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MASTER

The influence of presentation mode on individual choice behavior considering comfortability for a healthy public space design

Pagie, Yannick

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THE INFLUENCE OF PRESENTATION MODE ON INDIVIDUAL CHOICE BEHAVIOR CONSIDERING COMFORTABILITY FOR A HEALTHY PUBLIC SPACE DESIGN

Research Thesis

Yannick Pagie – 1002013

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Colophon

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Author	Yannick Pagie
ID Number	1002013
TUE email	y.pagie@student.tue.nl

Institute	University of Technology Eindhoven
Faculty	Department of the Built Environment
Master program	Construction Management and Engineering; Architecture, Buiding & Planning, track Urban Systems and Real Estate
Adress	Den Dolech 2 - 5612 AZ Eindhoven

Chairman (USRE)	Prof Dr. Theo Arentze
Chairman (CME)	Ir. Aloys Borgers
Graduation supervisor (USRE)	Dr. Gamze Dane
Graduation supervisor (CME)	Dr. Qi Han

This master's thesis is open to the public and has been carried out in accordance with the rules of the TU/e Code of Scientific Intergrity

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Preface

This report is a graduation thesis of the masters Urban Systems and Real Estate (USRE) & Construction Management and Engineering (CME) at the Eindhoven University of Technology. The report evaluates choice behavior in different presentation modes and does so by testing the comfortability rating of a public space design through text and videos. It addresses my interest in technologies in the built environment sector and tries to provide insights in the implications of using technology in the sector.

Hereby I would like to thank my supervisors, Aloys Borgers, Gamze Dane, Theo Arentze and Qi Han. Special thanks to Aloys Borgers and Gamze Dane, who ensured great guidance of the project and helped greatly in the setup of the research as well as the interpretation of the results. Also, their valuable feedback has contributed to the value of this thesis.

Furthermore, I would like to express my gratitude to my friends and family, as well as the SERVICE community, for supporting me throughout the process of writing this thesis. Special thanks to Dennis Andreoli for the help in writing a python script, and Luc Snoeren, Joep Dirx, Sanne Wandel, Britt van de Laar and Koen Verspaij for the motivational conversations, brainstorm sessions and all other moments we shared on the graduation floor in the faculty of the built environment. Lastly, a special mention to Käthe Vogelaar, who has been there for me throughout the entire process, and whose support was invaluable.

I sincerely hope this thesis contributes to the scientific community, and I hope you enjoy reading it!

Yannick Pagie
Eindhoven, January 2024

Summary

In recent years, there is an increasing interest in the densification of existing cities in western societies due to increasing population and the need to house more people in cities. This significant change in layout and densities has an immediate effect on the quality and amount of public open spaces and greenery within these cities. Also, it appears that private green spaces are sacrificed for urban densification, especially impacting lower social classes (Lin et al., 2015). Therefore, the amount and quality of public spaces in densifying cities should be closely monitored, evaluated and most importantly appropriately designed to assure the health and preferences of its future users and inhabitants. For this reason, it is important to understand what people prefer and need in terms of healthy public spaces. The term 'healthy' is used to indicate the possibility of public spaces to enhance the wellbeing of individuals. It can do so by reducing stress through the possibility of recreation and the encouragement of becoming socially and physically active (El Khateeb & Shawket, 2022). In this thesis, healthy public spaces refer to the creation of public spaces in which the participants, in their opinion, would have the highest level of wellbeing.

To take into account future inhabitants' and users' preferences and needs for healthy public spaces, good communication with them is crucial. This requires participatory practices while designing and regenerating the existing public spaces. In addition, public participation will become essential in urban development with the implementation of the new Environmental and Planning Act in the Netherlands. This means that plans and design scenarios should be properly communicated with the public. Participatory urban design can follow different paths, from physical workshops to online surveys, and with text or with visuals. However, it is rather undiscovered whether different modes of presentation would lead to different urban design outcomes. Therefore, this thesis tries to seek answer to the following main research question:

"To what extent is there a difference in individual choice behavior considering comfortability in textual scenarios and video-based scenarios for a healthy public space design?"

Different presentation modes have different advantages and disadvantages. By representing a design textually, one can reach a vast online audience with low costs and exposure time, possibly leading to a bigger sample size. On the other hand, textual descriptions may lead to different interpretations and imagery by respondents. This is reduced when using visuals, for example videos or immersive virtual environments, which also report higher entertainment value and level of vividness. However, these methods are associated with higher costs and are more time intensive. Additionally, immersive virtual environments (IVE) require a physical workshop for respondents to participate in the experiment. Three case studies in this thesis give insights into the use of text, videos, and IVE in choice experiments.

Using the literature and the research by CoHeSIVE (Dane & Evers, 2023), a survey was constructed that examined the choice behavior of respondents regarding different designs for the Eindhoven station plaza. These designs varied on several attributes: the presence or absence of a fountain, the number of lampposts, the amount of grass coverage, the number and grouping of trees, the number of benches, and the building height of the surrounding buildings. An efficient orthogonal fractional factorial experiment design was used to create 32 different alternatives, varying on the attribute levels. The dataset gathered from these surveys consisted of ratings of design scenarios, meaning that the dataset had to be transformed to choice data in order to perform an MNL model. This was done by transforming the ratings 1-5 as 'not comfortable' and rating 6-10 as 'comfortable', creating a choice between two alternatives: 'not comfortable' and 'comfortable'. The videos were created utilizing a SketchUp model of the Eindhoven station plaza, and by rendering the videos in Lumion. The experiment

consisted of 2 different surveys, one portraying the scenarios in text, the other in videos. Each survey presented 8 random design-scenarios per respondent, so either in text or video (or respondents could choose to do both surveys). The duration of the videos is approximately 52 to 60 seconds. The respondent was then required to rate the design alternative on comfortability. Additionally, some socio-demographics were registered, as well as the most preferred attribute levels according to the respondent. The results of these surveys are then also compared to the results of the IVE experiment conducted by the CoHeSIVE research team (Dane & Evers, 2023).

Utilizing the gathered data, a descriptive analysis was performed on the socio-demographics to statistically compare the two datasets to each other. It also provided insights in the distribution of the data. In total, 111 respondents successfully completed the text-format survey, while 105 respondents successfully completed the video-format survey.

To examine the datasets, multiple Multinomial Logit Models (MNL) were utilized given the choices between comfortable (alternative 1) and non-comfortable (alternative 2). First of all, the importance of the attributes was examined. This model disclosed that for both the text-format survey and the video-format survey the presence of 15 benches had the biggest effect on comfortability. Also the presence of trees was preferred. The absence of a fountain and the minimum number of lampposts negatively influenced the probability of a scenario being comfortable. The building height was not deemed relevant as there were few statistically significant results.
Regarding a difference in choice behavior between the two presentation modes, five statistically significant differences were found in an extended MNL model. These were found for the constant in the model, fountain being present, 15 trees clustered, 9 trees present, and 4 benches present. This model therefore answers the main research question as it proved a difference in choice behavior regarding different presentation modes.
The MNL model that includes the socio-demographic characteristics found relations that were in line with the literature, such as the lower probability for females and higher age categories to consider a design scenario as comfortable. Also, respondents with a background in architecture and/or urbanism were more critical regarding comfortability, as well as respondents who filled in both the textual and video survey.
In the end, the results of the MNL models in this thesis were compared to the most preferred attribute levels in a similar IVE experiment conducted by the CoHeSIVE research team (Dane & Evers, 2023). From this, differences regarding the most preferred attribute levels were found, although the sample for the IVE experiment was also rather small and slightly different from the other samples. By means of chi square tests attribute level preferences were tested for each pair of presentation modes (text-video, text-IVE, and video-IVE). Significant differences were observed in 10 out of the 21 cases. Worth noting, especially the preferences for building height varied over the three presentation modes, where low-rise was preferred in text, medium-rise was preferred in videos, and high-rise in IVE.

In the end, this graduation thesis proves a difference in choice behavior if design scenarios of the Eindhoven station plaza are presented in text or video. Therefore, one must be cautious in a participatory design process that the research outcomes might differ relative to the presentation mode. Limitations of this research are found in the number of respondents for the experiments, the exclusion of dynamic environments, and the subjective choice of the researcher for aesthetics in the model (others might have used different looks of trees etc.). Other limitations are the inefficient utilization of the gathered data, the survey being to extensive, and a generalization of the ratings provided (e.g. a rating of 10 is regarded the same as a rating of 6 after the data transformation).

Future research could explore the full potential of videos and IVE by adding dynamic effects. In this case, the choice was made to make the scenarios as comparable as possible to compare choice behavior. However, videos and IVE bear the potential to implement moving people, day- and nighttime scenarios, and many different textures.

Samenvatting

De afgelopen jaren was er een verhoogde interesse in de verdichting van bestaande steden in het Westen door een groeiende populatie, en de noodzaak om meer mensen te huisvesten in steden. Deze verandering in de stad heeft een effect op de kwaliteit en hoeveelheid publieke ruimte, en het hoeveelheid groen in de stad. Ook worden privé-tuinen opgeofferd voor verstedelijking, iets wat vooral invloed heeft op de lagere sociale klassen (Lin et al., 2015). Daarom moet de hoeveelheid en kwaliteit van openbare ruimtes in verdichtende steden nauwlettend worden gemonitord, geëvalueerd en vooral adequaat worden ontworpen om de gezondheid en voorkeuren van toekomstige gebruikers en bewoners te waarborgen. Om deze reden is het belangrijk om te begrijpen wat mensen verkiezen en nodig hebben op het gebied van gezonde openbare ruimtes. De term 'gezond' wordt gebruikt om de mogelijkheid van openbare ruimtes aan te duiden om het welzijn van individuen te verbeteren. Dit kan worden bereikt door stress te verminderen door recreatiemogelijkheden en de aanmoediging van sociaal en fysiek actief zijn (El Khateeb & Shawket, 2022). Gezonde openbare ruimtes verwijzen naar openbare ruimtes waarin de deelnemers, naar hun mening, het hoogste welzijnsniveau zouden hebben.

Om rekening te houden met de voorkeuren en behoeften van toekomstige bewoners en gebruikers voor gezonde openbare ruimtes, is goede communicatie met hen cruciaal. Dit vereist participatieve sessies bij het ontwerpen en regenereren van bestaande openbare ruimtes. Bovendien wordt publieke participatie essentieel in stadsontwikkeling met de implementatie van de nieuwe Omgevingswet in Nederland. Dit betekent dat plannen en ontwerpscenario's goed gecommuniceerd moeten worden met het publiek. Participatief stedelijk ontwerp kan verschillende paden volgen, van fysieke workshops tot online enquêtes, en met tekst of visueel. Het is echter nog onontdekt of verschillende presentatiemodi zouden leiden tot verschillende stadsontwerpen. Daarom probeert dit afstudeerproject antwoord te geven op de volgende hoofd-onderzoeksvraag:

"In hoeverre is er een verschil in individueel keuzegedrag met betrekking tot comfort in tekstuele scenario's en video-gebaseerde scenario's voor het ontwerp van een gezonde openbare ruimte?"

Verschillende presentatiemodi hebben verschillende voor- en nadelen. Door een ontwerp tekstueel voor te stellen, kan men een groot online publiek bereiken met lage kosten en blootstellingstijd, wat mogelijk leidt tot een grotere steekproefomvang. Aan de andere kant kunnen tekstuele beschrijvingen leiden tot verschillende interpretaties en beelden bij respondenten. Dit wordt verminderd bij het gebruik van visuele elementen, zoals video's of immersieve virtuele omgevingen, die ook een hogere entertainmentwaarde en levendigheid bieden. Deze methoden zijn echter geassocieerd met hogere kosten en zijn tijdsintensiever. Bovendien vereisen immersieve virtuele omgevingen (IVE) een fysieke workshop voor respondenten om deel te nemen aan het experiment. Drie casestudies in dit project bieden inzichten in het gebruik van tekst, video's en IVE in keuze-experimenten.

Met behulp van de literatuur en het onderzoek van CoHeSIVE (Dane & Evers, 2023) werd een enquête opgesteld die het keuzegedrag van respondenten onderzocht met betrekking tot verschillende ontwerpen voor het plein van het station Eindhoven. Deze ontwerpen varieerden op verschillende kenmerken; de aanwezigheid of afwezigheid van een fontein, het aantal lantaarnpalen, de hoeveelheid grasbedekking, het aantal en de groepering van bomen, het aantal bankjes en de hoogte van de omliggende gebouwen. Een efficiënt orthogonaal fractioneel factoriaal experimenteel ontwerp werd gebruikt om 32 verschillende alternatieven

te creëren, variërend op de kenmerkniveaus. De dataset verzameld uit deze enquêtes bestond vervolgens uit beoordelingen van ontwerpscenario's, wat betekent dat de dataset moest worden omgezet naar keuze-data om een MNL-model te kunnen toepassen. Dit werd gedaan door een beoordeling van 1-5 te beschouwen als 'niet comfortabel' en een beoordeling van 6-10 als ‘comfortabel’. Zo werden twee alternatieven gegenereerd: ‘comfortabel en niet comfortabel. De video's werden gemaakt met behulp van een SketchUp-model van het plein van het station Eindhoven en door de video's te renderen in Lumion. Het experiment bestond uit 2 verschillende enquêtes, waarvan één de scenario's in tekst weergaf en de andere in video's. Elke enquête presenteerde 8 willekeurige ontwerpscenario's per respondent, dus ofwel in tekst of video (of respondenten konden ervoor kiezen om beide enquêtes te doen). De duur van een video is ongeveer 52 tot 60 seconden. De respondent moest vervolgens het ontwerpalternatief beoordelen op comfort. Daarnaast werden enkele socio-demografische gegevens geregistreerd, evenals de meest gewaardeerde attribuutniveaus volgens de respondent. De resultaten van deze enquêtes worden vervolgens ook vergeleken met de resultaten van het IVE-experiment uitgevoerd door het onderzoeksteam van CoHeSIVE (Dane & Evers, 2023).

Met behulp van de verzamelde gegevens werd een beschrijvende analyse uitgevoerd op de sociaal-demografische gegevens om de twee datasets statistisch met elkaar te vergelijken. Het verschafte ook inzichten in de verdeling van de gegevens. In totaal hebben 111 respondenten succesvol de enquête in tekstformaat voltooid, terwijl 105 respondenten succesvol de enquête in videoformaat hebben afgerond.

Voor de analyse van de data werden multinomiale logitmodellen (MNL) gebruikt, gegeven de keuzes voor ‘comfortabel’ (alternatief 1) of ‘niet comfortabel’ (alternatief 2). Allereerst werd de invloed van attributen op de comfortbeoordeling onderzocht. Dit model onthulde dat zowel in de enquête in tekstformaat als in de enquête in videoformaat de aanwezigheid van 15 bankjes de grootste invloed had op de comfortbeoordeling. Ook de aanwezigheid van bomen werd gewaardeerd. Het ontbreken van een fontein en het minimum aantal lantaarnpalen beïnvloedden de kans op het beoordelen van een scenario als comfortabel negatief. De aanwezigheid van gras werd gewaardeerd door respondenten, aangezien de kans op het beoordelen van een scenario als comfortabel toenam bij hogere niveaus van deze attributen. De bouwhoogte werd niet als relevant beschouwd, omdat er te weinig statistisch significante resultaten waren.

Wat betreft een verschil in keuzegedrag tussen de twee presentatie-modi werden vijf statistisch significante verschillen gevonden in een uitgebreider MNL-model. Deze werden gevonden voor de constante in het model, de aanwezigheid van een fontein, 15 bomen gegroepeerd, 9 bomen aanwezig en 4 banken aanwezig. Dit model beantwoordt dus de hoofdonderzoeksvraag omdat het een verschil in keuzegedrag aantoonde met betrekking tot verschillende presentatiemodi.
Het MNL-model dat de sociaal-demografische kenmerken omvatte, vond relaties die in lijn waren met de literatuur, zoals de lagere waarschijnlijkheid voor vrouwen en hogere leeftijdscategorieën om een ontwerpscenario als comfortabel te beoordelen. Ook respondenten met een achtergrond in architectuur en/of stedenbouw waren kritischer wat betreft de comfortbeoordeling, evenals respondenten die zowel de tekstuele als video-enquête hadden ingevuld.

Uiteindelijk werden de resultaten van de MNL-modellen in dit project vergeleken met de meest favoriete attribuutniveaus in een vergelijkbaar IVE-experiment uitgevoerd door het CoHeSIVE-onderzoeksteam (Dane & Evers, 2023). Hieruit werden verschillen gevonden met betrekking

tot de meest favoriete attribuutniveaus, hoewel de steekproef voor het IVE-experiment vrij klein was en enigszins verschilde van de andere steekproeven. Met chikwadraattoetsen zijn de voorkeuren voor de attribuut-niveaus vergeleken voor elk paar van presentatie-modi: (tekst-video, tekst-IVE en video-IVE). Significant verschil werden gevonden 10 van de 21 gevallen. Het is vermeldenswaard dat met name de voorkeuren voor bouwhoogte varieerden over de drie presentatiemodi, waar laagbouw de voorkeur had in tekst, had middelhoogbouw in video's de voorkeur en hoogbouw in IVE.

Uiteindelijk toont deze afstudeerscriptie aan dat er een verschil is in keuzegedrag wanneer ontwerpscenario's van het station Eindhoven plein worden gepresenteerd in tekst of video. Daarom moet men voorzichtig zijn in een participatief ontwerpproces, omdat de onderzoeksresultaten kunnen verschillen afhankelijk van de presentatiemodus. Beperkingen van dit onderzoek worden gevonden in het aantal respondenten voor de experimenten, de uitsluiting van dynamische omgevingen en de subjectieve keuze van de onderzoeker voor esthetiek in het model (anderen zouden mogelijk verschillende boomsoorten hebben gebruikt, enz.). Andere beperkingen zijn een inefficiënte manier van datagebruik, de enquête is te uitgebreid, en een generalisatie van de gegeven beoordelingen (bijvoorbeeld, een beoordeling van 10 wordt beschouwd als hetzelfde als een beoordeling van 6 na de gegevenstransformatie).

Toekomstig onderzoek zou het volledige potentieel van video's en IVE kunnen verkennen door dynamische effecten toe te voegen. In dit geval is de keuze gemaakt om de scenario's zo vergelijkbaar mogelijk te maken om keuzegedrag te kunnen vergelijken. Echter, video's en IVE hebben het potentieel om bewegende mensen, dag- en nachtscenario's en verschillende texturen te implementeren.

Abstract

This graduation research thesis aims to investigate the influence of different presentation modes on individual choice behavior in the context of public space design, using the Eindhoven station plaza as a case. The main research question centers on the extent of differences in individual choice behavior between textual scenarios and video-based scenarios of a public space design. The research therefore aims to fill a gap by addressing whether choice behavior differs based on presentation modes, considering attributes' importance and socio-demographic influences. The methodology involves the incorporation of text and video presentation modes in a quantitative research design. Stated preference experiments are used to investigate differences in choice behavior. Case studies and insights from an immersive virtual environment (IVE) experiment by the CoHeSIVE research team (Dane & Evers, 2023) contribute to the scenario creation. The scenarios focus on attributes such as the presence of a fountain, lampposts, trees, benches, grass coverage, and building height. The study comprises two experiments presenting design scenarios of the Eindhoven station plaza in text and video formats, utilizing a multinomial logit (MNL) model to estimate attribute importance and compare presentation modes. The findings indicate that attributes such as the number and grouping of trees significantly influence respondents' comfort ratings. Socio-demographic characteristics, including gender, age, household composition, and station plaza visit frequency, contribute to variations in choice behavior. Finally, the research establishes a difference in choice behavior between textual and video presentation modes, providing valuable insights for urban design decision-making. Additionally, the results are compared to the IVE experiment by the CoHeSIVE research team, showing some differences regarding the most preferred attribute levels per presentation mode. The study contributes to the literature by addressing the influence of presentation modes on choice behavior in public space design, offering practical implications and suggestions for future research.

Keywords

Built environment, Multinomial logit model, Design preferences, Presentation modes

Terminology & Abbreviations

IVE	Immersive Virtual Environments
MNL	Multinomial Logit
QoL	Quality of Life
RUT	Random Utility Theory
SCE	Stated Choice Experiment
SDG	Sustainable Development Goal
UPS	Urban Public Space
VR	Virtual Reality

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1. Introduction

Making cities and human settlements inclusive, safe, resilient and sustainable is of high priority in current society. Therefore, it is also stated as one of the UN Sustainable Development Goals (SDGs), SDG 11 Sustainable Cities and Communities, which is particularly related to the urban design and planning dimension, incorporating housing, transport, water management and air quality. Other SDGs (i.e., SDG 3 and SDG 6) also focus on promoting public health improvements in cities (UN, 2015). The built environment such as the composition and form of human settlements, green infrastructure and transport, has a significant influence on the health of residents. This entails a far-reaching impact on our well-being, both physically, mentally, socially, environmentally and economically (Barton et al., 2015; Barton, 2009).

In recent years, there is an increasing interest in changing the urban planning of existing cities in western societies due to increasing population and the need to house more people in cities. Existing trends are for example densification and, previously, the trials of Transit Oriented Developments (TOD). This significant change in layout and densities has an immediate effect on the quality and amount of public open spaces and greenery within these cities. First of all, with an increase in density an increase in crowdedness is inevitable. The study by Honey-Rosés and Zapata (2021) indicated that the perceived quality of a public space goes hand in hand with the crowdedness and noisiness of the public space. To a certain level, although very dependent on the location, the addition of people in the streetscape did not change the general sentiment. However, crowdedness and noisiness are, from a certain level, perceived as negative. In addition to this research, Arnberger (2012) also reports on the social carrying capacity in a case study in Vienna. Here, the crowdedness again played a vital role in the usage of public space, where the interviewees reported a reduced frequency and shorter visits, as well as even avoiding the space. Furthermore, the study by Lin et al. (2015) highlights an important issue regarding urban densification; *"it can lead to a general loss of two important reservoirs of urban green infrastructure (public parkland and residential tree cover)"* (Lin et al., 2015). Also, it appears that private green spaces are sacrificed for urban densification, especially impacting lower social classes (Lin et al., 2015).

Due to the aforementioned trends, the amount and quality of public spaces in densifying cities should be closely monitored, evaluated and most importantly appropriately designed to assure the health and preferences of its future users and inhabitants. For this reason, it is important to understand what people prefer and need in terms of healthy public spaces. The term 'healthy' is used to indicate the possibility of public spaces to enhance the wellbeing of individuals. It can do so by reducing stress through the possibility of recreation and the encouragement of becoming socially and physically active (El Khateeb & Shawket, 2022). In this thesis therefore, healthy public spaces refer to the creation of public spaces in which the participants, in their opinion, would have the highest level of wellbeing.

To take into account future inhabitants' and users' preferences and needs for healthy public spaces, good communication with them is crucial. This requires participatory practices while designing and regenerating the existing public spaces. In addition, public participation will become essential in urban development with the introduction of the new Environmental and Planning Act in the Netherlands. This means that plans and design scenarios should be properly communicated with the public.

This research project focuses on one common aspect of both preference measurement and communication: presentation mode of urban designs. Stated choice experiments are commonly used in urban and landscape design research and practice to consult inhabitants for measuring their preferences towards different design scenarios. Alternatives design scenarios are presented to individuals who are asked to choose the alternative they prefer. SCE usually utilizes text-based descriptions of attributes. In recent years, the visual presentation of attributes in SCE surveys has increased due to the

developments in the realm of virtual reality. Advantages include, among others, a higher entertainment value and higher level of vividness of the material (Grosser et al., 2020).

1.1 Public Participation

The importance of reviewing different methods for evaluating designs also finds origins in public participation. Often, urban developments and designs are reviewed by locals in the design process. By retrieving feedback from the inhabitants that actually experience the urban environment, several advantages can be achieved when designing urban environments. Using this involvement of inhabitants results in both a wider range of information gathering, as well as a higher level of inclusiveness. As such, this research can be seen as a simulation of public participation, where people with different backgrounds are reviewing design alternatives of the station plaza in Eindhoven.

