VIDEO - One car

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,711	,204	12,189	1	,000	-1,110	-,312
	[Preference_Score = 2]	,044	,198	,050	1	,822	-,344	,433
	[Preference_Score = 3]	,469	,199	5,565	1	,018	,079	,858
	[Preference_Score = 4]	1,039	,201	26,577	1	,000	,644	1,434
	[Preference_Score = 5]	1,656	,207	64,196	1	,000	1,251	2,061
	[Preference_Score = 6]	2,498	,217	132,795	1	,000	2,073	2,922
	[Preference_Score = 7]	3,720	,243	234,405	1	,000	3,244	4,196
	[Preference_Score = 8]	4,859	,299	263,280	1	,000	4,272	5,446
	[Preference_Score = 9]	6,375	,495	165,888	1	,000	5,405	7,345
Location	[Street_Design=0]	,352	,130	7,367	1	,007	,098	,606
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,328	,130	6,392	1	,011	,074	,582
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,056	,129	,190	1	,663	-,197	,310
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,082	,129	,403	1	,526	-,171	,335
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,197	,129	2,329	1	,127	-,056	,451
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,515	,189	63,905	1	,000	1,143	1,886
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,800	,185	18,784	1	,000	,438	1,162
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,447	,183	5,954	1	,015	,088	,807
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	599,593			
Final	516,154	83,440	8	,000

Link function: Logit.

VIDEO - Multiple cars

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Preference_Score = 1]	-,496	,207	5,766	1	,016	-,902	-,091
	[Preference_Score = 2]	,437	,199	4,826	1	,028	,047	,827
	[Preference_Score = 3]	1,173	,202	33,681	1	,000	,777	1,569
	[Preference_Score = 4]	1,768	,208	72,436	1	,000	1,361	2,175
	[Preference_Score = 5]	2,489	,217	131,870	1	,000	2,064	2,913
	[Preference_Score = 6]	3,478	,233	223,653	1	,000	3,022	3,934
	[Preference_Score = 7]	4,625	,263	308,167	1	,000	4,109	5,142
	[Preference_Score = 8]	5,601	,319	309,047	1	,000	4,976	6,225
	[Preference_Score = 9]	7,898	,741	113,658	1	,000	6,446	9,350
Location	[Street_Design=0]	,336	,130	6,723	1	,010	,082	,591
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,733	,131	31,092	1	,000	,475	,991
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,275	,130	4,491	1	,034	,021	,529
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,471	,130	13,074	1	,000	,216	,726
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,390	,130	9,036	1	,003	,136	,645
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,331	,188	50,076	1	,000	,962	1,699
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,795	,185	18,487	1	,000	,433	1,158
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,462	,184	6,328	1	,012	,102	,822
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	568,916			
Final	461,413	107,503	8	,000

Link function: Logit.

TEXT-ONLY - One car

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,450	,227	40,651	1	,000	-1,896	-1,004
	[Preference_Score = 2]	-,707	,199	12,648	1	,000	-1,096	-,317
	[Preference_Score = 3]	,117	,186	,397	1	,529	-,248	,483
	[Preference_Score = 4]	,966	,187	26,627	1	,000	,599	1,333
	[Preference_Score = 5]	1,878	,196	92,088	1	,000	1,495	2,262
	[Preference_Score = 6]	2,720	,206	174,354	1	,000	2,317	3,124
	[Preference_Score = 7]	3,856	,223	298,952	1	,000	3,419	4,293
	[Preference_Score = 8]	5,674	,289	384,577	1	,000	5,107	6,241
	[Preference_Score = 9]	6,620	,380	303,735	1	,000	5,875	7,364
Location	[Street_Design=0]	,162	,121	1,792	1	,181	-,075	,399
	[Street_Design=1]	0^a	.	.	0	.	.	.
	[Parking_type=0]	,492	,122	16,298	1	,000	,253	,730
	[Parking_type=1]	0^a	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,738	,123	35,975	1	,000	,497	,979
	[Speed_slowing_measures=1]	0^a	.	.	0	.	.	.
	[Playground_neighborhood=0]	,419	,122	11,869	1	,001	,181	,657
	[Playground_neighborhood=1]	0^a	.	.	0	.	.	.
	[Pond_neighborhood=0]	,110	,121	,835	1	,361	-,127	,347
	[Pond_neighborhood=1]	0^a	.	.	0	.	.	.
	[HighGreen=0]	1,475	,177	69,535	1	,000	1,129	1,822
	[HighGreen=1]	0^a	.	.	0	.	.	.
	[MiddleGreen=0]	1,466	,177	68,723	1	,000	1,120	1,813
	[MiddleGreen=1]	0^a	.	.	0	.	.	.
	[LowGreen=0]	,938	,173	29,311	1	,000	,599	1,278
	[LowGreen=1]	0^a	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	639,434			
Final	486,860	152,575	8	,000

Link function: Logit.