The reviewing and rating of design scenarios in this case can be classified in different stages. Arnstein (1969) constructed the so-called 'Ladder of Participation', a framework in which the level of participation and influence of citizens is explained, as visible in Figure 1. From the bottom to the top, the level of participation increases. At the bottom, 'Nonparticipation' can be explained by the will of powerholders to educate the participants, rather than enabling people to participate in the decision making process. In the middle levels, falling under 'Tokenism', participants are heard and have a voice. However, there is no power that ensures their voices are incorporated in the to be developed solution. Lastly, 'Citizen Power' incorporates participants in decision-making, with even full managerial power as a top level.

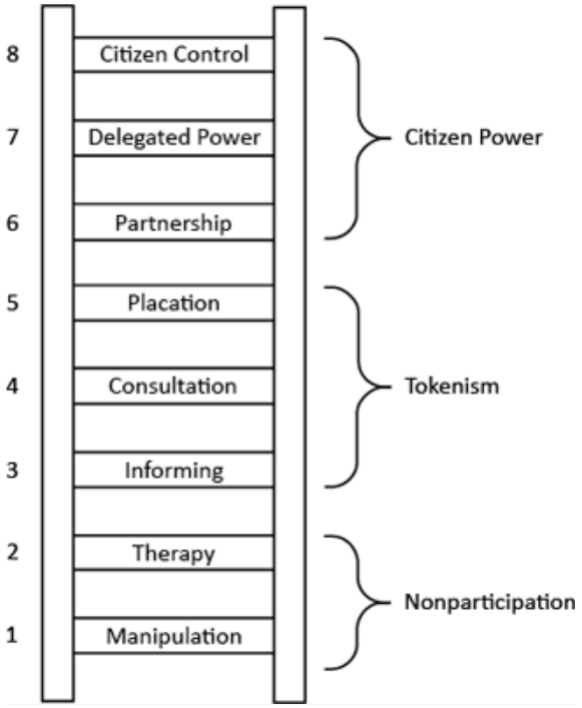


Figure 1: Ladder of Participation (Arnstein, 1969; The Open University, n.d.)

After Arnstein, more research has been done on the development of public participation. The development of several frameworks is visible in Appendix A. In general, the same trend is visible in other research, with some slightly different wordings. For instance, the International Association for Public Participation (2018), as seen in Appendix B, speaks of the terms

'inform', 'consult', 'involve', 'collaborate', and 'empower'. When comparing to the Ladder of Participation, these are similar to the scope of levels 3 to 8.

Furthermore, the research by Geekiyanage et al. (2021) focuses on finding the best participatory method in urban developments, and also classifies different levels of participation, which is visible in Figure 2. Here, the influence of the Ladder of Participation by Arnstein (1969) is, again, within ken.

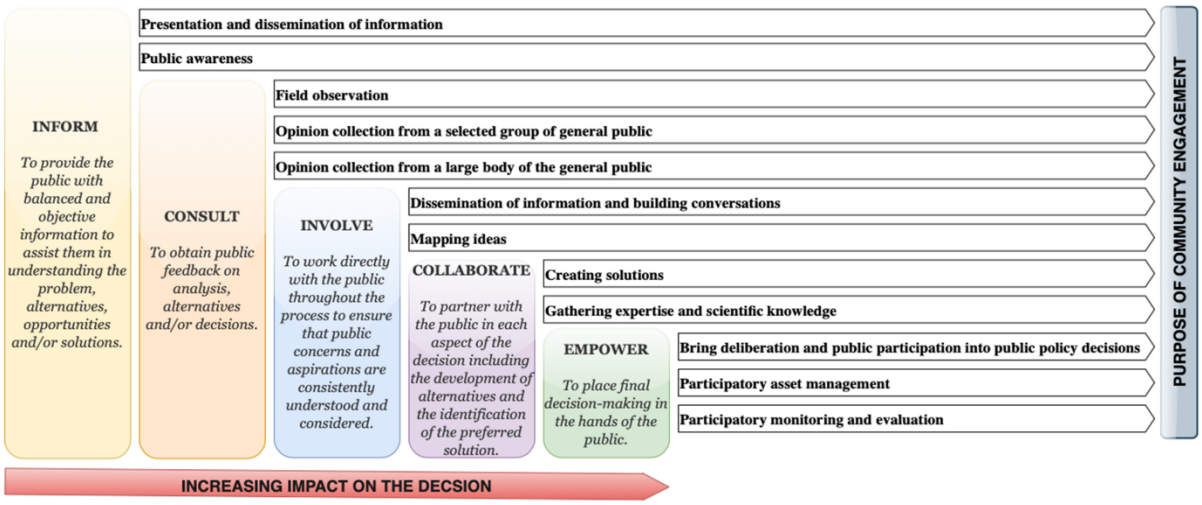


Figure 2: Purposes of each level of public participation (Geekiyanage et al., 2021)

This graduate thesis will focus on the level of 'consult', as it aims to use feedback of inhabitants on alternative design decisions (inhabitants provide feedback on decisions made by experts, by assessing different alternatives):

- Consult: This level focusses on providing an opportunity for residents to give feedback on certain plans. Typically, this level is used in cases of low complexity. It can be achieved through surveys, interviews and polls. The advantage of surveys and polls is that a high number of people can bring in their opinion, thus focusing more on the quantity (Geekiyanage et al., 2021).

As a result, this leads to increased chances of the community accepting the urban plans, as they have had the chance to express their desires (Brody et al., 2003).

Finally, findings of this research could support decision making in the participatory process of urban developments. As such, it should aware decision makers that design preferences could be influenced by the mode of presentation used in the process.

1.2 Research problem

This section elaborates the questions required to answer the entire research problem. The following research question is stated to be the main question of this paper:

"To what extent is there a difference in individual choice behavior considering comfortability in textual scenarios and video-based scenarios for a healthy public space design?"

For this, relevant built environment attributes should be selected to be included in the design scenarios in the different presentation modes.

The sub questions, as seen below, will address important aspects which are required to answer the full research problem.

- What attributes are important in the preferred choice for a design scenario in general?
- What attributes are important in the preferred choice for a design scenario of station plazas?
- What are the major modes for presenting built environment design scenarios, and what are the limitations and advantages of these modes?
- How to represent design scenarios in the incorporated presentation modes?
- How can choice behavior in different presentation modes be compared?
- To what extent is there a difference in the choice behavior when comparing choice behavior regarding the same scenarios in immersive virtual environments?

1.3 Target area

The target location for this research is KnoopXL in Eindhoven, which can be seen in Figure 3. It incorporates the area between the Philips stadium on the westside, until the Dommel river on the eastside. Currently, this area houses about 200 people. However, this will grow to a number of 15000 people in the coming years. It will be a mixed function area, combining living, working and leisure. In addition, the renewal of the public transport facilities is a significant aspect in the plans, focusing on improving the train and bus connections to the country and the city itself (KnoopXL, 2022). This research will focus on the station plaza on the city center side of the central station, and the surrounding buildings. The location is visible in Figure 4.

Figure 3: Location of KnoopXL in EIndhoven

Figure 4: Eindhoven station plaza on city center side

1.4 Public space definition

The paper intents to investigate the use of different presentation modes regarding people's preferences on built environment characteristics for the design of public spaces, and therefore also the difference in choice behavior in these different presentation modes. There is quite a large array in which the spectrum of public spaces fall. Mehta (2013, p.54 cited Madanipour 1996, p.144) provides a few definitions, one of them is the following: "space that is not controlled by private individuals or organizations, and hence is open to the general public". Also, the level of accessibility of a space can be leading in the definition, as Mehta (2013, p.54 cited Carr et al. 1992, p.50) provides the definition; "publicly accessible places where people go for group or individual activities". Lastly, Metha (2013) specifies a definition as well, namely: "Public space is the space that is open to the general public, which generates public use and active or passive social behavior, and where people are subject to the general regulations that govern the use of the space." In general, the red thread is set at the fact whether a space is open to the general public. This is confirmed by the definition provided by Greater Wellington Regional Council (2009): "A place or area to which the public has visible or physical access." These places are then divided into three segments:

- Green spaces (parks, playgrounds, sports facilities and recreational green areas)
- Blue spaces (waterways, waterfront paths and rivers)
- Grey spaces (streets, squares, centers and shopping streets)

For this graduation thesis, the definition of public space is set as follows: "The combination of green spaces, blue spaces and grey spaces that are open to the general public and generates public use and active or passive social behavior, and where people are bound to the general regulations in place."

The target location, the station plaza of Eindhoven Centraal, fits perfectly into this definition. First of all, the plaza will contain all three types of spaces. Green and grey spaces will be newly designed in the project, whereas also the 'blue spaces' will take up a more prominent role compared to the current situation. The vision is to make the Dommel and the Gender (which is currently an underground stream of water in the center of Eindhoven) an essential part of the new design (Gemeente Eindhoven, 2022). Secondly, the plaza is open to the general public, and acts as a pass through to the central station. Lastly, general laws apply to the location, and people should adhere to and comply with these regulations.

1.5 Academic & practical relevance

This research is an extension of- and is executed in- cooperation with CoHeSIVE (Dane & Evers, 2023), a seed-fund project funded by the alliance between University of Technology Eindhoven, Utrecht University, and Wageningen University and Research. CoHeSIVE aims to contribute to current Urban Public Spaces (UPS) design practices and literature by investigating possible differences in choice behavior for different presentation modes. Whereas the alliance project CoHeSIVE focusses on the co-design aspect and the creation of a viable immersive tool with the appropriate attributes, this graduate thesis will focus on the comparison between different presentation modes, and the possible differences in choice behavior when using different modes as a result. It tries to understand whether the preferences for the selected built environment attributes of people differ when using different modes of representation. Additionally, it seeks answer to the importance of certain attributes regarding the overall comfortability rating on the Eindhoven station plaza. In the end, it should also contribute to awareness in the participatory process, as plausibly the choice for presentation mode can influence the outcome of the process.

There are few studies systematically comparing the presentation modes. This comparison would give insights on the choice of presentation mode options for certain attributes. Urban designs can be presented by different presentation modes and this project investigates how different presentation modes influence the preferences for the attributes constituting the urban designs. The location used for the research is the station plaza of Eindhoven Centraal (city center side) within the to be developed KnoopXL area in Eindhoven.
The outcome of this thesis first of all consists of a set of design alternatives of the Eindhoven station plaza. The design alternative presented in one mode, should be as similar as possible in the other mode in order to test for differences in choice behavior among these presentation modes. The results can be separated into two sections. Firstly, the importance of the incorporated attributes per presentation mode can be analyzed. For instance, the amount of grass on the plaza could have a bigger influence on the preference for a design scenario than the number of lampposts. Therefore, per presentation mode the relative importance of attributes is determined. Secondly, and the main goal of this research, the choice behavior in the presentation modes is compared. As such, an answer is sought to whether the used presentation mode influences the preferences for design scenarios.

1.6 Reading guide

The thesis follows a stepwise approach to reach the main goal, addressing the main research question. Chapter 2 dives deeper into relevant literature, discussing among others possible approaches, attributes, presentations modes. Chapter 3 elaborates on the research method, providing a theoretical framework for the models used, as well as an explanation on the survey and scenarios used in this research. Chapter 4 gives insights in the gathered data and visualizes the differences between the datasets extracted from the textual and video survey. Consequently, chapter 5 shows the results from the analysis, that includes the output from the MNL models. These models dive deeper into the importance of different attribute levels, compares choice behavior between different presentation modes, and compares the most optimal design according to respondents in the different presentation modes. Lastly, chapter 6 draws the final conclusions, and discusses the limitations, learnings, implications, and recommendations of this research.

2. Literature review

In this chapter the relevant built environment attributes are discussed. Furthermore, available presentation modes are evaluated. On top of that, additional research is conducted in the alternative research methods, cybersickness, and some case studies are assessed in order to gain insights in the pros and cons of certain methods. To end, interesting socio-demographics are discussed to be included in the research.

2.1 Relevant built environment attributes

In order to investigate the preferred design alternatives, relevant built environment attributes need to be selected. As healthy urban environments are strived for, it is interesting to consider the built environment attributes that influence the QoL of inhabitants in high density areas.

There are multiple attributes contributing to the QoL of an inhabitant. These can be subdivided into 5 categories: Cultural attributes, Environmental attributes, Social attributes, Infrastructural attributes, and Economic attributes. An overview of the relevant factors is provided in Table 1 (Baig et al, 2019).

Table 1: Attributes related to the QoL of inhabitants (Baig et al, 2019).

Category	Attributes
Cultural	Availability of restaurants Availability of public amenities Availability of worship places
Environmental	Availability of garbage collection services Regular maintenance of public parks Availability of parks and playgrounds
Social	Security Access to health facilities Provision and proximity to schools
Infrastructural	Regular maintenance of streets and neighborhood's lighting Reliability of utilities (electricity, water, gas) Availability of public transport
Economic	Availability of affordable housing Access to shops Employment opportunities

Considering Table 1, the main focus in this research is laid on the environmental and infrastructural characteristics, as these factors enable the creation of various design scenarios through using different levels of e.g. grass coverage, amount of trees, and lighting. Since a predefined location is used, it is harder to model cultural, social and economic factors in the design scenarios. Therefore, to create urban designs, relevant built environment attributes have to be determined. This research focusses on relevant built environment attributes that may influence preferred design choices on the Eindhoven station plaza. During a workshop by CoHeSIVE (a seedfund project funded by alliance between University of Technology Eindhoven, Utrecht University, and Wageningen University and Research) (Dane & Evers, 2023)(EWUU, 2022) relevant built environment attributes that were derived from literature were discussed in the context of healthy public space design. The outcome of the literature review and workshop discussion was a list of 29 attributes, which can be seen in Table 2 (Evers et al., 2023).

Table 2: Relevant built environment attributes

Presence of trees	Presence of parasols	Presence of benches
Amount of driving cars	Variety in facades	Pavement or grass surface
Designated or shared paths	Presence of fountain	Amount of parked cars
Width of paths	Size of urban public space	Building height
Presence of sculptures	Presence of active plinth	Amount of people
Colors among facades	Presence of drinking fountain	Different levels of surface
Presence of bollards	Size of trees	Presence of vegetable garden
Direct routes of paths	Mixed land-use	Presence of lighting posts
Vertical greening	Presence of parked bicycles	Presence of meeting place
Presence of fitness	Presence of playground	

The different attributes influence various aspects, such as walkability, cycleability, but also health. For instance, environments play a role in the encouragement of physical activity, which is of course related to health benefits. Houlden et al. (2018) did a comprehensive database search and screening of articles to assess the link between greenspace and wellbeing. There were positive associations with mental wellbeing, however there was not enough evidence to guide planning decisions. In addition, the use of greenery and vegetation is positively associated with both physical and mental wellbeing. Research by Wang et al. (2019) concluded from a population sample and greenery/vegetation street view data that both factors were positively associated with wellbeing. Partial mediators were physical activity, stress, air quality and noise, and social cohesion. Van Vliet et al. (2021) concluded that the presence of many trees had the largest positive influence on preferences in the design of a park.

Contrary to the other research, the research by Gubbels et al. (2016) concluded there was no consistent positive result regarding the link between greenery and physical activity and mental health. However, small links were found regarding the positive effects of greenery on health within certain subgroups. For example, the greenery was linked to increased leisure walking time for male adolescents and older adults. Similarly, the research by Zapata-Diomedi & Veerman (2016) also found unconvincing/insufficient evidence that there is a relationship between design and physical activity. In this case, design entails aspects as street network, road traffic, street-lights, and greenery and recreational space.

The research by Carr et al. (2006) also speaks of comfort, where it relates to relieve and shelter from the sun. This could either be from greenery/trees, but also other objects such as parasols and buildings. In addition, comfortable and sufficient seating is required for a successful public space. Furthermore, it stresses the importance of natural elements, especially water, to accentuate the contrast to the built environment. Besides water, trees and other greenery where also found to be a dominant factor in providing the opportunity for relaxation. The research dives deeper into passive and active engagement. Passive engagements contain activities that require a low effort, such as watching a fountain or ‘people watching’. Active engagement refers to direct contact with people and activities such as sports. This can be achieved by providing adequate paths, but also facilities as grass and a fountain in which children can wade. In addition, it refers to activities that are hard to model in a virtual environment in this study, such as the possibility to host events and festivities.

Looking at other amenities, such as parking areas and roads, a relation with unhealthy lifestyles can be found. Car dependence has an influence on both ecological and public health. Impacts include inactivity, obesity, accidents resulting in injuries and death, air pollution, noise and climate change (Douglas et al., 2011). On the other hand, car accessibility is an important factor in a living and working environment. Zapata-Diomedi & Veerman (2016) even found that the accessibility is positively linked with physical activity in the area.

It is also interesting to delve into the concept of comfort, diving deeper into the subjective and multidimensional nature of comfort. The feeling of being comfortable is addressing the positive emotions an environment can induce and can be described as “a pleasant state of physiological, psychological and physical harmony between a human being and its environment” (Ortiz et al., 2017). It is influenced by a biological component, consisting of an emotional, behavioral and physiological reaction to the environment. As such, environments potentially cause stress, but on the other hand can also have restorative effects and influence wellbeing. It can also affect behavior, for example by exercising habitual actions (Ortiz et al., 2017). Besides the environmentally provoked emotional and behavioral reaction, there is also a direct effect of the environment on health. For example, air pollution can lead to acute as well as chronic effects on human health (Kampa & Castanas, 2008).
Secondly, there is a link between emotions and health. The research by Diener & Chan (2010) provides insights into the relationship between positive emotions and among others lower blood pressure levels, reduced inflammatory processes and cardiovascular and immune strengthening. On the other hand, negative emotions can induce stress, depression, anxiety and detrimental effects on the cardiovascular system (Diener & Chan, 2010). This relationship can also be reversed, as people with worse health are also emotionally more vulnerable (Meier et al., 2001).

To conclude, environments provide stimuli that trigger an emotional response in people. As such, both negative and positive emotions can occur from an environmental stimulus. These different emotions can have different effects on the human body. Furthermore, environments can also influence health, whereas a worse health can also lead to negative emotions. These factors combined can influence the level of comfortability one experiences at a certain location. In this thesis therefore, the link is laid between the comfortability of a public space, and the impact on health. The higher the level of comfortability, the more positive the impact on health. There are relationships between aspects as health, physical activity, and the amenities on an urban plaza. Multiple research projects found relations between greenery and health, although this is not an undebatable result as other research concluded a lack of significant results (Zapata-Diomedi & Veerman, 2016). Also, other amenities, such as a fountain, street lights and seating were found to have a positive effect on the comfort of a plaza (Carr et al., 2006: Van Vliet et al., 2021).

2.2 Presentation modes

There are various ways to present information, ranging from basic techniques as written language, to newer technologies as immersive virtual environments. Geekiyanage et al. (2021) performed a structured and comprehensive literature review in order to identify methods available for information conveying and community engagement. A selection of the most important results is visible in Table 3.

Table 3: Methods for community engagement purposes in urban development (Geekiyanage et al., 2021).

Method	Tools	Strengths	Limitations
	Presentation and dissemination of information		
Printed material	- Newsletter - Letters - Posters - Fact sheets - Reports - Brochures	- Easy to use - Low costs	- limited reach to the younger generation

Displays/Exhibits	- Set up at relevant public locations (e.g., libraries)	- Provides project information and raises awareness about particular issues - Can be personalized and interactive - Can be readily accessible	- Brief attention spans - Limited amount of information that can be conveyed - Competition for attention at events
Presentations, live streaming videos	- PowerPoint - Visme - Haiku Deck - Canva - YouTube Live	- A creative and attractive way of engaging people - A great tool to convey messages quickly and succinctly	- Need creative knowledge and skills in designing - Need specific software in designing
Public awareness			
Public meetings	- Presentation followed by questions and answers - Town-hall meeting - Panel/roundtable - Large group/small group	- Relatively easy to convene, familiar procedures can involve a wide range of stakeholders - Provides an opportunity to relay information, explain processes and gather feedback with a large group of people	- Discourages those not used to speaking in large groups - Can be difficult to control - Attendance levels can be low unless people feel deeply connected to the issue and / or make the time to attend - Ensure the meeting place is accessible
Opinion collection from a selected group of general public			
Interviews	- Face to face - Using virtual tools such as Microsoft Teams - Telephone	- Generate in-depth information on a specific topic	- Time-consuming - Should continue until a data saturation point is reached
Focus groups	- Face to face - Virtual tools such as Microsoft Teams	- Can explore different perspectives of small groups of people of a common issue/goal	- Not effective for providing information to the public
Opinion collection from a large body of the general public			
Polls	- Physical polling booths - Postal vote - Online vote (SmartSurvey)	- Are highly representative nature - Using scientifically developed techniques, samples from polls generate an accurate match of the population - Allow issue specific with immediate feedback	- Measure an immediate response to a question, thereby granting little opportunity for informed opinions or discussion of issues - Polling information is meaningless if it is not statistically valid
Surveys	- Paper survey - Postal survey - Email survey - Online survey (Google Forms)	- Provide a baseline for measuring changes in people's views - Inform people about the project that is taking place	- Time-consuming process - Results may be statistically incorrect if a large sample is not involved

		- Prompt further involvement by asking if people would like to receive information or invitations to future events	
Bring deliberation and public participation into public policy decisions			
Citizen juries	- Round tables - Virtual meeting tools	- Bring new thinking to the issue at hand - Develop a deep understanding of an issue - Help build participant capacity through involvement and increased knowledge - Can dispel misinformation - Could build credibility	- Group selection may be mistrusted - Participants may not show up on the day - Sessions can lose focus - The costs can be expensive - Time-consuming for all involved - The sample of the community is small
Creating solutions			
Workshop, open space events	- Physical workshop - Remote workshops using Mentimeter, Slido, Go Create	- Help to translate detailed discussions into action plans - Provide an opportunity to bring together the knowledge of all participants and is attractive because they set the workshop agendas	- Participants attending may have very disparate skills and knowledge - Logistics-It can be difficult to arrange meetings and workshops for different geographical locations and time zones

By comparing and analyzing these available methods, a distinction can be made. These methods are conveying information through different modes. For example, printed material, presentations and surveys can be presented in text. Other modes are also available, such as the use of videos or audio in presentations, online surveys or workshops. Physical meetings such as workshops and focus groups also provide the opportunity for interactive information conveying, for which one can consider immersive environments. In the end, this research is using an urban station plaza as design case. Considering the scope of the research, the most likely used methods for informing people in such cases are by means of text, videos or immersive environments. These methods are elaborated on in the following paragraphs.

2.2.1 Textual information

Textual information is a traditional method of conveying information, which has been used for centuries. As with all methods, using text as a mode comes with advantages as well as disadvantages.

In general, conveying information textually leads to the lowest exposure time, meaning people take up information fast. In addition, the ratio of information recalling/exposure time (effectiveness) is high for text, meaning that people take up a lot of information relative to the time spent in the process of doing so. Furthermore, creating a piece of text, or survey in text, provides the opportunity for online and physical survey usage, and people can fill out the survey at a for them convenient time of day. This provides possibilities for a higher response

rate of the survey (Schneiders, 2020). Lastly, creating a piece of text does not require high-cost software or specialists in technologies. Thus in general, this presentation mode is cheap compared to other modes of presentation.

However, with the emergence of technologies such as videos, differences can be seen. One of these disadvantages is that, compared to videos, conveying textual information comes with a lower level of information recalling (Schneiders, 2020). Text also leaves more room for different interpretations of people and can have lower effects on for example feelings of guilt, and activating people (Schneiders, 2020).

In the end, the following list of pros and cons can be stated for using text as information conveyor, as seen in Table 4 below:

Table 4: Pros and cons of text as information conveyor

Pros and cons of text as information conveyor	
Pros	Cons
Low exposure time	General lower level of information recalling
High effectiveness: $\frac{Information\ recalling}{Exposure\ time}$	Different interpretations of respondents
Online & physical survey spreading (bigger sample size)	
Low costs	

2.2.2 Videos

Videos, as a way to present VR-environments, have the possibility to significantly increase the perception compared to text (Goldberg et al, 2019). Although the effectiveness was found to be higher for text, the level of information recalling is higher for videos. However, for videos the effectiveness is negatively influenced by exposure time, which is higher for videos than text (Schneiders, 2020). Similarly to text, videos have the possibility for online survey handling, although these are more time consuming to create and fill in. Online survey handling can increase the response rate, considering that for example with immersive environments the experiment has to be done on location.

The advantages of using imagery might seem obvious, but they also have support in cognitive psychology theory. Specifically, there's something called the "picture-superiority effect" (McBride and Dosher, 2002; Paivio and Csapo, 1973; Whitehouse, Maybery, & Durkin, 2006, as cited in Patterson et al., 2017) that backs up this idea. Additionally, Bateman et al. (2009) have argued that including visuals can make it easier for people to evaluate choices, drawing from research that focuses on emotional rather than analytical processes in decision-making. Video's also have a higher entertainment value than text, as well as a higher level of vividness of the material (Grosser et al., 2020). The use of virtual reality however can lead to a side effect called cybersickness, which is also elaborated on later in this chapter (LaViola Jr., 2000). The predefined route in videos however greatly reduces the level of interaction between the virtual environment and the respondents, which is more apparent when using an immersive virtual environment (Zhao, 2023). Table 5 below summarizes the pros and cons of using videos as information distributor.

Table 5: Pros and cons of videos as information distributor

Pros and cons of videos as information distributor	
Pros	Cons
Higher level of information recalling	Need creative knowledge and skill in designing
Easier to evaluate choices	Need specific software in designing
Online survey spreading (bigger sample size)	Physical spreading not possible
Higher entertainment value than text	Higher costs
Higher level of vividness of the material	Cybersickness
	Restricted by predefined route in video (restricts interaction)

2.2.3 IVE

Immersive environments are a relatively new way of conveying information. However, due to the technology being in an early stage of development, this leads to high production difficulties, as well as costs. In general, there is a lack of interest from software developers to invest time and money into developments due to the small market size of the construction sector in these technologies, as well as a lack of interest of possible clients such as municipalities at the moment. Market reports have also indicated that user experiences are influenced by bulky hardware and technical glitches. These limitations resulted in VR still not being mainstream in our society (Perkins Coie, 2018).

On the other hand, the construction sector is more likely to invest in developments that contribute to construction in general, as well as overall project management (Wang, 2020). Other reported disadvantages of the technology is the tendency of viewers to get lost in the three-dimensional space, and the lack of efficiency since it's easier to watch a video on e.g. a personal mobile phone (Wu et al., 2021). Lastly, immersive VR can lead to physiological problems when in use. Reported issues are for example dizziness, disorientation and visual discomfort. Therefore, a guideline stating the optimal usage of the system should be established (Loyola et al., 2019).

On the other hand, advantages are noticed in the consumption behavior. Immersive environments induce people to actively explore desired information, in contrast to passive consumption of videos. Also, a higher sense of comprehensive knowledge is achieved when adopting the bystander's perspective in immersive environments. Users also reported an increased experience, as well as less temporary distraction when immersed (Wu et al., 2021; Chowdhury & Schnabel, 2019).

However, immersive environments have not yet fully reached its adoption potential in current society. Chuah et al. (2018) and Zhang et al. (2020) summarized the factors influencing the adoption of VR technology as follows:

- Perceived benefits: the perception that VR could increase work efficiency and optimize the outcome in a built environment project, and then thus the willingness to use the technology.
- Perceived risks: inexperience with technology can lead to hassle in a project.
- Individual differences: Whether an employee is open to new experiences and willing to see the added value. This is on its turn influenced by the person's traits, demographics and experiences.
- Manufacturer-related variables: brand attitude and pricing of the VR services.
- Psychological variables: the influence of the perception of others on the product, so-called social influence.
- Situational variables: The availability of adequate resources and support.

These factors are supposably shifting in favor of the use of IVE. Taking for example into consideration the reducing costs of production, the increase in amount of people with knowledge and resources, and the reduced technological limitations of the software, can lead to a higher general acceptance of the technology. With the increased adoption and growing potential of immersive virtual environments, it is therefore relevant to investigate the influence of the method on choice behavior. In Table 6 below, the pros and cons of immersive virtual environments are summarized.

Table 6: Pros and cons of IVE as information distributor

Pros and cons of IVE as information distributor	
Pros	Cons
Actively explore desired information	Time-consuming process
Easier to evaluate choices	Higher costs
Less temporary distraction	Need creative knowledge and skill in designing
Increased experience	Physical meeting required
	Cybersickness
	Bulky and glitchy hardware
	People can get lost in the environment

2.3 Experiment methodologies

In this subchapter, suitable experiment methods are evaluated. These methods are extracted from methods found in literature, and later evaluated on their suitability for this research.

2.3.1 Qualitative vs Quantitative research

Distinguishing between qualitative and quantitative research methodologies is crucial when determining the most appropriate approach for a specific research goal. For this research, both methods are appropriate to test the designs in the three chosen presentation methods: text, video, and immersive virtual environments. Table 7 below elaborates on the pros and cons of both methods:

Table 7: Qualitative vs quantitative research (Anpar Research LTD, 2023).

Pros and Cons of Qualitative Research vs Quantitative Research	
Qualitative Research	**Quantitative Research**
Pros	Pros
Explores attitudes and behavior in-depth	Larger sample sizes
Encourages discussions	Impartiality and accuracy
Flexibility	Faster and easier
	Anonymous data
	Offers reliable and continuous information
Cons	Cons
Small sample size	Limited set of answers in survey
Bias in sample selection	Research not carried out in normal environment (claiming behavior)
Lack of privacy	Inability to follow-up on given answers
Inexperience of moderator	

Qualitative research is used to explore attitudes and more in-depth behavior. This can both be done by incorporating random people, or by selecting an expert panel. Qualitative research provides more opportunities for discussions and brings a level of flexibility. This is, as one can continue to ask deeper questions, or respond to certain remarks. On the other hand, due to the time intensiveness of this method, often only a small sample size is used. If people are not randomly selected, one can speak of bias in the sample selection, as the researcher approaches for example an expert for an interview. It also comes with reduced privacy of respondents, as especially in expert interviews quotes have to be noted and the credibility of the researcher, as well as the research, is at stake. An inexperienced moderator can also lead to inadequate results of the research (Anpar Research LTD, 2023).

On the other hand, quantitative research focusses on gathering larger sample sizes, which is often done through survey spreading both online and physique. With the emergence of the internet, people are currently able to fill in a survey at any given moment of the day, whenever they feel able to. Due to the larger size, the results are more precise and statistically significant. The data is gathered fast, as well as anonymously. Suspicious data can be filtered, leading to a reliable data set. However, answer possibilities are limited to the answers provided in the survey. In contrast to the qualitative research, there often is no possibility to follow-up on given answers by respondents, encouraging a discussion. Lastly, research may possibly not be carried out in the respondent's normal environment, meaning that people could claim they do something or want to do something, but can't be checked (Anpar Research LTD, 2023).

Given the argument, both methods could be viable for this research. However, in order to investigate nuanced distinctions in individual choice behavior within varying urban public space design scenarios, quantitative research offers more potential due to the possibility of analyzing larger samples (Anpar Research LTD, 2023). Since the difference in choice behavior is tested, as well as the importance of attributes, a larger data sample can statistically validate outcomes, whereas qualitative research focusses more on the opinion and experiences of experts. In conclusion, this research thrives by using a quantitative research method.

2.3.2 Stated choice experiments

There are different forms of stated choice experiments. Participants are often asked to make choices between different options presented in sets. Typically, they are given a number of these sets to evaluate. Researchers have found that when people have to make too many comparisons, like 18 or more, they can get bored, as noted in studies by Hanson et al. (2005) and Christofides et al. (2006). In addition, the number of attributes and choice sets should be limited to prevent respondent fatigue (Gell, 2023). However, it is essential to understand that the exact point at which boredom sets in can vary. It depends on factors such as how many choice sets there are, how complex they are, and the characteristics of the people taking part in the study. Knowing this can help researchers design their experiments better to keep participants engaged and get more accurate results. Therefore, adapting the experiment to fit the preferences and patience of the people involved is an important consideration in making research more effective. While it is common to use images in studies about landscape preferences, the practice isn't as widespread in Stated Choice Experiments. However, researchers have recognized the importance of presenting these images in a way that helps respondents understand the tasks. This includes using images to convey information in choice tasks, which can make surveys feel more real and improve the reliability of the data collected (Patterson et al., 2017).

The use of 3D visualizations in stated choice experiments is still relatively new and undiscovered. Especially the use of immersive virtual environments can lead to issues regarding the feasibility, as participants often have to visit a lab facility for the experiment. For these experiments often a large sample size is required, making it possibly very costly. On the contrast, videos provide the opportunity to be played in an online environment, making it possible to be distributed to a large sample. In SCE's, it is still unclear how respondents handle the choice task, as they have the possibility to play multiple videos at once, or sequentially. This may introduce presentation-order bias, which is also present when showing multiple text variants. In general, the effect of this setup on the results is still unknown (Zhao, 2023).

Similar case studies using SCE

In the field, some research has already been conducted in which the researcher used a stated choice experiment. The main goal is to learn from these experiments, and to include related and relevant aspects in this graduation thesis. First of all, different options for distributing the surveys are found. As such, Patterson et al. (2017) as well as Mokas et al. (2019) used a physical workshop in which people were randomly assigned to a survey (with different modes of presentation). Looking at Van Vliet et al. (2021), an online/social media distribution is also possible. Hereby a difference is also seen in the number of respondents, where the research by Van Vliet et al. (2021) reached as much as 739 respondents (of which 697 useful cases), a lot higher than studies using a physical workshop. The research by Patterson et al. (2017) has over a 1,000 observations, however this incorporated multiple trained interviewers on different locations through the city of Montreal, on multiple days, which is not viable for this graduation thesis.

Also, the scenario visualization provides options and differs between the three studies. First of all, Patterson et al. (2017) compared text-only scenarios to a virtual reality environment on gaming platform Unity. Through this mode, respondents could navigate through a neighborhood themselves. In the end, the choice task was visualized as seen in Figure 5.

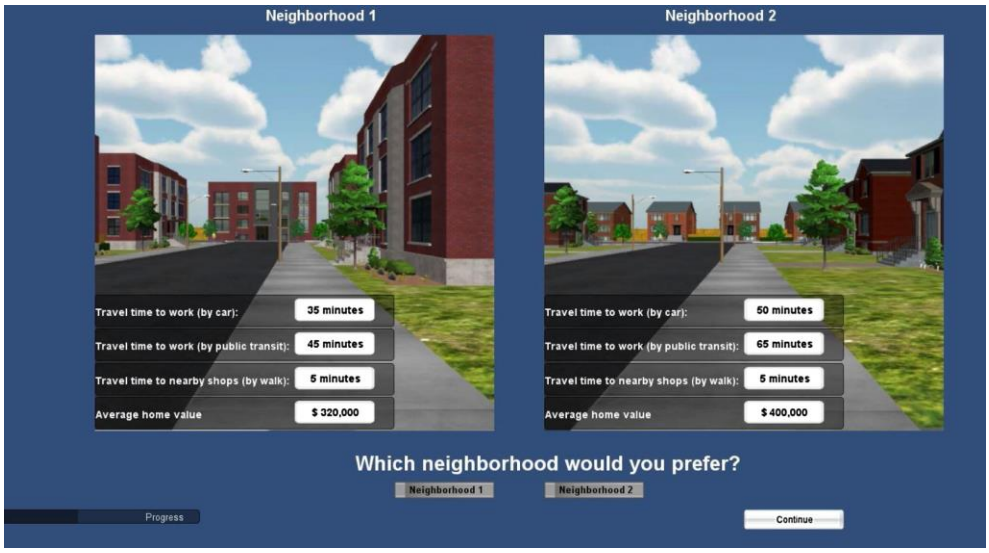


Figure 5: Choice task with virtual reality environment by Patterson et al. (2017)

This is quite similar to the experiment performed by Mokas et al. (2019), who in a similar survey provided three short videos after which the most preferred one has to be chosen. This is visible in Figure 6, where the respondent is presented three alternative design scenarios. Van Vliet et al. (2021) used a similar approach with the presenting of their videos.

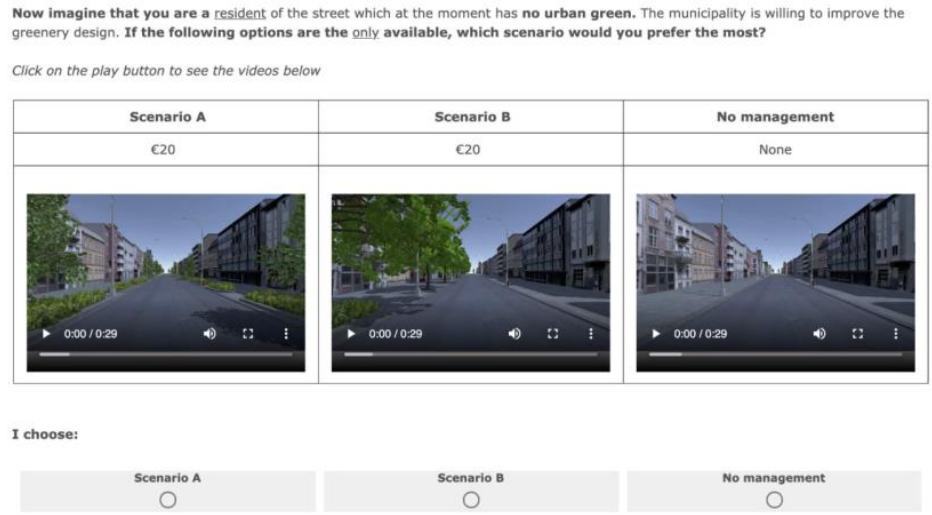


Figure 6: Choice task with videos in a survey by Mokas et al. (2019)

Regarding the results of these studies, some similarities are found. The studies used MNL models to estimate the coefficients. Patterson et al. (2017) as well as Mokas et al. (2019) concluded there were more significant coefficients in case of the visual modes of presentation. Therefore, it was stated that visually showing scenarios could increase the evaluability of the choice tasks for the respondents, and leads to an increased understanding of the project. Both studies also found different coefficients when comparing the presentation modes. In the study by Patterson et al. (2017) the coefficients took a smaller size when visually presented, so these did not have a greater importance when compared to textual presentation. Mokas et al. (2019) even found some reversed estimates regarding the willingness to pay when comparing the text to the visual modes. The provided reason was that in the text variant there was an effect of imagination of the respondents.

Limitations mentioned by the studies are for example the difficulty to recruit large sample sizes, and the high costs associated with the experiment (Mokas et al., 2019).
The study by Van Vliet et al. (2021) mentions a few limitations that may apply to this research paper as well. First of all, people do not evaluate real environments exactly the same as virtual environments. Therefore, one must be cautious when translating findings to real environments. In addition, the study mentions it uses a static daytime environment, whereas showing evening scenarios might influence the results. In addition, there is a limit on the number of attributes that can be incorporated without inducing participant fatigue.
Lastly, Patterson et al. (2017) mentions the effect of the choices made in the design scenarios. The survey designer has the obligation to choose a certain representation of elements of the virtual environment, which might not correspond with the respondents view of that element.

To conclude, the studies by Patterson et al. (2017), Mokas et al. (2019) and Van Vliet et al. (2021) all prove the potential of using virtual environments in combination with a stated choice experiment. The studies provide insights in how to represent scenarios in a survey, as well as aspects to take into account when resuming this research.

2.4 Cybersickness

Since the implementation of virtual reality, cybersickness has been noted as a side effect. Symptoms include nausea, disorientation, headaches, sweating and eye strain (LaViola Jr., 2000). The experiences of cybersickness however vary greatly between individuals. Influencing factors can be the technologies being used, the design of the environments, as well as the required tasks to be performed (Johnson, 2005). In some cases, the percentage of people experiencing cybersickness is remarkably high, which demonstrates that at least in some virtual environments there is a widespread usability issue that reduces the implementation potential so far. A reported issue in the understanding of cybersickness is the lack of an objective measure of the symptoms, as up to now research is dependent on the subjective self-reporting of subjects. This makes it hard to objectively quantify cybersickness symptoms. Finally in the case of cybersickness, there are individual factors influencing the chance of getting cybersickness. For example, older people as well as women are more susceptible to cybersickness (Davis et al., 2014).

Symptoms of cybersickness

Motion sickness, simulator sickness, and cybersickness are conditions that show similar symptoms but originate from different scenarios. Motion sickness, often known as car sickness or sea sickness, is characterized by discomfort, including symptoms like nausea, dizziness, and vomiting, which typically occur during travel in moving vehicles. This condition is not limited to cars but can also occur on submarines, aircraft, and trains. Interestingly, it can even be triggered by seemingly innocent activities such as amusement rides or swings in playgrounds. Astronauts may also experience a related form known as 'space adaptation syndrome' when exposed to zero-gravity conditions. Interestingly, susceptibility to motion sickness is more prevalent in younger children aged 4-12. In addition, it has been observed that this susceptibility serves as a reliable indicator of vulnerability to cybersickness (Davis et al. 2014; Golding, 1998).

Cybersickness is a specific subset of motion sickness experienced by users of virtual reality. It occurs when users perceive themselves as moving within a virtual environment while they remain physically stationary. This contrast between perceived self-motion in the virtual scene and physical stillness (which is referred to as vection) is believed to underlie this condition.

Stanney et al. (1997) identified typical symptoms of cybersickness to include nausea, eye strain and dizziness. Interestingly, cybersickness is approximately three times more severe than simulator sickness (e.g. pilots training in a simulator). In this research, the symptoms are categorized into three clusters: disorientation, nausea and oculomotor. This leads to for example dizziness and vertigo in the disorientation cluster. Regarding nausea, respondents may experience stomach awareness, an increase in saliva production, and burping. Lastly, the oculomotor cluster refers to issues regarding vision, including for example eye strain and blurred vision (Stanney et al., 1997). In addition, Ames et al. (2005) found a similar list of symptoms when using virtual reality. This study found concentrating issues, general discomfort, fatigue, and boredom as additional symptoms. The list of symptoms is summarized in Table 8.

Table 8: Symptom clusters (Stanney et al., 1997; Davis et al., 2014; Ames et al., 2005).

Disorientation	*Nausea*	*Oculomotor (eye movement)*
Dizziness	*Stomach awareness*	*Eyestrain*
Vertigo	*Increased salivation*	*Difficulty focusing*
Concentration issues	*Burping*	*Blurred vision*
Fatigue	*General discomfort*	*Headache*
Boredom		

To conclude, cybersickness is a possible side-effect that should be taken into account when using virtual reality. This can be done by informing the respondents on beforehand, as well as providing them the option to quit the experiment at any given time. In addition, people who are more susceptible to cybersickness could also benefit from sitting down during the experiment (Davis et al., 2014).

2.5 Socio-demographics

Besides the interest in the importance of attributes and the difference in choice behavior regarding the presentation modes, also the influence of socio-demographics on this choice behavior is interesting. For that, the aim is to find relations between socio-demographic characteristics and attribute levels, and therefore a separate model is created during the analysis to test for these relationships.
As discussed in a previous section, research was performed by Van Vliet et al. (2021), Mokas et al. (2019), and Patterson et al. (2017). The study by van Vliet et al. (2021) aims to find the relative importance of attributes defining an urban park. It accomplishes this by executing an online stated-choice experiment with virtual environments. More importantly, the study found that socio-demographics play an important role when predicting the choice behavior of people. For example, the study concluded that people in a higher age group, as well as people with a higher income and education level, belong to a nature loving class. People who don't work fulltime and people with children are more likely to appreciate amenities more, whereas people of higher age value the presence of benches as well. In the end, the research found effects for the following socio-demographics: gender, age, household composition, occupation, education level and income (Van Vliet et al., 2021). Also, Mokas (2019) included the age, gender, education level, occupation and income in the model, however, only to test for differences between the datasets. Patterson et al. (2017) also did not use the data on gender and age for the analysis on neighborhood choice.

As seen in the case studies, socio-demographics are included, however only in case of the research by van Vliet et al. (2021) the variables play an important role in predicting the choice behavior of respondents. Other research might provide additional insights in the prediction of effects of socio-demographics. The research by Shan (2014) tested for the association of recreational activities with socio-demographic variables. The research found relations for gender, occupation, age, and education regarding the activities performed in public space, ranging from walking and sitting alone, to sporting. Additionally, retired and older people were more likely to visit a public space more frequently. Another example is the type of public space people prefer, where lower educated respondents preferred squares and plazas more than green spaces and parks compared to higher educated respondents. These different preferences could also lead to different opinions regarding the design of such spaces. Imaginably, people who prefer sporting in such plazas could prefer higher levels of grass compared to people who use the space for walking and thus prefer paths. Furthermore, Carro et al. (2008) found that there are also other differences regarding gender. On average, women have a higher score regarding the level of insecurity in a public space, as well as a lower level regarding satisfaction. In addition, aesthetics of walking environments are more important for females than for males (Fonseca et al., 2021)

Furthermore, the aim is to compare the results of this experiment to the results of the IVE experiment of CoHeSIVE (Dane & Evers, 2023). The IVE workshop gathered data on gender, age, urbanization level, whether the respondent had an architectural/urban design background, life satisfaction, influence of station plazas on health, and the frequency of

Eindhoven station plaza visits. Thus, the implementation of these socio-demographics is at least required for comparisons.

To conclude, in this research the following characteristics are included:

- Gender
- Age
- Household composition
- Income
- Education level
- Occupation
- Living environment
- Frequency of station plaza visits
- Life satisfaction
- Influence on health
- Background in architecture/urban design
- Pre-knowledge

2.6 Conclusion & Research Gap

Several presentation modes and methodologies are suitable for examining the influence on choice behavior. The three selected modes of presentation each have their own advantages and disadvantages, ranging from different levels of efficiency (information recalling/time exposure) to costs and time evaluations. The case studies gave insights in how to use certain methodologies in comparable studies, but also in what might influence the experiment. From these studies therefore different covariates could be extracted, but also practical aspects such as how to create and present different scenarios, reducing order-bias and taking into account fatigue and cybersickness. In the end, also predetermined by the IVE experiment of CoHeSIVE (Dane & Evers, 2023), the following set of attributes in considered in the scenario creation, for which the attribute levels will differ per profile:

- Presence or absence of a fountain
- Number of lampposts
- Number and composition of trees
- Presence of benches
- Amount of grass coverage
- Height of the new buildings

An objective of the research is to create healthy public space. This on the one hand considers the influence of being comfortable on health, but on the other hand also the physical influences of certain attribute on health. As discussed, greenery (number and composition of trees, as well as grass coverage) and water (fountain) have a beneficial effect on both comfortability and health. This is partly also due to the shading for example trees create. Adjacent buildings might also influence the shading on the plaza and are therefore also influencing the comfortability as well as the overall feeling on the plaza (enclosed or open). Amenities also contribute to feeling comfortable in a public space. A feeling of safety also contributes, which might be addressed by lampposts (although nighttime scenarios are not taken into account in this research).

To finalize, there is a research gap that the current study is trying to fill, namely whether preferences of people differs when the presentation mode differs (Van Vliet et al., 2019). Older studies focus on text and images, in which a difference is seen when people evaluate scenarios (Patterson et al., 2017). In addition, there is no guideline for the choice of

presentation mode. Furthermore, there is a lack of research that incorporates both the importance of attribute levels and the socio-demographic influences on preferences, while also testing for differences between presentation modes. Moreover, no research was found that incorporates all these aspects into one research. If the choice behavior of respondents differs per presentation mode, the results of this research should be considered in the decision-making process of policy makers in urban design (for example in the participatory process). People should be aware that the chosen presentation mode could have an influence on the preferences of participants. Furthermore, it provides insights in the importance of different attributes and attribute levels regarding public space design. One should however consider that this research is case specific, and the importance of attributes might be space specific. Therefore, generalizing these results to public spaces in general should be done with caution.

3. Research Methodology

In this chapter an elaboration on the research approach will be discussed. To start, the design of the research is provided. To go deeper into the matter, the experiment design is elaborated on, and a theoretical framework is provided regarding the models. Furthermore, the survey design and scenario creation are provided, as well as the required software.

3.1 Methodological Justification

The research will be conducted in 4 stages, which are visible in Figure 7.