TEXT-ONLY - Multiple cars

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,508	,209	5,900	1	,015	-,918	-,098
	[Preference_Score = 2]	,145	,199	,528	1	,467	-,245	,534
	[Preference_Score = 3]	,664	,198	11,255	1	,001	,276	1,052
	[Preference_Score = 4]	1,266	,202	39,372	1	,000	,871	1,662
	[Preference_Score = 5]	2,090	,212	97,480	1	,000	1,675	2,505
	[Preference_Score = 6]	3,034	,225	182,314	1	,000	2,594	3,474
	[Preference_Score = 7]	4,169	,242	297,089	1	,000	3,695	4,643
	[Preference_Score = 8]	5,545	,282	386,317	1	,000	4,992	6,097
	[Preference_Score = 9]	6,789	,379	321,027	1	,000	6,046	7,531
Location	[Street_Design=0]	-,032	,129	,061	1	,805	-,284	,220
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,407	,129	9,955	1	,002	,154	,660
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,478	,129	13,659	1	,000	,224	,731
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	1,028	,133	60,058	1	,000	,768	1,288
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,223	,128	3,020	1	,082	-,029	,475
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,798	,191	88,864	1	,000	1,424	2,172
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,633	,189	74,433	1	,000	1,262	2,004
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,238	,186	44,326	1	,000	,874	1,603
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	674,114			
Final	487,823	186,291	8	,000

Link function: Logit.

Appendix T – SPSS output ordinal regression sub-group parking type

VIDEO - Own property

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,359	,169	4,536	1	,033	-,690	-,029
	[Preference_Score = 2]	,450	,166	7,322	1	,007	,124	,775
	[Preference_Score = 3]	,957	,168	32,461	1	,000	,628	1,286
	[Preference_Score = 4]	1,492	,172	75,689	1	,000	1,156	1,829
	[Preference_Score = 5]	2,224	,178	155,683	1	,000	1,875	2,573
	[Preference_Score = 6]	3,217	,191	283,981	1	,000	2,843	3,591
	[Preference_Score = 7]	4,553	,224	411,971	1	,000	4,113	4,993
	[Preference_Score = 8]	5,673	,292	376,964	1	,000	5,100	6,245
	[Preference_Score = 9]	7,544	,606	154,895	1	,000	6,356	8,732
Location	[Street_Design=0]	,306	,108	7,963	1	,005	,093	,518
	[Street_Design=1]	0^a	.	.	0	.	.	.
	[Parking_type=0]	,501	,109	21,154	1	,000	,287	,714
	[Parking_type=1]	0^a	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,181	,108	2,811	1	,094	-,031	,393
	[Speed_slowing_measures=1]	0^a	.	.	0	.	.	.
	[Playground_neighborhood=0]	,375	,109	11,957	1	,001	,163	,588
	[Playground_neighborhood=1]	0^a	.	.	0	.	.	.
	[Pond_neighborhood=0]	,284	,108	6,876	1	,009	,072	,496
	[Pond_neighborhood=1]	0^a	.	.	0	.	.	.
	[HighGreen=0]	1,420	,158	81,058	1	,000	1,111	1,729
	[HighGreen=1]	0^a	.	.	0	.	.	.
	[MiddleGreen=0]	,780	,154	25,505	1	,000	,477	1,082
	[MiddleGreen=1]	0^a	.	.	0	.	.	.
	[LowGreen=0]	,394	,153	6,614	1	,010	,094	,695
	[LowGreen=1]	0^a	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	638,336			
Final	505,085	133,251	8	,000

Link function: Logit.