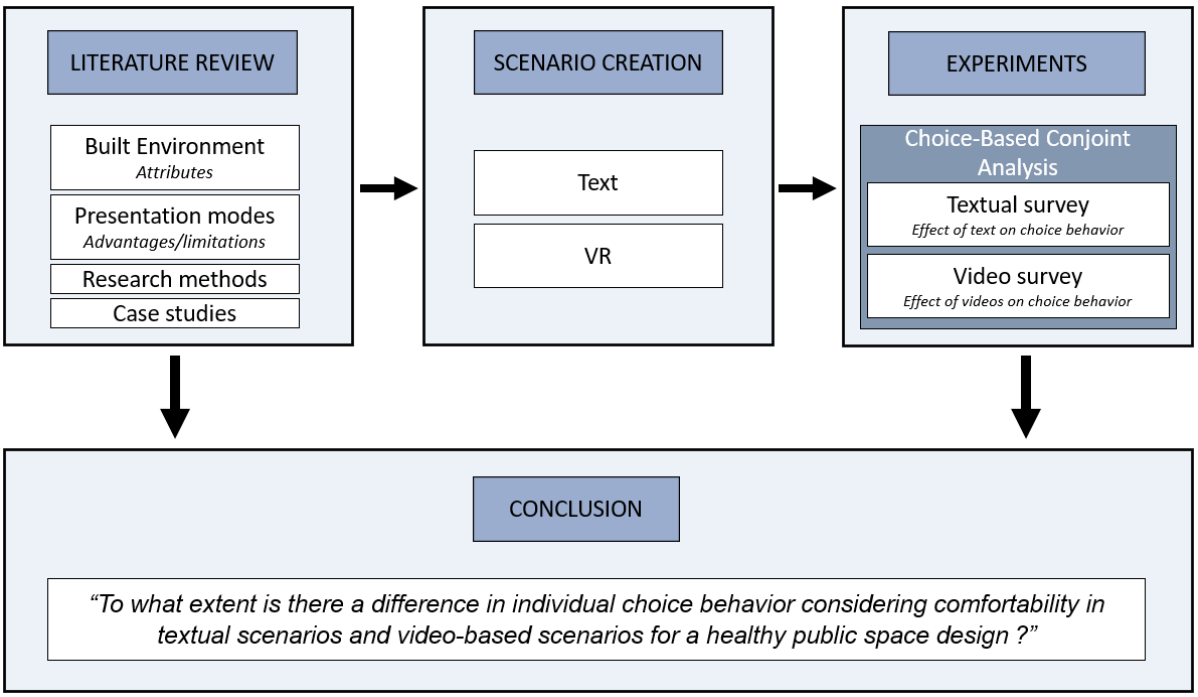


Figure 7: Research stages

Figure 8 gives a more in-depth insight in the process of each step. To start, the literature review provides insights into some aspects, such as the advantages of the different presentation modes and the selected relevant built environment attributes, which are required for the research to commence. This review will form the basis of, and contains vital information to construct the next steps, which consist of the scenario creation and the surveys for the stated choice experiment.

The scenario creation step includes the creation of the "test area", which is the Eindhoven station plaza. In this research, a text based and video based scene of the location is created. As a base, a SketchUp model is formed and used for the video scenarios. The video-based scenario is then created using "Lumion".

In the next stage, the text based and video-based scenarios are evaluated using a stated choice experiment. This survey is sent out online and requires a high number of respondents. In the survey respondents get presented design alternatives, which differ in the relevant built environment attributes as established in the literature review. The respondents then have to rate the design alternative on comfortability, leading to a data set of comfortability ratings on different design alternatives. However, for the analysis the dataset requires to be transformed to create a choice: whether the scenario contributes to a comfortable environment, yes or no.

This will be elaborated on in section 3.2. The choice behavior for the design alternatives of the respondents is then predicted using a multinominal logit model. This process is elaborated on later in this chapter, and chapter 5. In the end, it is interesting to see whether different choices are made relative to the different presentation modes, as well as the importance of attributes in these designs and of socio-demographic characteristics. It is also compared to the IVE experiment conducted by the CoHeSIVE research team (Dane & Evers, 2023), to try and distinguish differences between text, videos and immersive virtual environments.

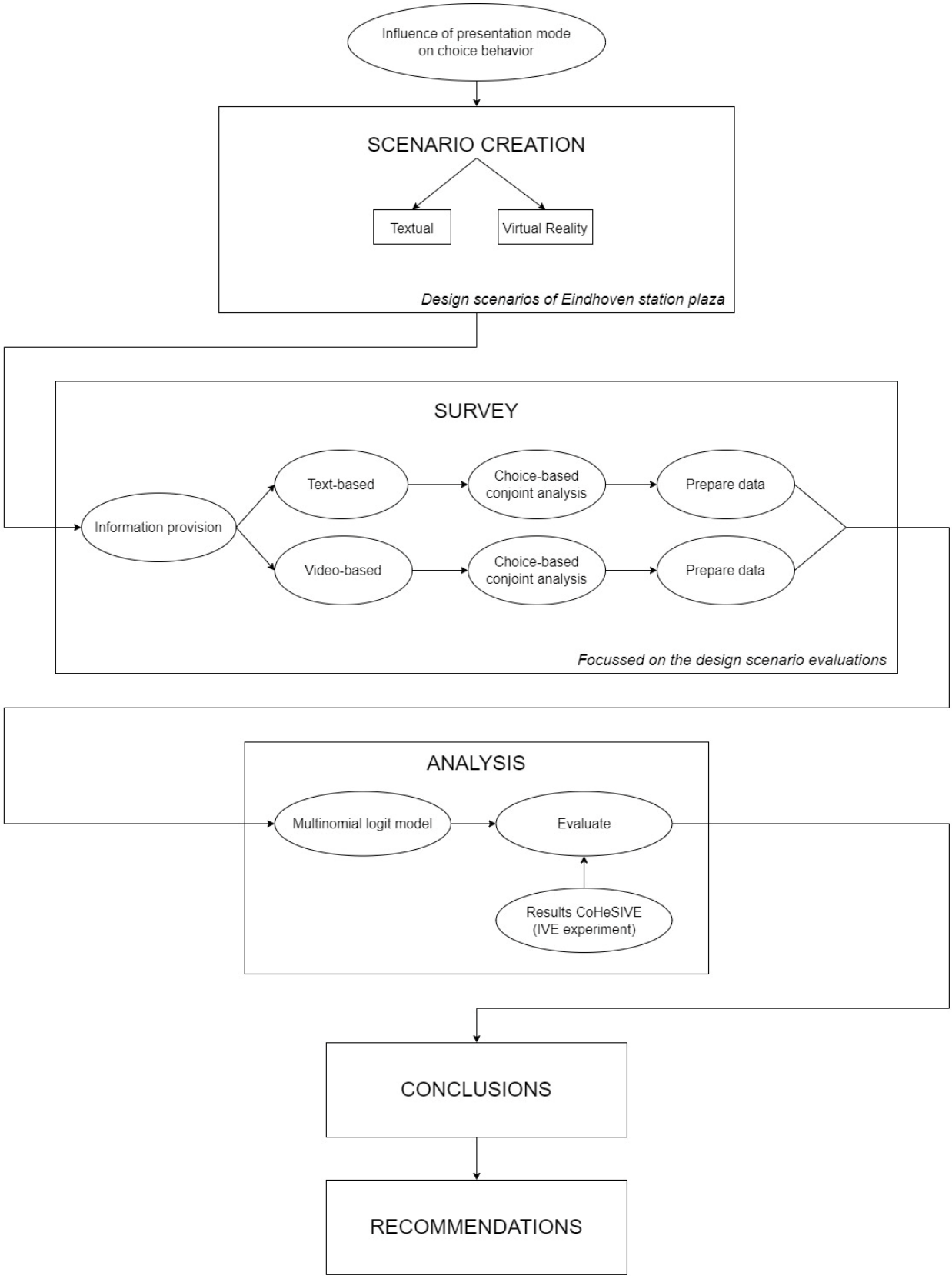


Figure 8: Experiment set-up

3.2 Experiment design

Hensher et al. (2015) provides an elaborate explanation on the process of stated choice experiments. The entire process is visible in Figure 9, ranging from the initial problem refinement, to the creation of the survey instrument. Already in the first stages, the later research method should be considered. In step 2, the attributes are identified. Considering too many attributes for the research, could lead to a big experimental design in stage 4.

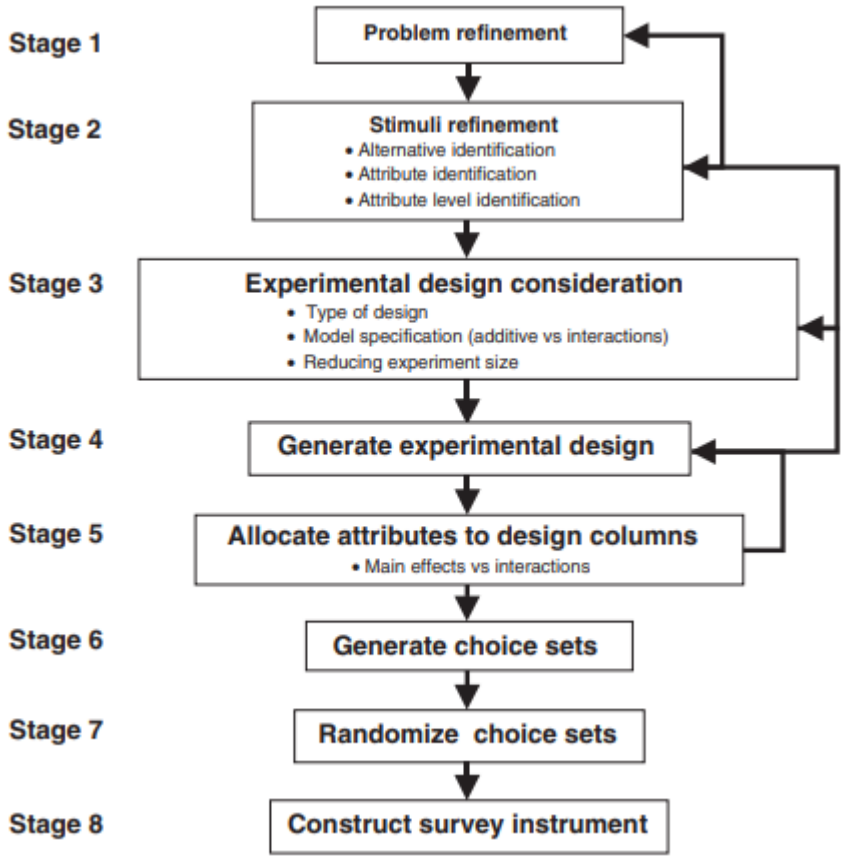


Figure 9: Experimental design process (Hensher et al. 2015)

However, introducing more levels to one attribute does provide the opportunity to the researcher to gather more detailed information on the utility relationships. For instance, as seen in Figure 10, one could conclude from the first graph that the relationship is linear. However, introducing additional levels may prove a non-linear relationship between the attribute levels (Hensher et al. 2015).

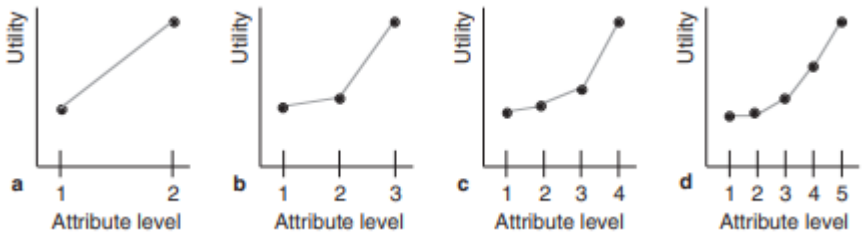


Figure 10: Mapping part-worth utility (Hensher et al. 2015)

After selecting the attributes and the attribute levels, the experiment design can be composed or generated using software. Because of the complexity of composing it without software, in this research the experimental design is created using SAS. This generates an efficient

orthogonal fractional factorial experimental design in this case. The randomization of the choice is done within the survey instrument LimeSurvey.

Data analysis background

In this section an elaboration on the data analysis is provided. The section adopts a stepwise approach by explaining the descriptive analysis, as well as the theory behind the multinomial logit model. Lastly, the model performance is discussed.

Descriptive analysis

After data gathering, the data is tested to examine the differences between the personal characteristics in the textual survey data and the video survey data. If there are no differences, then differences in choice behavior cannot be traced back to differences in the samples. This test is done through the following chi-square formula:

$$X^2 = \Sigma \frac{(O - E)^2}{E} \qquad \textit{Equation 1}$$

Where:
X^2 = chi-square test statistic
0 = the observed frequency (the observations of the text survey in this case)
E = the expected frequency (the observations of the video survey in this case)

The chi-square test statistic is then compared to the critical value. If the test statistic is greater than the critical value, the difference between the observations in the two datasets is statistically significant. If the test statistic is smaller than the critical value the difference between the observations in the datasets is not statistically significant (Turney, 2023). For this research, the significance level of α = .05 is used.

Choice analysis

For an MNL model, it is required to have choice data, in which the respondent compares multiple scenarios. In this case however, the respondents only rate one scenario at a time. Therefore, the dataset is transformed from a 1 to 10 rating scale to a dataset in which a design scenario is comfortable, yes or no. This is done by looking at the distribution of the data, trying to merge ratings as such that two approximately equal groups remain. This could result in the rating 1 to 5 being regarded as ‘not comfortable’, and rating 6 to 10 as ‘comfortable’. A disadvantage of this method however is that a rating is generalized. For example a rating of 1 is then considered the same as rating 5.
So in stated choice experiments, respondents are asked to choose the most preferred alternative from a set of alternatives. These choices are analyzed by means of discrete choice models, which are based on Random Utility Theory (RUT), see e.g., Hensher, Rose, and Green (2015). One of the assumptions underlying the RUT is that individuals choose the alternative that has the highest utility. Therefore, if provided a choice, the alternative with the highest utility will be chosen (Cascetta, 2009). Utility is assumed to consist of two components: the structural utility and the random utility component. The structural component is defined by attribute levels, which are weighted by parameters. There are also other attributes that might be relevant, but that are not taken into account. These are assumed to be represented by the

random utility component (Manski, 1977). The random utility can also be referred to as the error term. In the equation defining the utilty of an alternative, the subscript '*i*' refers to alternative *i*, where '*q'* refers to decision maker *q* (Hensher et al., 2015).

$$U_{iq} = V_{iq} + \varepsilon_{iq} \qquad \textit{Equation 2}$$

U_{iq} = Utility value of alternative *i* for respondent *q*
V_{iq} = Structural utility of alternative *i* for respondent *q*
ε_{iq} = Random utility of alternative *i* for respondent *q*

The structural utility is, as visible in Equation 3, defined as follows (Hensher et al., 2015):

$$V_{iq} = \sum_{n} ß_n \cdot X_{inq} \qquad \textit{Equation 3}$$

V_{iq} = Structural utility (observed) of alternative *i* for respondent *q*
$ß_n$ = Weight of attribute *n*
X_{inq} = The score of alternative *i* on attribute *n* for individual *q*

Multinomial logit (MNL)
In this thesis, a focus is laid on the multinomial logit model, which is the basic random utility model. According to this model, the probability that an individual chooses a particular alternative is defined as follows (see Hensher et al. (2015):

$$P_{iq} = \frac{\exp(V_{iq})}{\sum_{i'} \exp\,(V_{i'q})} \qquad \textit{Equation 4}$$

P_{iq} = Probability of alternative *i* for individual *q*
V_{iq} = Structural utility of alternative *i* for respondent *q*

Log-likelihood

The model performance indicates the usefulness of the results. To do so, the McFadden Rho Square test is performed. To perform the McFadden Rho Square test, the log-likelihood value is required. The log-likelihood value can be determined using the following formula (Hensher et al., 2015):

$$LL(ß) = \sum_s^S \sum_i y_{is} * \ln(P_{is}) \qquad \textit{Equation 5}$$

LL(ß) = Log-likelihood with estimated parameters
S = Total number of choice sets presented to the respondents
i = Alternative
y_{is} = Choice made for alternative *i* in choice sets *s* (chosen: 1, not chosen: 0)
P_{is} = Probability of alternative *i* in choice sets *s*

McFadden Rho Square test (Goodness of fit)

The performance of this model can be measured by using the McFadden Rho Squared. For this, the previously explained log-likelihood of the estimated model, as well as the log-likelihood of the null model is required. This leads to the equation as visible in Equation 6.

$$McFadden\ Rho - Square = \rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} \qquad \textit{Equation 6}$$

Where:
LL(β) = log-likelihood using estimated parameters
LL(0) = log-likelihood using null-model (all parameters β equal to 0.0, meaning equal choice probabilities)

The model is deemed adequate if the value of the McFadden Rho Squared is in the 0.2 to 0.4 range (McFadden, 1974).
The estimated parameters can be interpreted as the weight of the attribute levels. To investigate whether preferences differ across different presentation modes, these parameters should be compared by a MNL model. If parameters estimated on data obtained by one presentation mode are statistically significantly different from parameters estimated on data obtained by another presentation mode, it can be concluded that preferences are affected by presentation mode.

3.3 Survey design

The study's main objective is to assess respondents' preferences when presented with urban design scenarios, examining attribute levels, differences between presentation modes, and the effects of socio-demographics. To achieve this, an online questionnaire with three parts was created using LimeSurvey, available in both Dutch and English. To start, the survey setup was based on the literature found by incorporating the expected influential socio-demographics. Initially, respondents reach the front page of the survey, where consent has to be provided before continuing the survey. Then, a survey layout was created in which there were 3 main groups:

- Personal characteristics
- Experiment
- Design preferences

The personal characteristics were all combined within one question group in LimeSurvey, meaning these are all presented on the same page and can be filled in reasonably fast. An indication is visible in Appendix E, in which the presentation of the questions is seen. This question group is mandatory for all respondents and does not require any special handling within LimeSurvey.

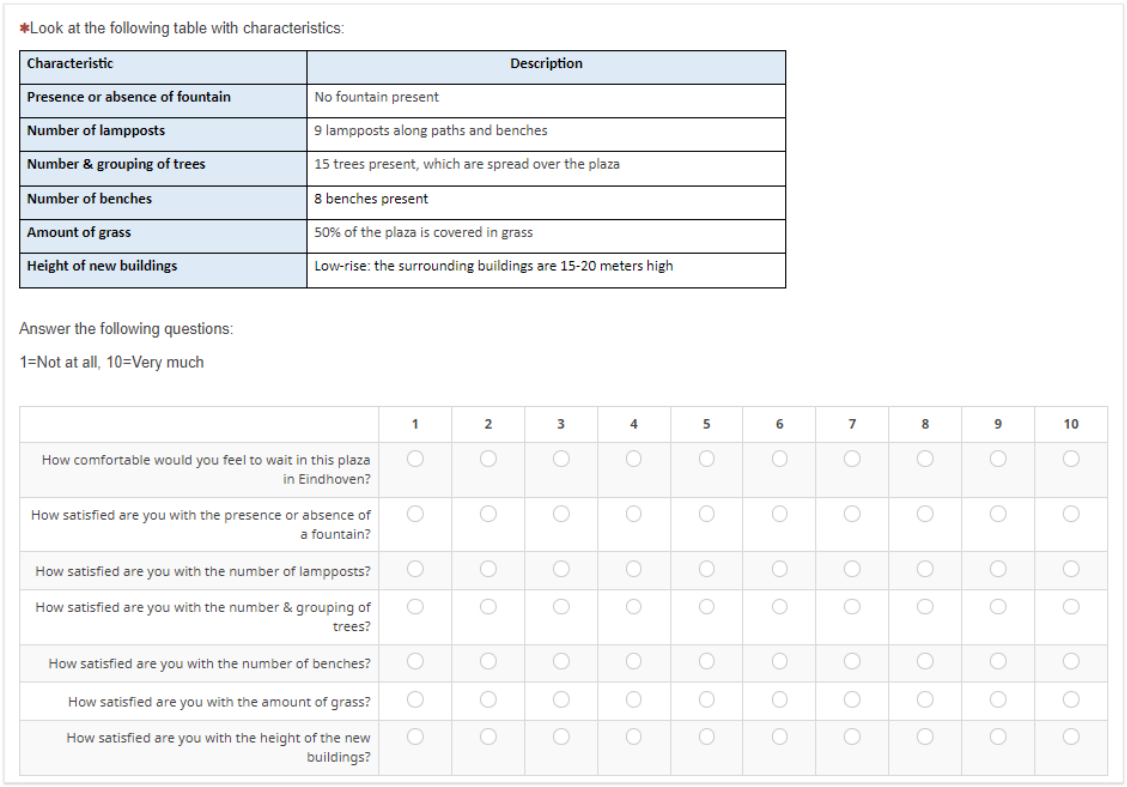
After completing filling in the personal characteristics, respondents are guided towards the actual experiment. In this part, respondents will first start with an explanatory page with a test question. This is done to provide the chance for respondents to familiarize themselves with the upcoming choice tasks. Therefore, the responses to this test choice task are not used during the analysis.

When respondents pass the test question, they are guided to the start of the experiment. For this approach, an efficient orthogonal fractional factorial design is generated with SAS, detailed in Appendix D. This means that not all possible combinations of attribute levels are used, as this would lead to a large number of different profiles. Thus, only a fraction of this is used, creating an efficient design (Hensher et al. 2015). The table in Appendix D illustrates the 32 profiles used in the experiment, specifying the attribute levels required for each profile. The table is constructed using six variables, with two variables having two levels, and four variables having four levels, as visible in Table 9.
As mentioned in the introduction, there are many relevant built environment attributes that can be implemented in the design scenarios. However, within the CoHeSIVE project a selection of attributes was made that were suitable for IVE creation (Dane & Evers, 2023), leading to a set of attributes that must be followed in order to retain the comparability between the different modes of presentation: text, video, and later IVE. As such, this list of attributes and levels is used in the scenario creation, as visible in Table 9.

Table 9: Built environment attributes and their levels (Dane & Evers, 2023)

	Level 1 (base)	Level 2	Level 3	Level 4
Presence or absence of fountain	Not present	Present		
Number of lampposts	Less (along paths -7)	More (along path and benches -9)		
Number & grouping of trees	No trees (0)	Some trees (9)	More trees (15), not clustered	More trees (15), clustered
Number of benches	None (0)	Few (4)	Several (8)	Many (15)
Amount of grass coverage	None (0% permeable)	Small (33% permeable)	Average (50% permeable)	Large (66% permeable)
Height of the (new) buildings	Skyscrapers (90-160m – 50 stories)	High-rise average (50-90m – 30 stories)	Medium-rise (30-50m – 15 stories)	Low-rise (15-20m – 5 stories)

In the experiment, the respondents will view 8 of the 32 profiles (design scenarios), which are randomly selected per respondent. As a result, every respondent is presented with a different set of 8 profiles, where also the order of the profiles differs. This is done to reduce the order effect, which means the order in which questions are presented can influence the answers of a respondent (Bontis, 2013). For each of these 8 profiles, respondents will answer the same set of questions, which are similar to the questions presented in the CoHeSIVE experiment using IVE (Dane & Evers, 2023). The first question seeks to answer the overall level of comfortability on the station plaza. The consequent six questions gather information on the level of comfortability of each individual attribute on the station plaza. In Figure 11 and Figure 12 an example of a text design scenario and video design scenario can be seen.



*Look at the following table with characteristics:

Characteristic	Description
Presence or absence of fountain	No fountain present
Number of lampposts	9 lampposts along paths and benches
Number & grouping of trees	15 trees present, which are spread over the plaza
Number of benches	8 benches present
Amount of grass	50% of the plaza is covered in grass
Height of new buildings	Low-rise: the surrounding buildings are 15-20 meters high

Answer the following questions:

1=Not at all, 10=Very much

	1	2	3	4	5	6	7	8	9	10
How comfortable would you feel to wait in this plaza in Eindhoven?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the presence or absence of a fountain?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the number of lampposts?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the number & grouping of trees?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the number of benches?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the amount of grass?	○	○	○	○	○	○	○	○	○	○
How satisfied are you with the height of the new buildings?	○	○	○	○	○	○	○	○	○	○

Figure 11: Example of text design scenario in LimeSurvey

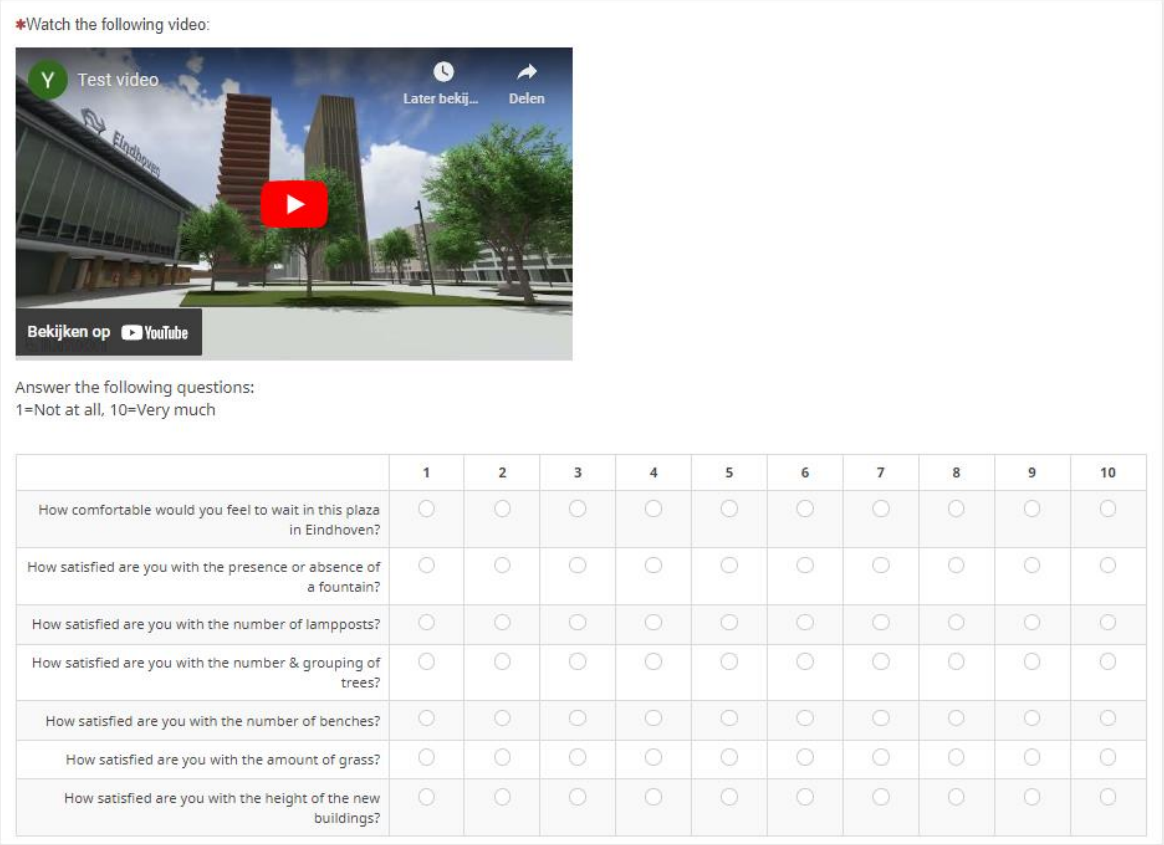


Figure 12: Example of video design scenario in LimeSurvey

Lastly, this research investigates the optimal design choices per attribute. This is done in the final section of the survey, where respondents will choose the most preferred attribute level per attribute. The respondent is presented with all attribute levels per attribute and has to tick the box containing the most preferred attribute level. In Figure 13 the text variant is visible, whereas Figure 14 shows the video survey variant.

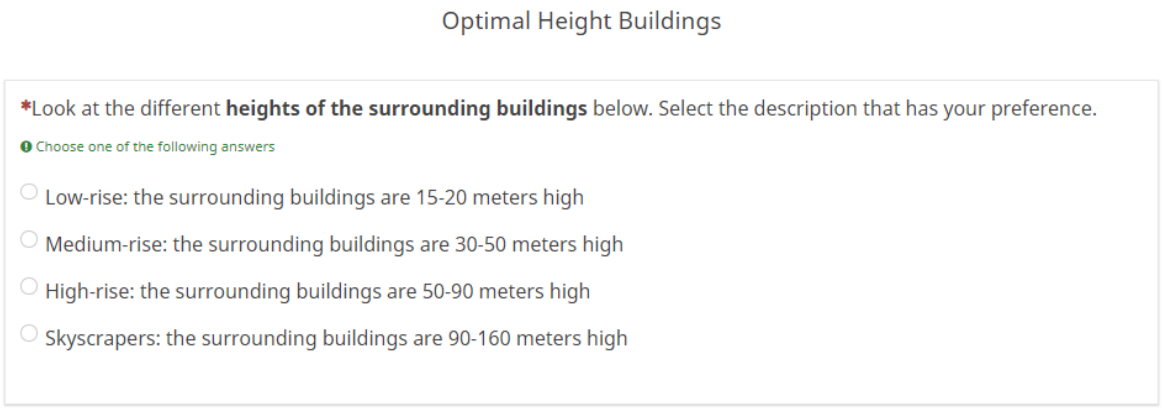


Figure 13: Retrieving the most preferred attribute level in the text variant survey

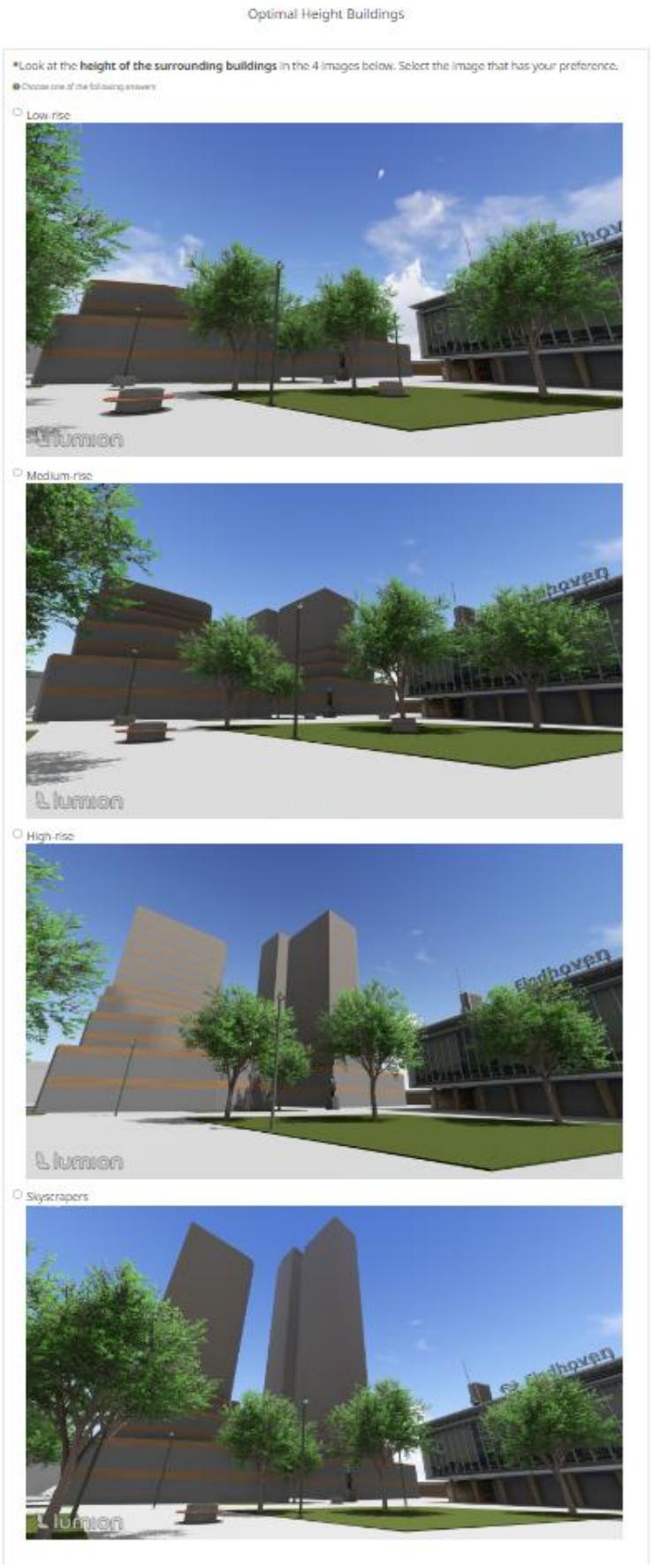


Figure 14: Retrieving the most preferred attribute level in the video variant survey

3.4 Scenarios

In this section the choices for the scenarios are elaborated on, as well as visually described. This includes aspects such as viewpoints, attributes and their levels, and locations/aesthetics of attributes.

Regarding the scenario creation, the visual boundaries are set by the IVE model made by CoHeSIVE (Dane & Evers, 2023). As a result, the viewpoints used in the video scenarios should be similar to the viewpoints used in the IVE scenarios. By keeping such factors similar, the comparability between the different presentation modes is preserved. The three viewpoints provide, when rotating around, a close view of all important aspects on the plaza. As such, a closer look is taken at a possible present fountain, the building height from all sides, as well as the other variables incorporated in the model. These viewpoints are visible in Figure 15 and are represented by the red angles, where the viewpoint turns round on the red filled circles, giving an over 180 degree view per viewpoint.

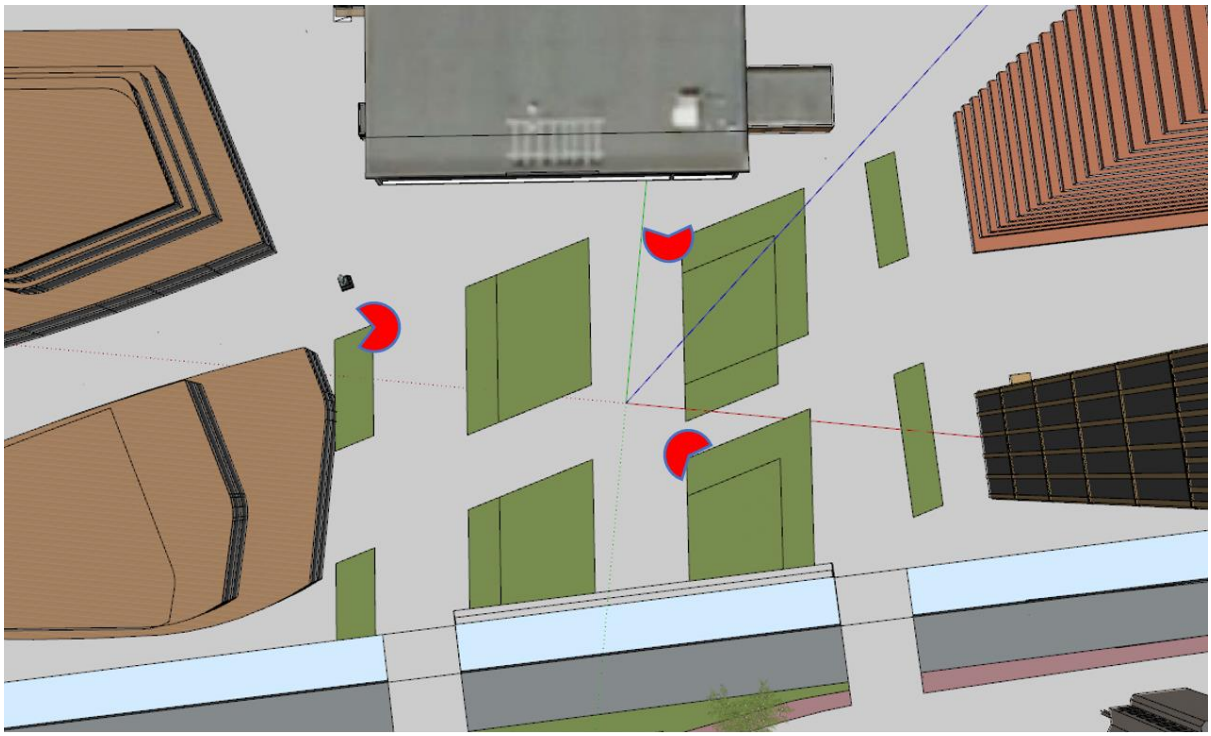


Figure 15: Location of the viewpoints in IVE model

3.4.1 Text scenarios

Regarding the textual design scenarios, short and formal sentences were formed to inform the respondent on the attribute level as seen in Table 10 below.

Table 10: Example of design scenario in text

Characteristic	Level
Presence or absence of fountain	No fountain present
Number of lampposts	9 lampposts along paths and benches
Number & grouping of trees	15 trees present, which are spread over the plaza
Number of benches	8 benches present
Amount of grass	50% of the plaza is covered in grass
Height of new buildings	Low-rise: the surrounding buildings are 15-20 meters high

3.4.2 Video scenarios

The video scenarios required some additional arguments for placement of certain objects and textures, as in this case objects are physically placed in locations that are visible for the respondent. In general, the decision for certain locations was mainly based on the aesthetics for the video, and how the difference between different attribute levels would become visible. In the remainder of this section, each attribute is elaborated on and visualized. All videos are visible in the following link: https://zenodo.org/records/10575620

Presence or absence of fountain:

There are two different levels:

- Level 1: No fountain present
- Level 2: Fountain present

The location for the fountain is visible in Figure 16 in red. This is the exact same location as used in the IVE model.

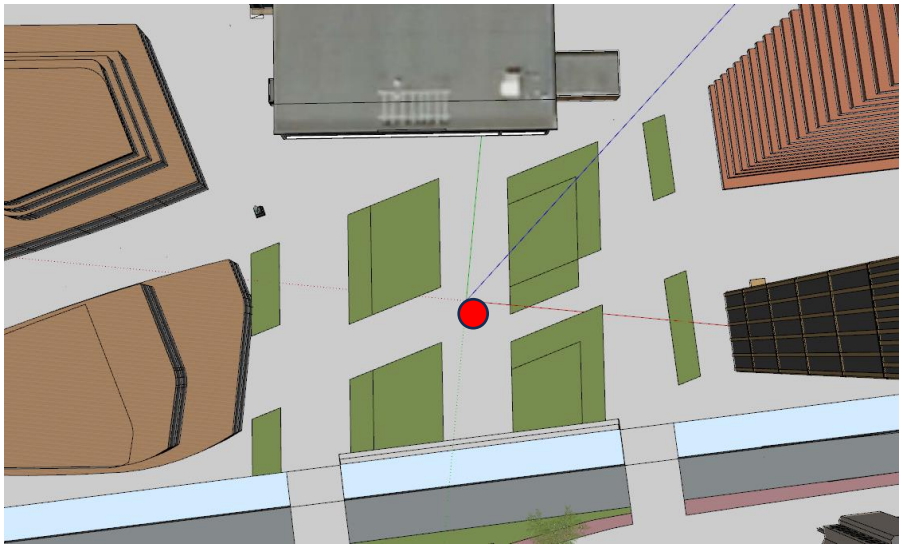


Figure 16: location of fountain in red

Number of lampposts:

The number of lampposts has two different levels, namely:

- Level 1: 7 lampposts along paths
- Level 2: 9 lampposts along paths and benches

The locations used in the design scenarios are visible in Figure 17 below. These choices are also related to the viewpoints discussed earlier in this chapter. Due to the relatively small difference in the two levels for this attribute, the choice was made to place the two additional lampposts for level 2 in direct sight of the viewpoints.

Figure 17: location of lampposts in the two different levels (Level 1 = blue, Level 2 = red + blue)

Number & grouping of trees:

The number & grouping of trees has four different levels, namely:

- Level 1: No trees
- Level 2: 9 trees present
- Level 3: 15 trees, which are spread over the plaza
- Level 4: 15 trees present, which are clustered in smaller groups

The trees are, as in the IVE model, located on the different stretches of grass. In case of the 15 trees, a distinction is made between the trees being clustered, and the trees being spread over the entire plaza. This is visible in Figure 18 and Figure 19 below.

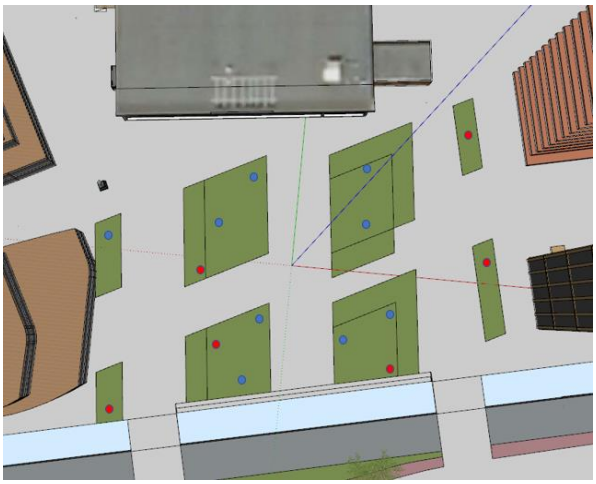


Figure 18: 9 trees (blue), 15 trees spread (red+blue)

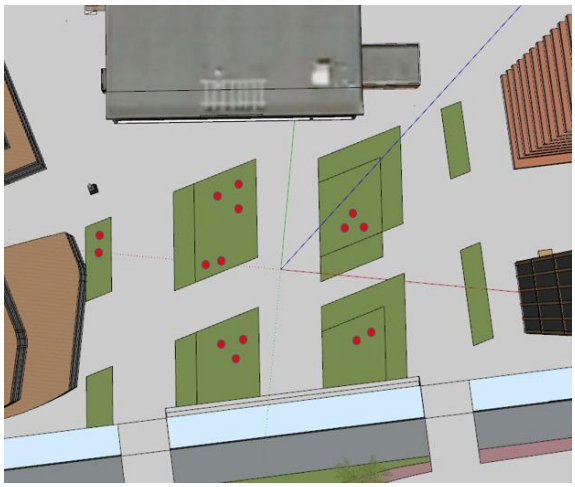


Figure 19: 15 trees clustered in red

Number of benches:
A distinction is also made in the number of benches present on the station plaza. The levels available in the models are:

- Level 1: No benches
- Level 2: 4 benches present
- Level 3: 8 benches present
- Level 4: 15 benches present

The location is decided on based on the usage of benches in the IVE model. However, in this case some benches were hardly visible in the videos. Therefore, the choice was made to relocate some benches in order to create a visible difference between the levels. The chosen locations are visible in Figure 20.

Figure 20: Location of benches (Level 2 = blue, level 3 = blue + red, level 4 = blue + red + yellow)

Amount of grass:
Furthermore, the grass coverage on the plaza is incorporated in the scenarios. This variable differs on the following levels:

- Level 1: 0% of the plaza is covered in grass
- Level 2: 33% of the plaza is covered in grass
- Level 3: 50% of the plaza is covered in grass
- Level 4: 66% of the plaza is covered in grass

The location of the grass planes are, similarly to the other attributes, retrieved from the IVE model to retain a comparable standard. The different levels for the grass coverage are visible in Figure 21 until Figure 24 below.

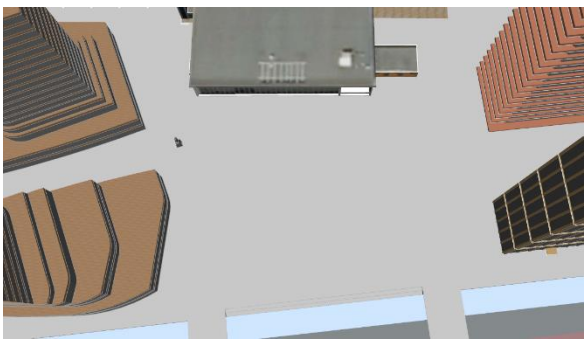


Figure 21: 0% grass coverage

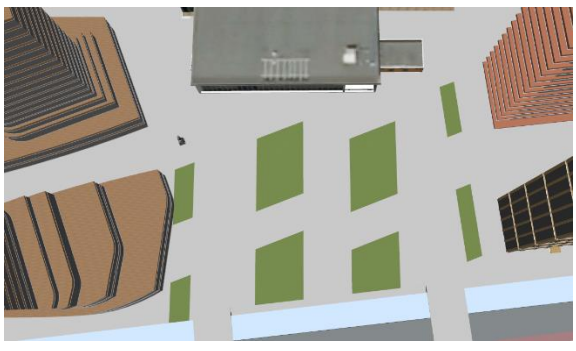


Figure 22: 33% grass coverage

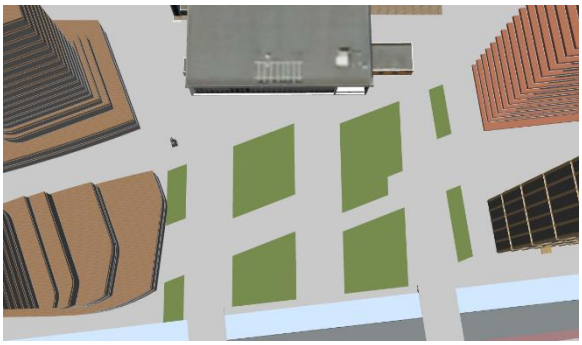


Figure 23: 50% grass coverage

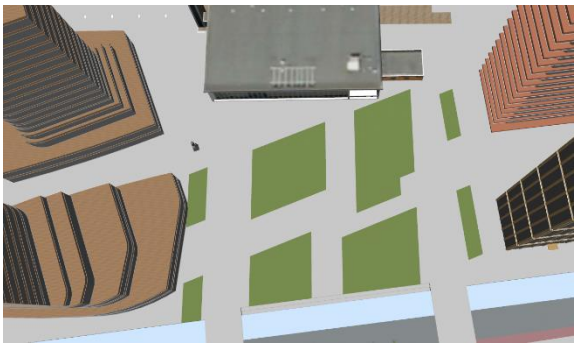


Figure 24: 66% grass coverage

Height of the new buildings:

The height of the new buildings is visualized on 4 different levels, namely:

- Level 1: Skyscrapers: the surrounding buildings are 90-160 meters high
- Level 2: High-rise: the surrounding buildings are 50-90 meters high
- Level 3: Medium-rise: the surrounding buildings are 30-50 meters high
- Level 4: Low-rise: the surrounding buildings are 15-20 meters high

Lastly again, this has exactly the same levels as the IVE model. The visualizations of these levels are visible in Figure 25 until Figure 28.

Figure 25: Skyscrapers

Figure 26: High-rise

Figure 27: Medium-rise

Figure 28: Low-rise

3.5 Softwares

First of all, the experiment design was created using SAS (Statistical Analysis Software). Using SAS, an efficient fractional factorial design was created with the required 6 variables and their levels.

The creation of the videos required the use of 2 different softwares; namely SketchUp Pro and Lumion. First of all, a model is created in SketchUp, in this case a model of the station plaza in Eindhoven including the surrounding area. Within SketchUp a plugin can be installed from the Extension Warehouse, called “Lumion LiveSync for SketchUp. This plugin creates a connection between the SketchUp model and Lumion, converting the model to a new file in Lumion. In this way, adjustments made in SketchUp can easily be transformed to Lumion. There are a few capabilities that are shared between SketchUp and Lumion, such as adding textures or colors to shapes, or adding objects such as trees. In order for Lumion to run smoother, as much data as possible should be removed from the Sketchup file. Data reduction means a lower pressure on the RAM of a laptop/computer, improving the working quality by evading malfunctioning software’s. This is why the shared capabilities are essential, as all trees and textures can be removed in the SketchUp file, and later added to the Lumion file in higher resolutions for rendering. Depending on the quality of the laptop/computer that is being used, the settings for rendering in Lumion should be changed accordingly. In this case, a laptop with a 2.60 GHz processor was used, for which the settings were adjusted to 30 frames per second and a 3 star (out of 5) render quality. Finally, as the videos would be uploaded to YouTube and later imported in LimeSurvey through YouTube, a 1280 x 720 format was used. On average, for the videos with a duration of 52 to 60 seconds, the rendering took about 1.5 to 2.5 hours per video.