VIDEO - Public property

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Preference_Score = 1]	-1,112	,237	22,002	1	,000	-1,576	-,647
	[Preference_Score = 2]	-,162	,216	,562	1	,454	-,584	,261
	[Preference_Score = 3]	,535	,213	6,294	1	,012	,117	,954
	[Preference_Score = 4]	1,283	,218	34,698	1	,000	,856	1,710
	[Preference_Score = 5]	1,904	,224	72,198	1	,000	1,465	2,343
	[Preference_Score = 6]	2,779	,236	138,664	1	,000	2,316	3,241
	[Preference_Score = 7]	3,797	,256	220,185	1	,000	3,295	4,298
	[Preference_Score = 8]	4,851	,292	275,448	1	,000	4,278	5,424
	[Preference_Score = 9]	6,053	,385	247,493	1	,000	5,299	6,807
Location	[Street_Design=0]	,477	,140	11,711	1	,001	,204	,751
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,630	,140	20,190	1	,000	,355	,905
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,150	,139	1,164	1	,281	-,122	,421
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,143	,139	1,067	1	,302	-,129	,415
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,409	,139	8,636	1	,003	,136	,682
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,705	,205	69,260	1	,000	1,303	2,106
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	,986	,199	24,502	1	,000	,596	1,376
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	,617	,197	9,800	1	,002	,231	1,004
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	591,661			
Final	485,752	105,910	8	,000

Link function: Logit.

TEXT-ONLY - Own property

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-1,209	,198	37,315	1	,000	-1,597	-,821
	[Preference_Score = 2]	-,508	,178	8,148	1	,004	-,856	-,159
	[Preference_Score = 3]	,266	,170	2,445	1	,118	-,068	,600
	[Preference_Score = 4]	1,075	,173	38,731	1	,000	,737	1,414
	[Preference_Score = 5]	1,897	,180	110,727	1	,000	1,544	2,250
	[Preference_Score = 6]	2,778	,190	213,890	1	,000	2,406	3,150
	[Preference_Score = 7]	3,971	,206	372,615	1	,000	3,568	4,374
	[Preference_Score = 8]	5,722	,265	467,940	1	,000	5,204	6,241
	[Preference_Score = 9]	7,078	,403	308,639	1	,000	6,288	7,868
Location	[Street_Design=0]	,056	,111	,255	1	,613	-,161	,273
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,398	,111	12,769	1	,000	,180	,616
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,518	,112	21,493	1	,000	,299	,737
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,667	,112	35,170	1	,000	,446	,887
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,181	,111	2,666	1	,102	-,036	,399
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,603	,163	96,476	1	,000	1,283	1,923
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,579	,163	93,744	1	,000	1,259	1,899
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,098	,160	47,244	1	,000	,785	1,412
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	715,017			
Final	522,741	192,276	8	,000

Link function: Logit.

TEXT-ONLY - Public property

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Preference_Score = 1]	-,649	,219	8,754	1	,003	-1,078	-,219
	[Preference_Score = 2]	,033	,204	,027	1	,870	-,365	,432
	[Preference_Score = 3]	,529	,200	7,002	1	,008	,137	,921
	[Preference_Score = 4]	1,117	,202	30,558	1	,000	,721	1,512
	[Preference_Score = 5]	2,069	,213	94,244	1	,000	1,651	2,486
	[Preference_Score = 6]	2,968	,226	172,273	1	,000	2,525	3,411
	[Preference_Score = 7]	4,040	,243	277,202	1	,000	3,564	4,516
	[Preference_Score = 8]	5,521	,282	382,451	1	,000	4,968	6,074
	[Preference_Score = 9]	6,606	,355	345,406	1	,000	5,909	7,302
Location	[Street_Design=0]	,123	,130	,901	1	,343	-,131	,378
	[Street_Design=1]	0[a]	.	.	0	.	.	.
	[Parking_type=0]	,518	,131	15,651	1	,000	,261	,774
	[Parking_type=1]	0[a]	.	.	0	.	.	.
	[Speed_slowing_measures=0]	,767	,132	33,616	1	,000	,508	1,026
	[Speed_slowing_measures=1]	0[a]	.	.	0	.	.	.
	[Playground_neighborhood=0]	,745	,132	31,793	1	,000	,486	1,004
	[Playground_neighborhood=1]	0[a]	.	.	0	.	.	.
	[Pond_neighborhood=0]	,226	,130	3,034	1	,082	-,028	,481
	[Pond_neighborhood=1]	0[a]	.	.	0	.	.	.
	[HighGreen=0]	1,783	,193	85,460	1	,000	1,405	2,161
	[HighGreen=1]	0[a]	.	.	0	.	.	.
	[MiddleGreen=0]	1,567	,191	67,302	1	,000	1,192	1,941
	[MiddleGreen=1]	0[a]	.	.	0	.	.	.
	[LowGreen=0]	1,193	,188	40,343	1	,000	,825	1,561
	[LowGreen=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	659,122			
Final	482,799	176,323	8	,000

Link function: Logit.