The output in the end was a folder of 32 textual design scenarios, and a folder of 32 video design scenarios.

Lastly, the analysis was performed using NLOGIT, a statistical software package designed for the estimation and analysis of discrete choice models.

3.6 Participant Recruitment

Participant recruitment was performed in two main ways. First of all, participants for this research were gathered through posting the survey online. This was done through the channels of Instagram and LinkedIn. In addition, a lot of mouth-to-mouth referrals at the built environment faculty of the Technical University of Eindhoven led to respondents filling in the surveys.

Secondly, the surveys were posted on a panel website called ‘Panelclix’. Through this panel, participants earn credits which can be exchanged for money on the platform. Panelclix contributed for slightly over half of the total number of recruited respondents.

Furthermore, respondents were not limited to one survey. There was a possibility to participate in all three surveys, which is schematically visible in Figure 29. The main goal of the research is to understand the differences in choice behavior when using different presentation modes. That means that the participation of respondents across the three different surveys is possible, as their choice behavior might differ within these surveys. As a check on the results a question is added in the survey that examines whether the respondent already participated in another survey. As such, the dataset per survey shows whether the respondent already had some pre-knowledge on the matter. For example, a respondent who filled in the video survey first might have a different view on the textual survey as this respondent had visual confirmation of different scenarios and attribute levels. In this research, only the textual and video survey are

created and spread, while the IVE experiment was created and handled by CoHeSIVE (Dane & Evers, 2023). As such, this thesis has no added value towards that specific workshop, it merely uses the results from it.

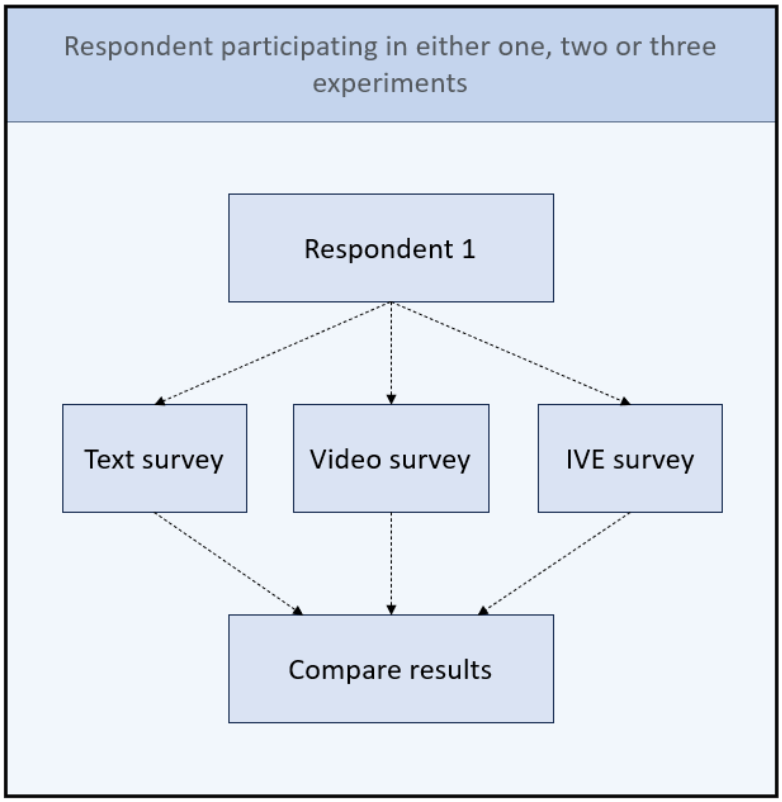


Figure 29: Schematic overview of participating possibilities

3.7 Conclusion

To conclude, this research will consist of two experiments. One experiment will present design scenarios of the Eindhoven station plaza in text format, while the other will present these in video format. These scenarios are implemented in a survey with the goal to compare choice behavior between these modes. In the end, the results of the IVE experiment conducted by the CoHeSIVE research team will also be used for comparisons with that mode. For this research, a MNL model will be used to estimate the importance of attributes regarding the comfortability rating of the scenario, and to compare the presentation modes. In addition, some socio-demographic characteristics are also incorporated to test for these effects on the comfortability rating. The scenarios presented are created using the IVE model by CoHeSIVE as a basis, and with trial and error based on aesthetics of the model. Softwares used are SAS, SketchUp, Lumion and NLOGIT. Participants for the research are found through network of the researchers, as well as through active promotion in the built environment faculty of the TU Eindhoven. In addition, the experiment was posted on Panelclix.

4. Descriptive Statistics

In this chapter the gathered data is explained and evaluated. This is done by providing the number of respondents and their characteristics.

4.1 General

Since there were two surveys, there are also two datasets for which the choice-behavior of people will be analyzed. Some responses were filtered out of the datasets as they did not reach the last page of the survey. Furthermore, respondents were filtered on their ratings per scenario on the seven aspects on a scale of 1 to 10. A respondent was filtered out if the rating on all seven aspects were identical, or very similar. Often this was also related to the time to complete the survey. Therefore, respondents who filled in the survey faster than 4 minutes were also removed. In the end, Table 11 presents the number of respondents that have successfully completed the textual and video survey.

Table 11: Number of respondents per survey

	Textual	Video
Number of respondents	111	105

The profiles these respondents would encounter, were randomized using LimeSurvey Logics. Theoretically, every profile would be presented equally frequent. However, practically this is not the case. This is visible in Figure 30, where the distribution of the presented profiles can be seen.

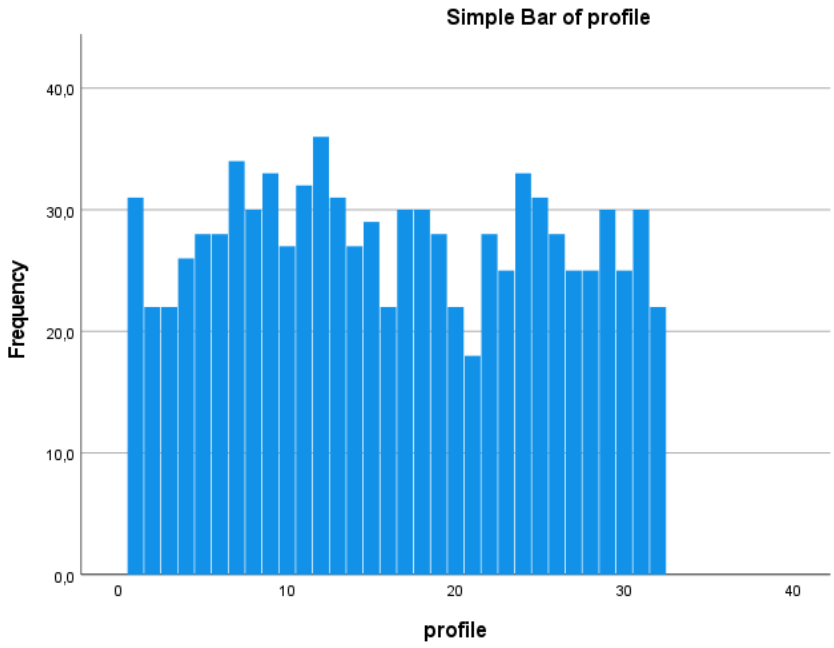


Figure 30: Frequency bar chart of profiles in the text-based survey

As visible, there is a difference in the number of displays per profile. The minimum can be seen for profile 21, which was rated 18 times by respondents. The maximum is set for profile 12, with 36 ratings by respondents. Although there is a relatively significant difference between the number of times a profile was presented, the minimum is high enough for statistical analysis.

The video survey has a similar number of respondents compared to the textual survey, with 105 useful cases. The profiles scattering is visible in Figure 31, where the minimal can be seen for profile 14 which was rated 18 times. The maximum is seen at profile 3, which was rated 36 times.

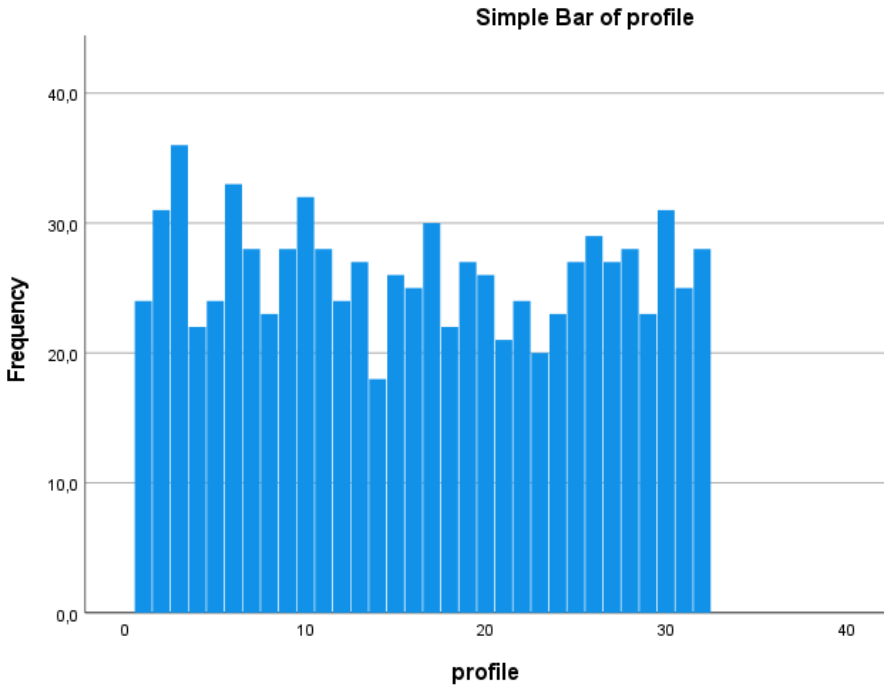


Figure 31: Frequency bar chart of profiles in the video-based survey

Furthermore, the database used for the analysis is visible in Table 12. This table provides an overview of the initial categories in the survey, as well as the recoded categories to create logical and sufficiently big categories. In the remainder of this chapter, each socio-demographic characteristic is elaborated on and compared between the text and video data sample.

Table 12: Overview of recoded categories and frequencies

Variable	Level	Frequency text	Frequency video	Recategorization	Frequency text	Frequency video
Age	18 – 24 years	25	30	18 - 34 years	53	57
	25 – 34 years	28	27			
	35 – 44 years	10	11	35 - 54 years	26	23
	45 – 54 years	16	12			
	55 – 64 years	14	11	≥ 55 years	32	25
	≥ 65 years	18	14			
Gender	Male	65	53	Male	65	53
	Female	46	51	Female	46	51
	Other	0	1	Other	0	1
Income	Lower than €1000 net per month	16	23	Lower than €2000 net per month	39	44
	Between €1001 and €2000 net per month	23	21			
	Between €2001 and €3000 net per month	43	31	Higher than €2000 net per month	63	52
	Higher than €3000 net per month	20	21			
	I'd rather not say	9	9	I'd rather not say	9	9
Education Level	Secondary education (VMBO/HAVO/VWO)	18	19	Secondary education	39	33
	Secondary vocational education (MBO)	21	14			
	Higher vocational education (HBO/Bachelor WO)	52	54	Higher education	72	71
	WO Master/PhD	20	17			
	I'd rather not say	0	1	I'd rather not say	0	1
Occupation	Student	26	29	Not working	47	47
	Other	5	5			
	Retired	16	13			
	Working part-time	18	19	Working	64	57
	Working full-time	46	38			
	I'd rather not say	0	1	I'd rather not say	0	1
Household Composition	Single-person household	20	21	Single-person household	39	41
	Other	19	20			
	Two-person household with partner	47	41	Two-person household with partner	47	41
	Household with children	25	23	Household with children	25	23
Living Environment	City center	26	30	City center	26	30
	City suburbs	43	40	City suburbs	43	40
	(Small) Town	35	31	(small) Town	42	34
	Rural	7	3			
	I'd rather not say	0	1	I'd rather not say	0	1
Station plaza visits Eindhoven	Daily	7	6	Weekly	24	22
	Weekly	17	16			
	1 - 2 times per month	22	15	Monthly	47	36
	Less than once per month	25	21			
	(Almost) never	40	47	(Almost) Never	40	47
Other station plaza visits	Daily	7	9	Weekly	31	41
	Weekly	24	32			
	1 - 2 times per month	30	25	Monthly	66	47
	Less than once per month	36	22			
	(Almost) never	14	17	(Almost) Never	14	17
Life satisfaction	Very dissatisfied	0	1	Dissatisfied	15	17
	Dissatisfied	4	3			
	Neutral	11	13			
	Satisfied	69	61	Satisfied	69	61
	Very satisfied	27	27	Very satisfied	27	27
Influence of station plaza on health	Very unimportant	5	0	Unimportant	20	13
	Unimportant	15	13			
	Neutral	42	49	Neutral	42	49
	Important	40	35	Important	49	43
	Very important	9	8			
Background in architecture/ urbanism	Yes	33	22	Yes	33	22
	No	78	83	No	78	83
Preknowledge	Yes	20	13	Yes	20	13
	No	91	92	No	90	92

4.2 Datasets

In this subchapter each socio-demographic characteristic is elaborated on, and most importantly compared between the textual survey database and the video survey database. Appendix J provides a full overview of the frequencies of the textual survey data, whereas Appendix K does the same for the video survey data. These differ in the categories used to describe the respondents, where the dataset used for the analysis consists of merged categories to increase group sizes for the analysis, while still maintaining important factors that could influence the prediction for choice behavior. Furthermore, each variable in this chapter is subject to a chi-square test to check whether the difference between the two datasets is due to chance, or if it is due to a statistical difference.

Age

The age category is one of the socio-demographics collected in the surveys. After data collection, the age categories are redistributed as seen in Figure 32. This is done to reduce the number of groups which then are sufficiently big and useable for the analysis in a latter part of this research. As visible, a large portion of the respondents are part of the youngest age category of 18 to 34 years old. Additionally, there are only minor differences between the datasets of the textual and video survey.

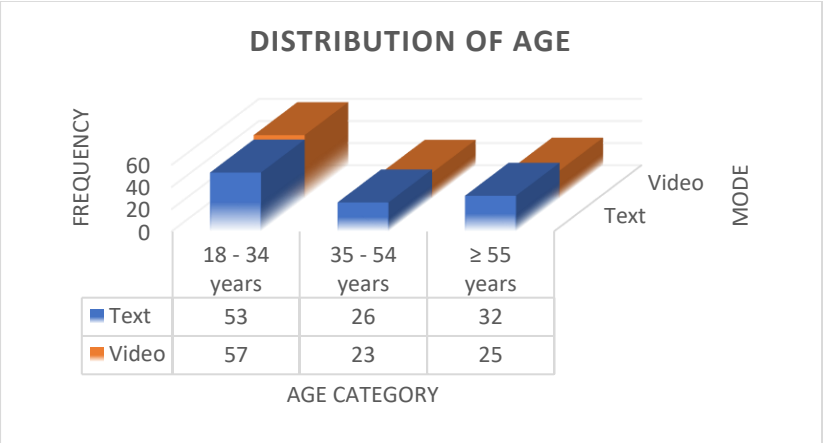


Figure 32: Distribution of age categories

The chi-square test statistic in this case is 2.63. In this case, the degrees of freedom (df) is 2, leading to a critical value of 5.99 (Turney, 2023). Therefore, the test statistic is lower than the critical value (2.63 < 5.99), and thus there is no statistical difference between the two datasets.

Gender

Figure 33 represents the distribution of gender in both datasets. Both the text and video dataset are comprised of a significant number of males and females, although the text variant was completed more often by males (65 against 53), whereas the video variant was completed more often by females (51 against 46). However, both groups are represented by a reasonable group size, and therefore are useable for analysis.

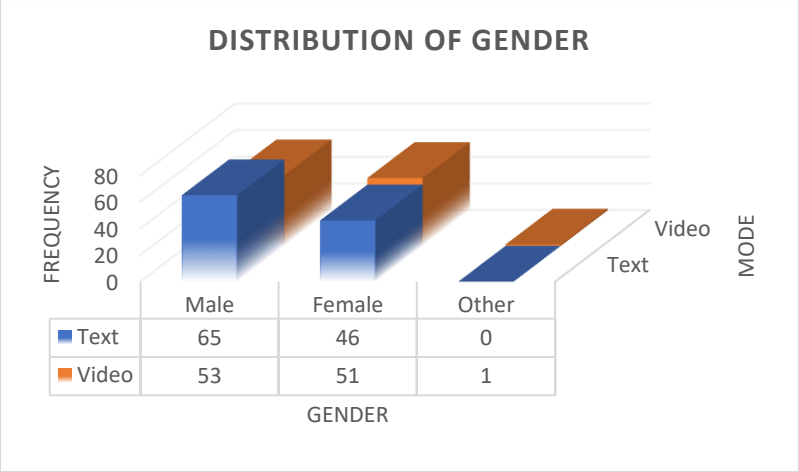


Figure 33: Distribution of gender

For the chi-square test statistic, de 'other' category is considered as missing, and therefore the degrees of freedom is reduced to 1. This leads to a test statistic of 3.78. As such, the conclusion is made that there is no statistical difference between the two datasets regarding gender as the test statistic is slightly lower than the critical value of 3.84 (with df = 1) (Turney, 2023).

Income

The income distribution is relatively similar when comparing the text and video datasets, as visible in Figure 34. The biggest fraction of respondents, for both datasets, is found in the category with an income higher than €2000 net per month. Also in this case, categories were merged to reduce the number of groups and create substantial groups for the analysis. Notably, respondents are slightly more hesitant to fill in their income range, which can be derived from the total of 18 respondents that reported 'I'd rather not say'.

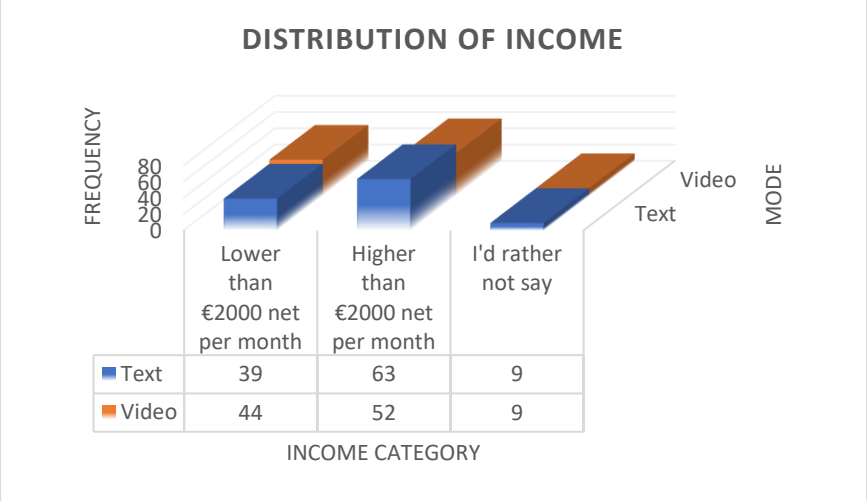


Figure 34: Distribution of income

The chi-square test statistic for income is 2.90. Again, considering the 'I'd rather not say' as missing, there is 1 degree of freedom, leading to a critical value of 3.84 (Turney, 2023). Therefore, the conclusion is made that there is no statistical difference between the text and video databases (2.90 < 3.84).

Education level

Similar to the previous characteristics the distribution of education levels is also very comparable between the two datasets, with 39 against 33 respondents in the Secondary Education group and 72 against 71 in the Higher Education group. As visible in Figure 35, the smallest portion reports to be in the category of Secondary Education, which translates to people having finished an education of VMBO, HAVO, VWO and/or MBO. The Higher Education category consists of a merger between HBO, Bachelor WO, Master WO and PhD. This leaves 2 significant categories useable for the analysis.

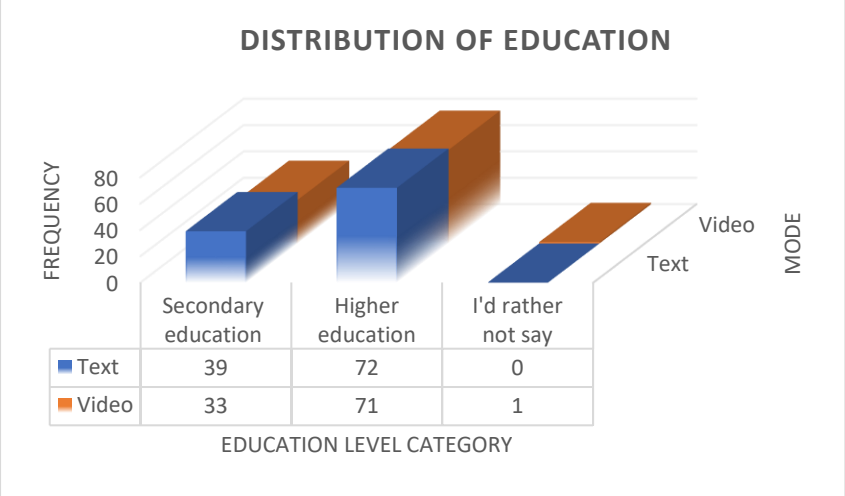


Figure 35: Distribution of education

Similarly as the previous socio-demographics, there is 1 degree of freedom in the education variable, leading to a critical value of 3.84 (Turney, 2023). In this case, the chi-square test statistic is 1.10, meaning that also for education there is no statistical difference between the two databases (1.10 < 3.84).

Occupation

The occupation groups were merged into categories of working and non-working population, which is in correspondence with the literature where a difference was found between these two categories. As visible in Figure 36, these categories are represented by a similar size, with 47 respondents corresponding to both the not working groups of the text and video dataset. The fraction of working people is slightly higher for the text dataset.

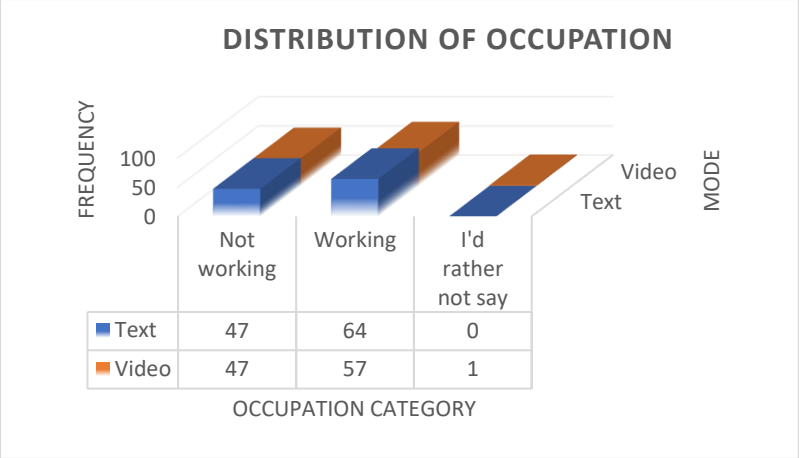


Figure 36: Distribution of Occupation

The chi-square test statistic for occupation is 0.86. Since there is 1 degree of freedom for the occupation variable, the critical value is set at 3.84 again (Turney, 2023). That being said, the conclusion is made that also for the occupation there is no statistical difference between the video and text database (0.86 < 3.84).

Household composition

The household composition was also merged in accordance with the literature, especially creating a group for households with children. As such, three considerable groups were created of single-person households, two-person households with partner, and households with children. As visible in Figure 37, all three groups are similarly represented when comparing between the text and video dataset.

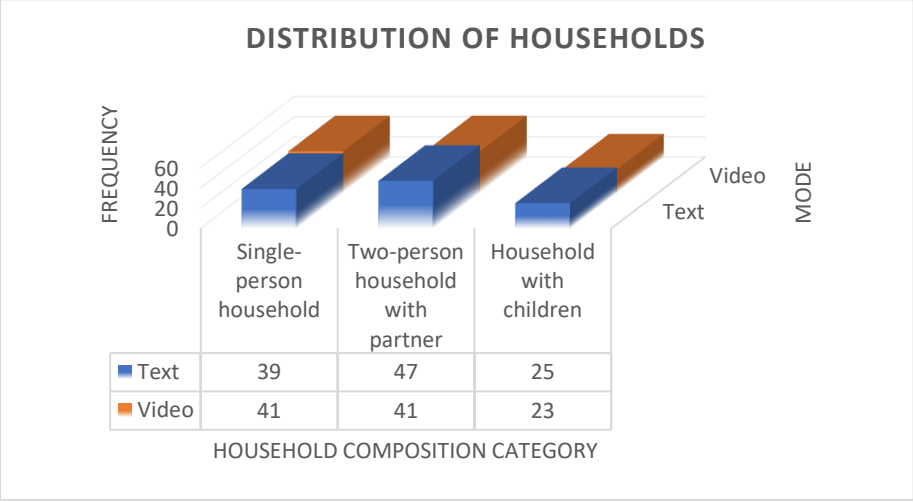


Figure 37: Distribution of households

The difference between the two datasets regarding the distribution of households is not statistically different. With a chi-square test statistic of 1.15, 2 degrees of freedom and thus a critical value of 5.99 (Turney, 2023), there is no statistical difference (1.15 < 5.99).

Living environment

The living environment of respondents was scattered over all categories, with only very few reports for ‘rural’. Therefore, these were merged with ‘(Small) Town’, as visible in Figure 38. This leaves the datasets with 3 substantial groups that are useable for the analysis, consisting

of respondents living in the city center, city suburbs and (small) towns. When comparing between the text and video dataset, again a similar trend is visible. The text dataset has slightly higher response rates for city suburbs and (small) town, whereas the video dataset has more participants on city center level.

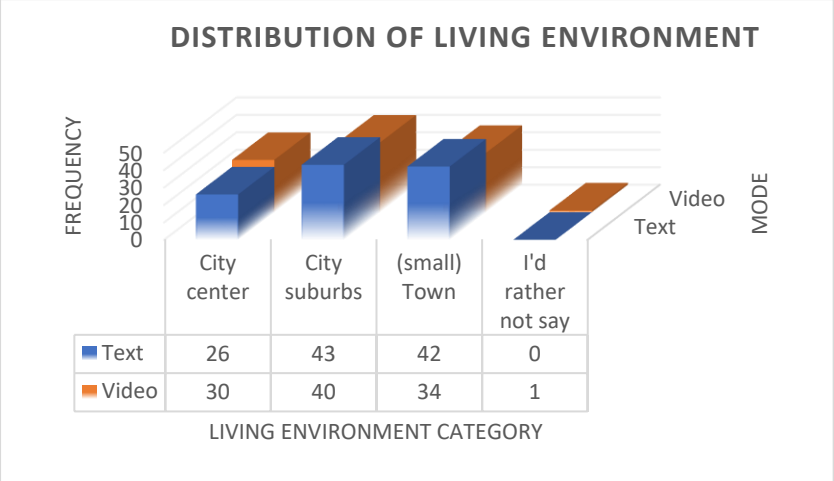


Figure 38: Distribution of living environments

The living environment of respondents has 2 degrees of freedom (considering 'I'd rather not say' as missing), meaning in this case the critical value is different, namely 5.99 (Turney, 2023). The chi-square test statistic is 2.64, meaning that for the distribution of living environments there also is no statistical difference between the database of the text survey and the database of the video survey (2.64 < 5.99).

Eindhoven station plaza visits

The familiarity of respondents with the Eindhoven station plaza is measured by the number of times the plaza is visited. These categories are merged to 'weekly', 'monthly', and '(Almost) never'. As visible in Figure 39, these categories are somewhat equally represented again when comparing the text and video dataset. However, the fraction for monthly is slightly higher for respondents visiting the plaza monthly in the text survey, whereas the contrary can be said for the category '(Almost) never'.

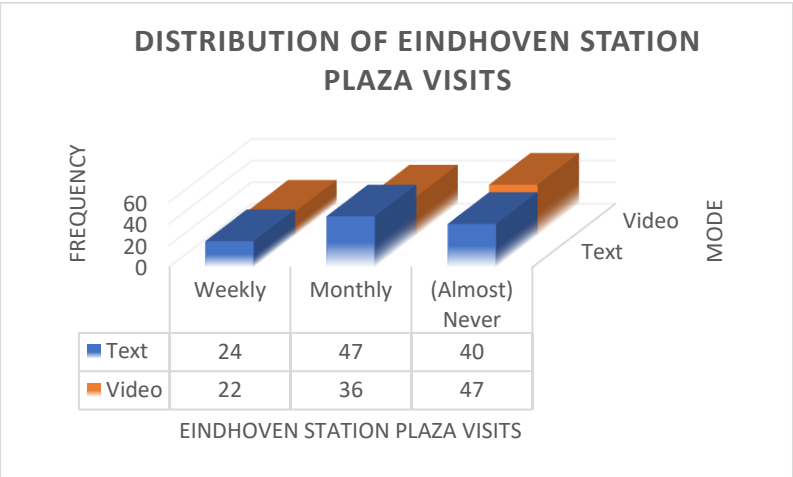


Figure 39: Distribution of Eindhoven station plaza visits

The chi-square test statistic of this variable, with 2 degrees of freedom, is 4.59 (Turney, 2023). Comparing that to the critical value of 5.99, the conclusion is made that for the distribution of Eindhoven station plaza visits there is no statistical difference between the text and video survey database (4.59 < 5.99).

Other station plaza visits

Next to the familiarity of the Eindhoven station plaza, the familiarity with other station plazas might also influence the insights of respondents. The categories are merged similarly as to the previous characteristic. Here, as visible in Figure 40, a smaller portion reports to '(Almost) never' visit other station plaza. Hence, a very big portion of the data sample is somewhat familiar with station plazas. Most respondents report visiting a station plaza other than Eindhoven monthly.

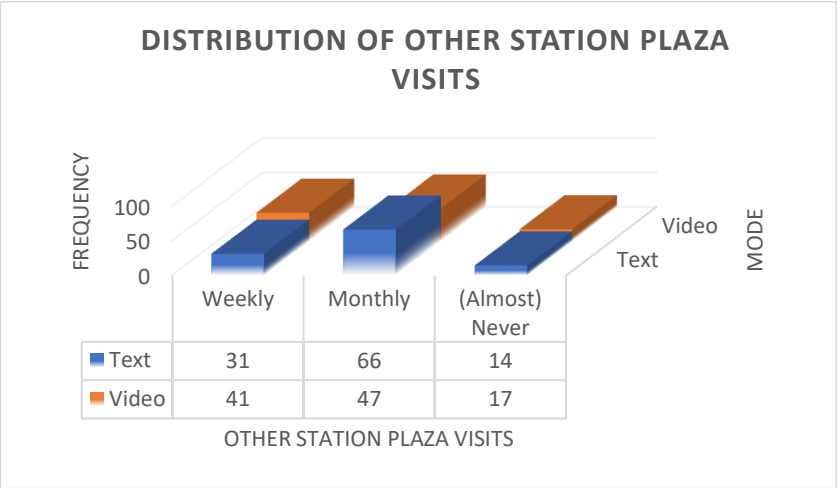


Figure 40: Other station plaza visits

The distribution of other station plaza visits again has 2 degrees of freedom, leading to a critical value of 5.99 (Turney, 2023). In this case however, the chi-square test statistic has a value of 10.65, meaning that for this variable there is a statistical difference between the two databases (10.65 > 5.99).

Life satisfaction

In addition, the life satisfaction level of respondents is asked, as this might influence choice behavior and can also be compared to the IVE scenario. These categories are merged to the following categories: Dissatisfied, satisfied, and very satisfied. The distribution of these categories is visible in Figure 41, where most people report to be satisfied in both the text and video dataset.

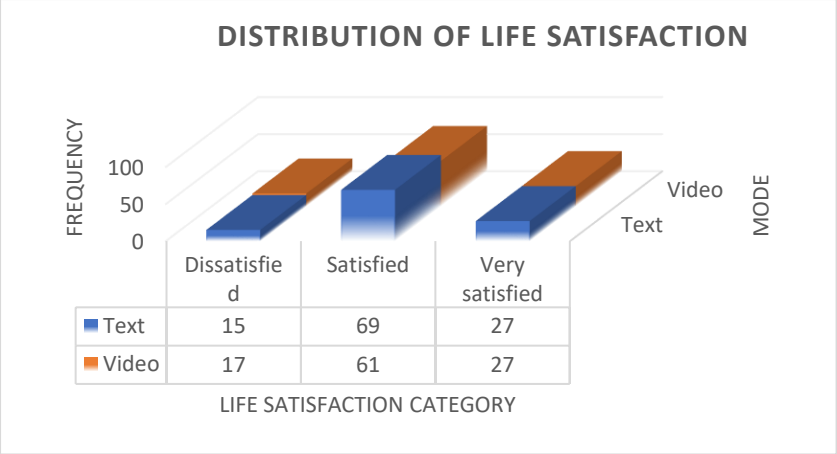


Figure 41: Distribution of life satisfaction

Regarding the distribution of life satisfaction, there is no statistical difference between the two datasets. With a critical value of 5.99 (df = 2) (Turney, 2023), and a chi-square test statistic of 1.28, the difference is not statistically different (1.28 < 5.99).

Influence of station plazas on health

The opinion on the influence of station plazas on health is also included. The distribution of this aspect is visible in Figure 42. The categories 'very unimportant' and 'very important' were reported scarcely, and therefore merged with respectively 'unimportant' and 'important'. Here, by far the largest portion is neutral or thinks it is important. This holds for both surveys.

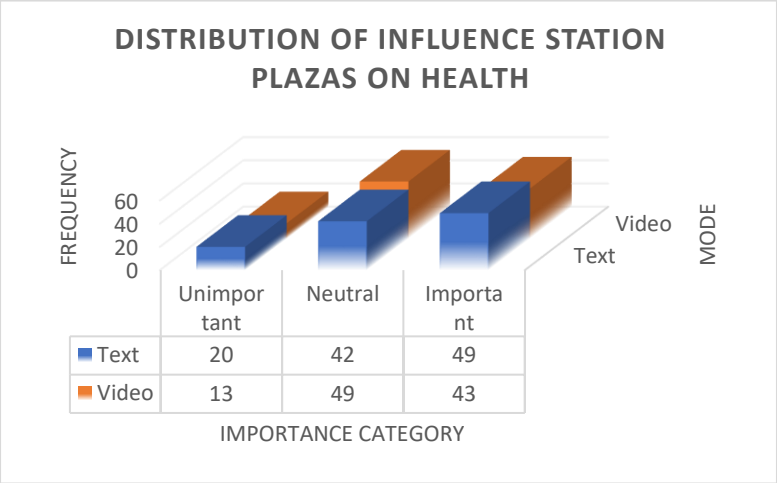


Figure 42: Distribution of influence of station plazas on health

Regarding the influence of station plazas on the health of respondents, there is no statistical difference between the two datasets. With 2 degrees of freedom and a critical value of 5.99 (Turney, 2023), the chi-square test statistic being 5.61 is lower than the critical value, and thus the difference is not statistically different.

Background in architecture/urbanism

It is important to know whether the respondent has a background in architecture and/or urbanism to test the influence on the choice behavior. As visible in Figure 43, the largest portion has no background in the field, whereas only 33 and 22 respondents report to have a background in respectively the text and video survey.

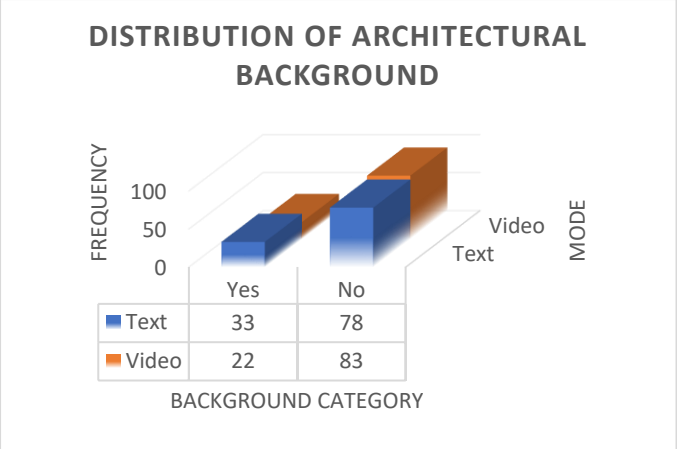


Figure 43: Distribution of architectural/urbanism background

The variable regarding the possible architectural background of respondents has 1 degree of freedom, leading to a critical value of 3.84 (Turney, 2023). The chi-square test statistic in this case is 5.80, meaning that the two databases of the text and video survey are statistically different in this case since 5.80 > 3.84.

Pre-knowledge

Lastly, the final question of the survey was to find out whether the respondent had pre-knowledge on the subject by filling in the other survey on beforehand. So in case a respondent filled in both surveys, the second survey would be filled in with pre-knowledge. As visible in Figure 44, only a small portion of the sample filled in both surveys, meaning that only that portion filled in a survey with pre-knowledge.

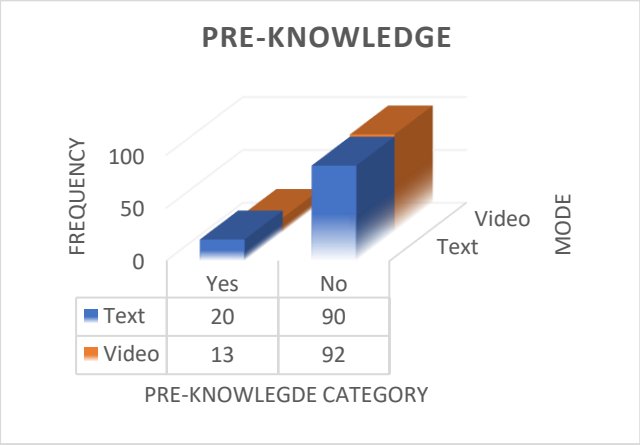


Figure 44: Distribution of pre-knowledge in the surveys

The chi-square test statistic for the variable pre-knowledge is 3.81. With only 1 degree of freedom, the critical value lies at 3.84 (Turney, 2023). Comparing the two, the conclusion is made that the two databases are not statistically different, as the chi-square test statistic is just smaller than the critical value (3.81 < 3.84).

4.3 Conclusion

As a rule of thumb, to perform an adequate statistical analysis, each profile would require at least 30 observations (California State University, n.d.). In this case, each respondent was presented with 8 profiles. With 32 profiles in the experimental design, this leads to approximately 120 respondents per survey.

Where 120 respondents would theoretically lead to 30 observations per profile, in the end only 111 useable cases were found for the text survey, as well as only 105 useable cases for the video survey. Additionally, the system used in LimeSurvey to randomize the profiles did not result in an even distribution, thus not every profile was assessed equally. As discussed in the first section of this chapter, the observations per profile differ. On average, the profiles in the text survey have 27.75 observations per profile, against 26.25 in the video survey. Although on the low side of the required minimum, a multinomial logit model is performed to predict the choice behavior and compare the choice behavior between the modes.

Furthermore, the merged categories are very similarly distributed when comparing the database of the text survey and the video survey. For the analysis the groups are merged as such to create big enough samples per category, as well as to conserve categories that are still relevant according to literature. An example is the category ‘household with children’ in the household composition variable, where Van Vliet et al. (2021) found that people with children value amenities more.

Lastly, per socio-demographic the chi-square test gives insights into statistical differences regarding socio-demographics between the two datasets. For this, the categories ‘other’ and ‘I'd rather not say’ are considered as missing, which reduces the degrees of freedom by 1. The findings are visible in Table 13.

Table 13: Statistical difference between the two datasets

Socio-demographic	Statistically different
Age	No
Gender	No
Income	No
Education level	No
Occupation	No
Household composition	No
Living environment	No
Station plaza visits Eindhoven	No
Other station plaza visits	Yes
Life satisfaction	No
Influence of station plaza on health	No
Background in architecture/urbanism	Yes
Pre-knowledge	No

With these very similar databases, a MNL model will be estimated to find the influence of attributes and their levels on the comfort rating, before another MNL model will be used to determine statistically significant differences in choice behavior between the textual and video survey.

5. Results

In this chapter the analysis method and the results are elaborated on. First of all, for this research a multinomial logit model (MNL) is used, as explained in chapter 3, for which the choice is made to merge the comfort rating into two categories (comfortable or not). With that database, an estimation of the influence of attributes on the comfortability rating of design scenarios is made. Then, the aim is to find statistically significant differences in choice behavior between the text and video survey. Finally, in the remainder of this chapter the results from these models are discussed. The full NLOGIT code and output is visible in Appendix L.

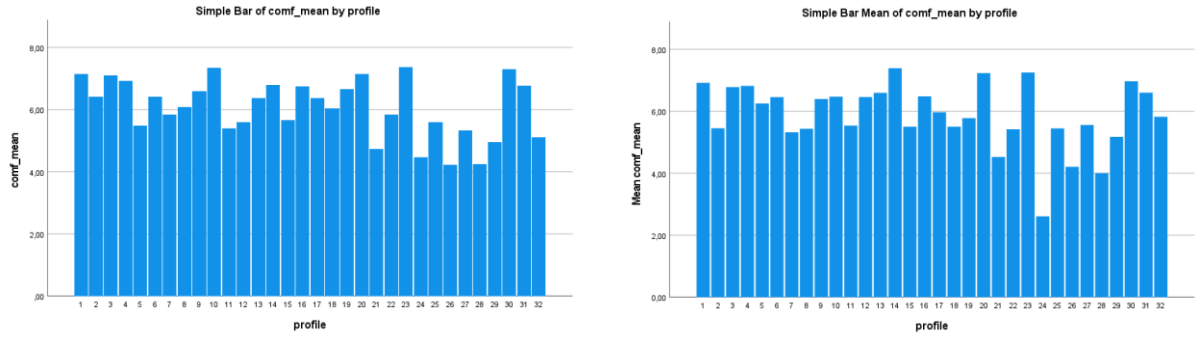


Figure 45 shows the mean comfortability rating per profile in the text mode (left) and the video mode (right). From these bar charts, already some similarities can be found. For example, profile 23 is regarded as comfortable in both modes. Further analysis in this chapter will provide insights in the choice behavior in the different modes.

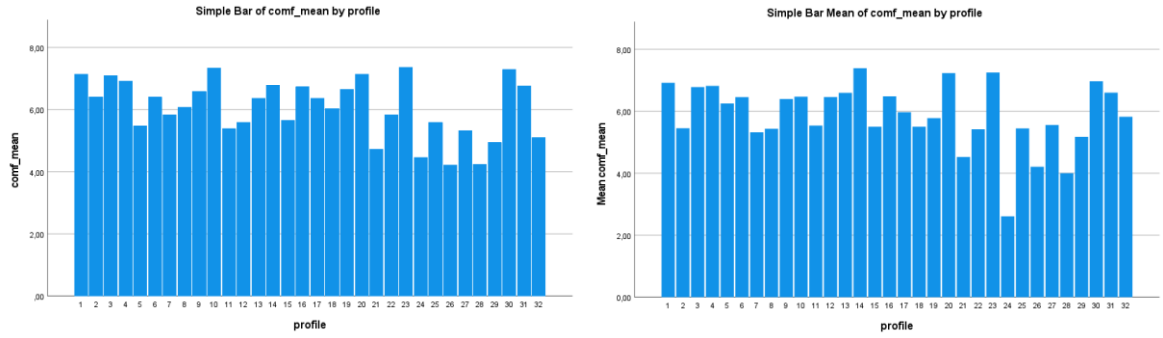


Figure 45: Bar chart of mean comfortability ratings per profile (left=text, right=video)

5.1 Attributes

First of all, an MNL model is used to find the importance of the attributes regarding the comfort rating. This means that the comfort rating that respondents provided per profile is used as the dependent variable, whereas the attribute levels in the presented profile are used as the independent variables.

In order to use an MNL to estimate the effect of attributes, respondents would need alternatives to choose from. The survey used in this research, only presented one scenario per task. Therefore, the 10 point comfort scale used in the survey is converted to a two level comfort scale, using the levels ‘feeling comfortable’ and ‘feeling not comfortable’, as was also elaborated on in section 3.3. The cut point was determined by looking at the distribution of the data, trying to create approximately equal groups. Therefore, the ratings 1 to 5 were merged to represent ‘Not comfortable’, and rating 6 to 10 were merged to represent ‘Comfortable. The dataset is then altered so that these two levels are the alternatives, and the provided rating by the respondents determines the chosen scenario (feeling comfortable or feeling not

comfortable). For example, if a scenario was rated with an 8 by a respondent, the dataset shows that the respondent chose a comfortable scenario. If the rating is in the range 1 to 5, the dataset shows that the respondent chose for the second alternative (as the respondent regarding alternative 1 as not comfortable). Furthermore, the datasets are converted to a long format data file. The python code used to transform the datasets, including elaborations, is visible in Appendix F to Appendix I. Finally, an MNL model can be used to estimate the effect of attributes to predict whether someone feels comfortable (yes or no) given the attributes of a scenario.
In order to perform the analysis, effect coding is used, of which the used levels are visible in Table 14. In the analysis, the text format data is represented by mode=1, while the video format data is represented by mode= -1.

Table 14: Effect coding attribute levels

Attribute	Level	A	B	C
Fountain	Present	1		
	Not present	-1		
Lampposts	9 lampposts	1		
	7 lampposts	-1		
Trees	15 trees clustered	1	0	0
	15 trees spread	0	1	0
	9 trees	0	0	1
	No trees	-1	-1	-1
Benches	15 benches	1	0	0
	8 benches	0	1	0
	4 benches	0	0	1
	No benches	-1	-1	-1
Grass	66% grass	1	0	0
	50% grass	0	1	0
	33% grass	0	0	1
	0% grass	-1	-1	-1
Building height	Skyscraper	1	0	0
	High-rise	0	1	0
	Medium-rise	0	0	1
	Low-rise	-1	-1	-1

5.1.1 MNL textual survey

The first model evaluates the attribute levels in the text survey, which is seen in Table 15. To do so, only the text data is included. There are 2 alternatives for each observation. The first alternative is defined as ‘Comfortable', the second as ‘Not comfortable’. The utility of the second alternative (V_{nc}) is equal to 0 by definition. The utility of the first alternative (V_c) depends on the constant and the attribute levels. The higher the value of V_c, the higher the probability the respondent feels more comfortable with the design scenario. Section 1.3 elaborated on the relation between health and comfortability. As the level of comfortability can influence health, the higher the value of V_c, the better the influence of that design scenario or attribute on health.

As discussed in the methodology section, first the model fit can be calculated by subtracting the ratio of the loglikelihood of the estimated model and the loglikelihood of the null model from 1. Using Equation 6, this leads to the following result:

$$\rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} = 1.0 - \frac{-479.82199}{-615.51470} = 0.22$$

With the McFadden Rho Squared within the range of 0.2 and 0.4, the model can be deemed adequate (McFadden, 1974).

According to the results, the constant is positive and significant, meaning that for the average design scenario, there is already a more than 50% probability the design yields a comfortable environment. The coefficients attached to the attribute levels reduce or increase the probability of people feeling comfortable with the scenario. Looking at the level fountain, which indicates there is a fountain present, the V_c is increased with 0.341. On the other hand, the absence of a fountain would decrease V_c by 0.341. This indicates that the presence of a fountain results in a more comfortable station plaza than the absence of a fountain.

Table 15: Results MNL model of the text survey

Variable level	**Coefficient MNL**	**Sign.**
Constant	0.837	***
fountain	0.341	***
9 lampposts	0.152	*
15 trees cluster	0.631	***
15 trees spread	0.288	**
9 trees	0.150	
15 benches	0.641	***
8 benches	0.389	***
4 benches	0.010	
66% grass	0.174	
50% grass	0.232	
33% grass	0.224	
Skyscrapers	-0.265	*
High-rise	-0.076	
Medium-rise	0.031	

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

From Table 15 the influence of the attribute levels on V_c can be calculated. Looking at the significance of the results, the attribute levels 'fountain present', '9lampposts', '15 trees clustered, '15 trees spread', '15 benches', '8 benches', and 'skyscrapers' are significant, of which most at a 1% level. The levels that are not included in Table 15, are implicitly included because of their value in the effect coded database. The coefficient however can be calculated by summing the coefficients of the other levels of that same attribute and multiplying that by -1. For example, the coefficient for 'no benches' is: -(0.641+0.389+0.010) = -1.039.
From the model, the following conclusions can be drawn:

- Respondents feel more comfortable with a fountain being present compared to the absence of a fountain.
- Respondents feel more comfortable with 9 lampposts compared to 7 lampposts
- Respondents feel most comfortable with 15 clustered trees.

- Respondents do not feel comfortable in a scenario with fewer benches, and feel most comfortable in a scenario with 15 benches.
- No conclusions can be drawn for the grass levels as there is no statistically significant level.
- Respondents feel less comfortable with the presence of skyscrapers. Other levels of building height are not significant.

Considering the values of the coefficients, it is visible that the number of benches has the biggest impact on feeling comfortable.

Figure 46 provides a schematic overview of the coefficients resulting from the MNL model.

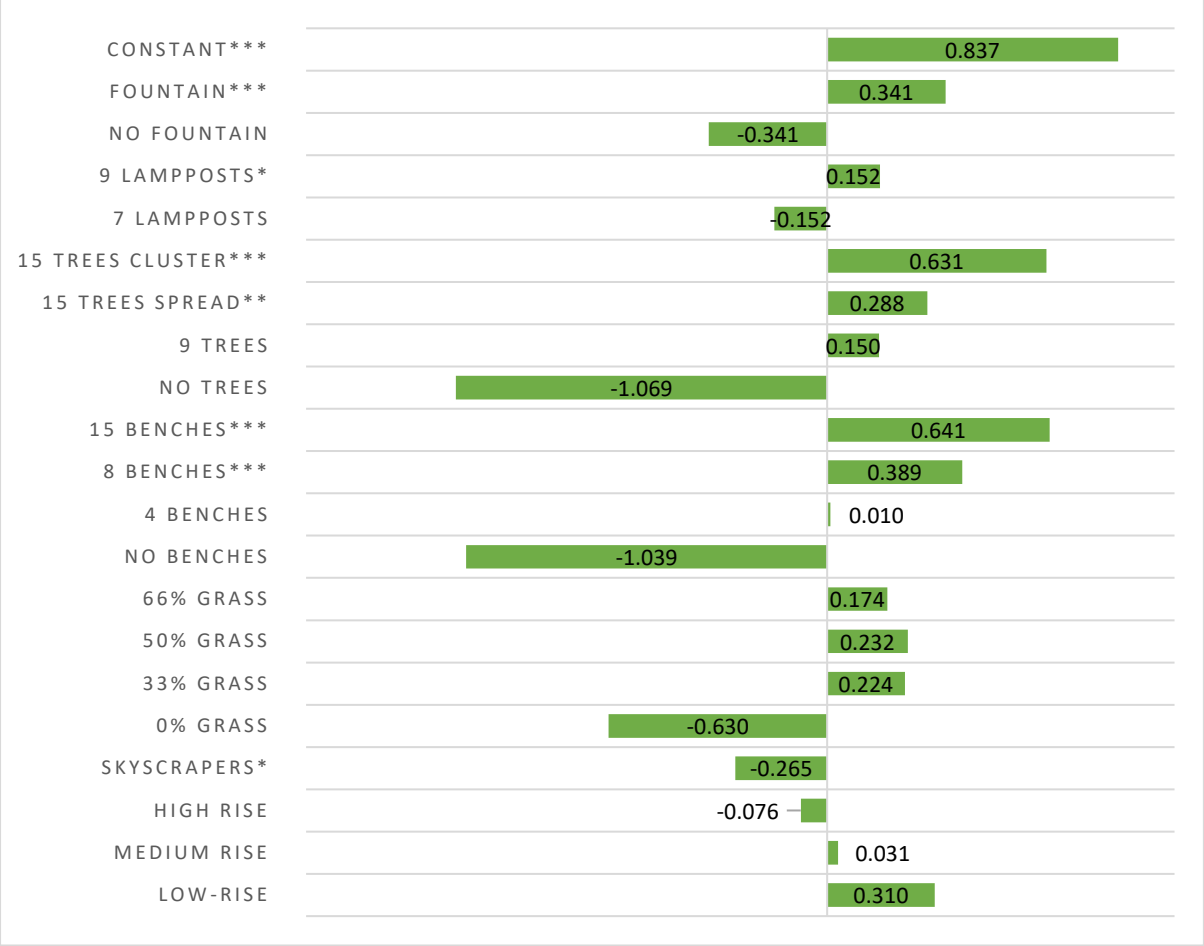


Figure 46: Chart of coefficients from the MNL model of the text survey

5.1.2 MNL video survey

In order to analyze the database retrieved from the video survey, this time the mode with value 1 (text) is excluded from the database. Initially, the McFadden Rho Square can be determined using Equation 6. In this case, this leads to the following result:

$$\rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} = 1.0 - \frac{-475.32369}{-582.24363} = 0.18$$

The McFadden Rho Squared is therefore just out of the range of 0.2 and 0.4. Conclusively, the model is not optimal, but still acceptable (McFadden, 1974).

A first model observation that is notable when looking at Table 16 is the lower constant. In general, this means that respondents watching and rating the video scenarios were more critical after seeing the videos compared to seeing the text scenarios.

Table 16: Results MNL model of the video survey

Choice	**Coefficient MNL**	**Sign.**
Constant	-0.631	***
fountain	0.110	
9 lampposts	0.177	**
15 trees cluster	0.283	**
15 trees spread	0.418	***
9 trees	0.545	***
15 benches	0.615	***
8 benches	0.200	
4 benches	-0.391	***
66% grass	0.338	**
50% grass	0.248	*
33% grass	0.267	*
Skyscrapers	0.048	
High-rise	-0.133	
Medium-rise	0.072	

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

Furthermore, Table 16 provides an overview of the attribute levels and their respective coefficients. The results are relatively similar compared to the results of Table 15 of the text survey. In this case, the significance of the following attribute levels is at least at a 10% level: ‘9 lampposts’, ‘15 trees clustered’, ‘15 trees spread’, ’9 trees’, ‘15 benches’, ‘4 benches’, ‘66% grass’, ‘50% grass’ and ‘33% grass’. Considering the coefficients, the following conclusions can be made:

- The constant is, in contrast to the first model, negative. This means that in the video survey, on average, the probability of respondents rating a scenario as comfortable is lower compared to a scenario presented in text.
- Respondents feel more comfortable with 9 lampposts compared to 7 lampposts.
- Respondents in this case feel most comfortable with 9 trees, although 15 trees spread over and clustered on the plaza is also regarded as comfortable. The implicitly included level of ‘no trees’ would have a part worth utility of: -(0.283+0.418+0.545)= -1.246. Therefore, it is assumed that respondents feel least comfortable in the scenario without trees, while 15 clustered trees is the least rated scenario among the scenarios including trees.

- Respondents feel least comfortable in a scenario without benches, but also a scenario with only 4 benches has a negative impact on the comfortability.
- Respondents feel most comfortable with the highest percentage of grass coverage. In contrast to the first model, the levels of grass coverage are statistically significant at at least a 10% level in this case. The fourth level, 'no grass', has a part worth utility of -0.853. Concluding, there is only a small difference in the part worth utilities of the grass levels with 33%, 50% and 66% coverage. Thus in general, respondents feel more comfortable with the presence of grass compared to the absence of grass, with 66% grass being the most comfortable option by a slight margin.
- The results regarding the building height are all insignificant.

Also in this case, the presence of 15 benches has the biggest impact on the comfortability, and therefore is regarded as most important factor in the comfort rating of respondents. Compared to the text model, the importance of benches is slightly reduced. In this case, the coefficients for levels of grass coverage on the plaza are statistically significant. The importance of the presence/absence of a fountain (not statistically significant) and the number of lampposts is limited in this case, whereas also the result for the building height is insignificant for all included levels.

Figure 47 provides an overview of the coefficients from this MNL model.

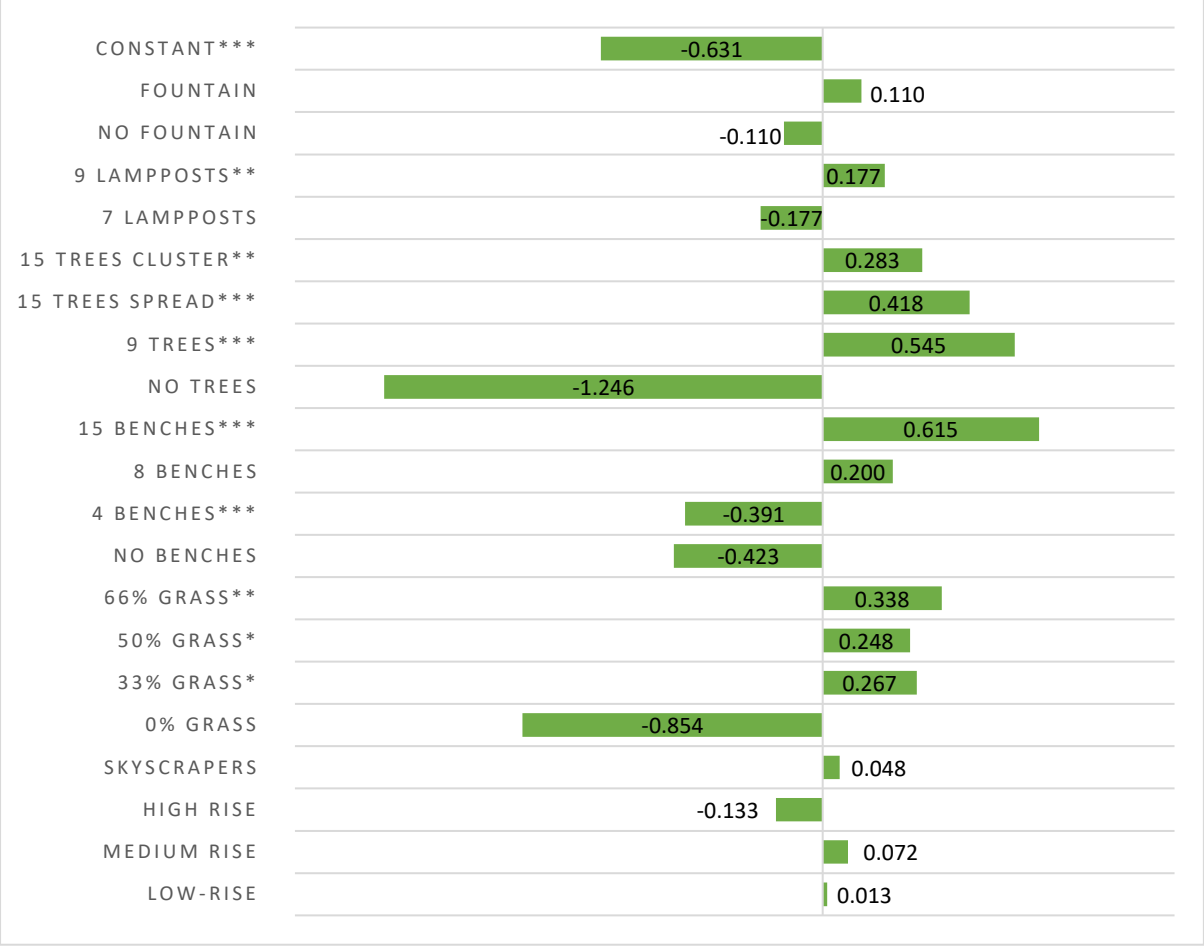


Figure 47: Chart of coefficients from the MNL model of the video survey

5.1.3 MNL all respondents

Lastly, an MNL model can be produced that incorporates both the text and video survey databases. This increases the number of respondents to 217 in total. An increase in respondents can lead to more significant outcomes in the MNL model. To start, the McFadden Rho Square is determined again. This is done using Equation 6 below:

$$\rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} = 1.0 - \frac{-1055.72887}{-1197.7583} = 0.12$$

In this case, the McFadden Rho Square is 0.12, indicating that the model estimated on the combines datasets performs less than the separate models. Apparently, perception of comfort shows contrasting results given different presentation modes. This will be investigated in this section.

These outcomes are visible in Table 17.

Table 17: MNL model of the total database

Choice	**Coefficient MNL**	**Sign.**
Constant	0.091	*
Fountain	0.218	***
9 lampposts	0.171	***
15 trees cluster	0.438	***
15 trees spread	0.367	***
9 trees	0.319	***
15 benches	0.517	***
8 benches	0.263	***
4 benches	-0.123	
66% grass	0.301	***
50% grass	0.197	**
33% grass	0.222	**
Skyscrapers	-0.073	
High rise	-0.003	
Medium rise	0.035	

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

Notably in Table 17, the level of significance of the constant drops to a 10% level. On the other hand, the significance of the attribute levels is at a 1% level for most of the significant levels. In this case, the significant attribute levels are 'fountain', '9 lampposts', '15 trees clustered', '15 trees spread', '9 trees', '15 benches', '8 benches', and '66% grass'. The levels '33% grass', and '50% grass' are significant at a 5% level. Using the given coefficients for these attribute levels, the following conclusions can be drawn:

- The constant is rather small in the model containing all respondents. Due to the differences in the previous model, there is a counter effect in the size of the constant. Whereas the constant is positive in the case of the text scenarios, it is negative in case of the video scenarios. As a result, there is a slightly positive constant, meaning that considering all respondents, there is a slightly over 50% probability that the design yields a comfortable design.
- In general, respondents feel more comfortable when a fountain is present compared to the absence of a fountain. The value of V_c is reduced when there is no fountain

present, meaning that the probability for respondents to choose a scenario with comfort rating 6 to 10 decreases. In other words, when the comfort rating is 6 to 10, there is a higher probability of a fountain being present.

- Respondents feel more comfortable with more (9) lampposts over fewer (7) lampposts, as the V_c is decreased for 7 lampposts.
- Respondents feel most uncomfortable with the absence of trees. Furthermore, the V_c increases as the number of trees increases. Also, respondents feel slightly more comfortable when the trees are clustered compared to spread, with respective coefficients of 0.438 and 0.367.
- Fewer benches is also regarded as uncomfortable, with the V_c increasing for 8 and 15 benches.
- The absence of grass on the plaza is also regarded as uncomfortable. Interestingly, the coefficient for 33% grass is higher than 50% grass, whereas the coefficient for 66% grass is highest with a value of 0.301. Therefore, the V_c is sligthly higher with the small (33%) and especially the large grass coverage (66%).
- No conclusions can be made on the building height as this attribute is not significant.

From this model, the conclusion can be made that the presence of 15 benches has the biggest impact, which is similar to the previous models. Again, the impact of the number of lampposts is limited, whereas the building height is once more not significant.

Figure 48 provides an overview of the coefficients from the MNL model containing all respondents.

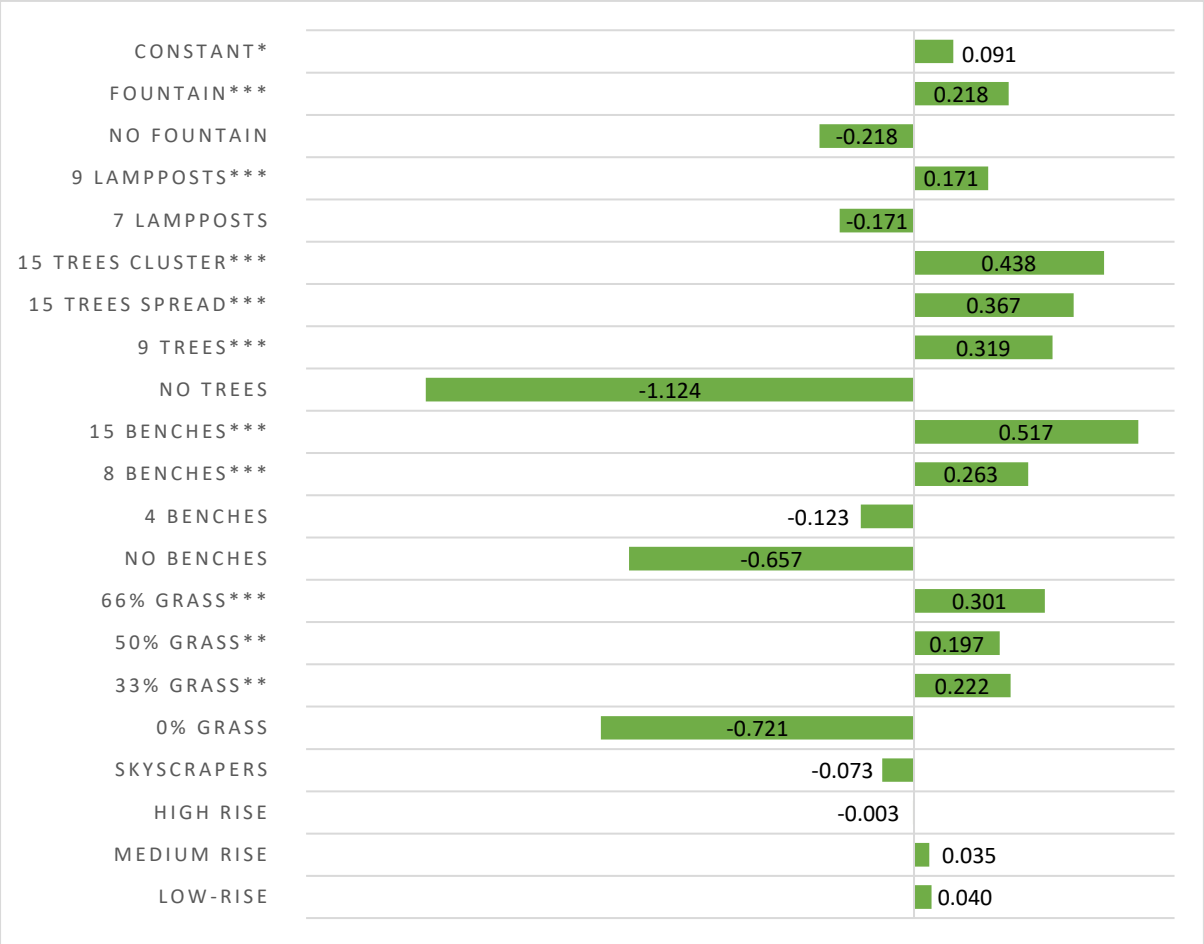


Figure 48: Chart of coefficients from the MNL model with all respondents

5.1.4 Conclusion

To conclude, there are some similarities between the produced models. In general, we can conclude that the presence of 15 benches has the highest influence on V_c and thus comfort rating of respondents, as this was found for all three models. Although literature did not state benches as the most important factor, it was mentioned as a positive effect on comfortability. Literature stated that the presence of greenery and the number of trees had the biggest impact on comfort. The MNL models do prove the importance of these aspects in the form of number and grouping of trees and grass coverage. For these attributes, the highest positive influence on V_c was found for the levels including greenery, which is thus in coherence with the literature. Furthermore, all three models proved that the number of lampposts has a slight positive impact on the overall comfort rating. Literature stated a positive effect for lampposts on a plaza. Although the impact on V_c is relatively small, it is coherent with the literature. Interestingly, as the building height turns out to be insignificant in most models, the attribute seems less relevant. Overall, the respondents prefer a scenario in which there is a fountain present, there are 9 lampposts, there are trees present (level depends on the model), 15 benches are present, and there is grass present (level depends on the model). Building height seems to be less important, although skyscrapers are not preferred in the text mode. Literature stated the relation between comfort and health, where for example greenery, amenities, lampposts and a fountain contribute to both comfort and health. Being comfortable contributes to health, but also certain attributes itself contribute to health (e.g. greenery vs cars). The results of this MNL model show that the choice behavior of people corresponds with what literature states as 'healthy'. This is seen in the preference for greenery over pavement, the preference for the maximum number of lampposts, the preference for the maximum number of benches, and the presence of a fountain.

Interestingly, the model containing the text mode performed best with a McFadden Rho Square of 0.22 (compared to 0.18 for the video mode and 0.12 for the model with the entire dataset). Literature stated that in videos there is a higher level of information recalling and it is easier to evaluate choices. There is also a higher level of vividness of the material. Respondents are presented a clearer model in the video mode, which leaves less room for interpretation compared to the text mode. Therefore, it was expected that the model including the video mode would perform better. This is thus not coherent with literature.

5.2 Choice behavior presentation modes

After determining the influence of individual attributes, the difference in choice behavior can be measured by means of an MNL model. To do so, an extra set of variables needs to be added to the datafile in order to measure the differences between attribute effects on the perception of comfort. All variables *X* related to the attributes are copied into *X'.* For the text mode *X'*=*X*, and for the video mode *X'*=-*X*, Estimating parameters for all *X* and *X'* variables results in parameters for *X* representing the part worth utilities for all respondents (like those presented in Figure 48), while the parameters for the *X'* variables measure the differences between the two samples. Thus, *βX* represents the part worth utility of a certain attribute level for all respondents, *βX-αX'* (or (*β-α)X*)) represents the part worth utility of that attribute level for the respondents in the text mode and *βX*+*αX'* (or *β*+*αX*)) for the respondents in the video mode. Here, *α* represents the difference in coefficients between the text mode data and video mode data. If *α* is significant, the difference between both modes is significant regarding that attribute level.

First, the McFadden Rho Square for this model can be computed with the help of Equation 6:

$$\rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} = 1.0 - \frac{-955.14568}{-1197.75833} = 0.20$$

As seen, it leads to a value of 0.2, meaning that the model has an adequate goodness of fit as it falls in the 0.2 – 0.4 range.
The output of the MNL model is visible in Table 18.

Table 18: MNL model to compare presentation modes

Choice	Coefficient MNL	Sign.	
*Constant**	0.103	*	Part worth utilities all respondents X
*fountain****	0.226	***	
*9 lampposts****	0.164	***	
*15 trees cluster****	0.457	***	
*15 trees spread****	0.353	***	
*9 trees****	0.348	***	
*15 benches****	0.628	***	
*8 benches***	0.294	**	
*4 benches***	-0.191	**	
*66% grass****	0.256	***	
*50% grass***	0.240	**	
*33% grass***	0.246	**	
Skyscrapers	-0.108		
High-rise	-0.108		
Medium-rise	0.051		
*Constant'****	0.734	***	Measuring differences between samples X'
*fountain'***	0.115	**	
9 lampposts'	-0.012		
*15 trees cluster'**	0.174	*	
15 trees spread'	-0.065		
*9 trees'**	-0.198	*	
15 benches'	0.013		
8 benches'	0.095		
*4 benches'***	0.201	**	
66% grass'	-0.082		
50% grass'	-0.008		
33% grass'	-0.022		
Skyscrapers'	-0.157		
High-rise'	0.285		
Medium-rise'	-0.020		

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

A first check will confirm the relation of this model with the previous models. This is done by for example taking the constant and subtracting the constant' (constant created by multiplying with the mode). This should lead to the constant provided in the model based on the video survey data. This would lead to 0.103 – 0.734 = -0.631, which is similar to the value of the constant in Table 16.

If the parameter estimates have a |z|>Z* value below 0.10, there is a significant difference between the two presentation modes. As seen in Table 18, there are some parameters that are statistically significant. These are found for the constant, fountain, 15 trees clustered, 9 trees, and 4 benches. Thus, this means that the choice behavior of respondents significantly differs for 4 attribute levels, as well as the overall comfort rating. The other attributes that have a |z|>Z* value above 0.10 are not statistically significant, and therefore choice behavior between the two presentation modes does not differ for these attributes.

Taking a closer look at the significant coefficients, an interpretation can be made. As mentioned in this section, the part worth utility for an attribute level in the text mode is calculated by $(\beta+\alpha)X$, and $(\beta-\alpha)X'$ for the video mode. Regarding the constant, this leads to a part worth utility of -0.631 for the video mode, and 0.837 for the text mode, also seen in Figure 49. From this, the conclusion can be drawn that in the text mode respondents are more likely to rate a scenario as more comfortable compared to the video mode. Similarly, the part worth utilities for the other statistically significant attribute levels can be constructed. Looking at the presence of a fountain; in the text survey the presence of a fountain has a statistically significantly more positive impact on the comfortability rating compared to the video variant. Regarding the presence of 15 clustered trees on the plaza, there is a slightly lower probability that respondents in the video mode regard this as comfortable compared to the text mode. In the video mode, respondents are also more likely to consider 4 benches present as comfortable compared to the text mode.

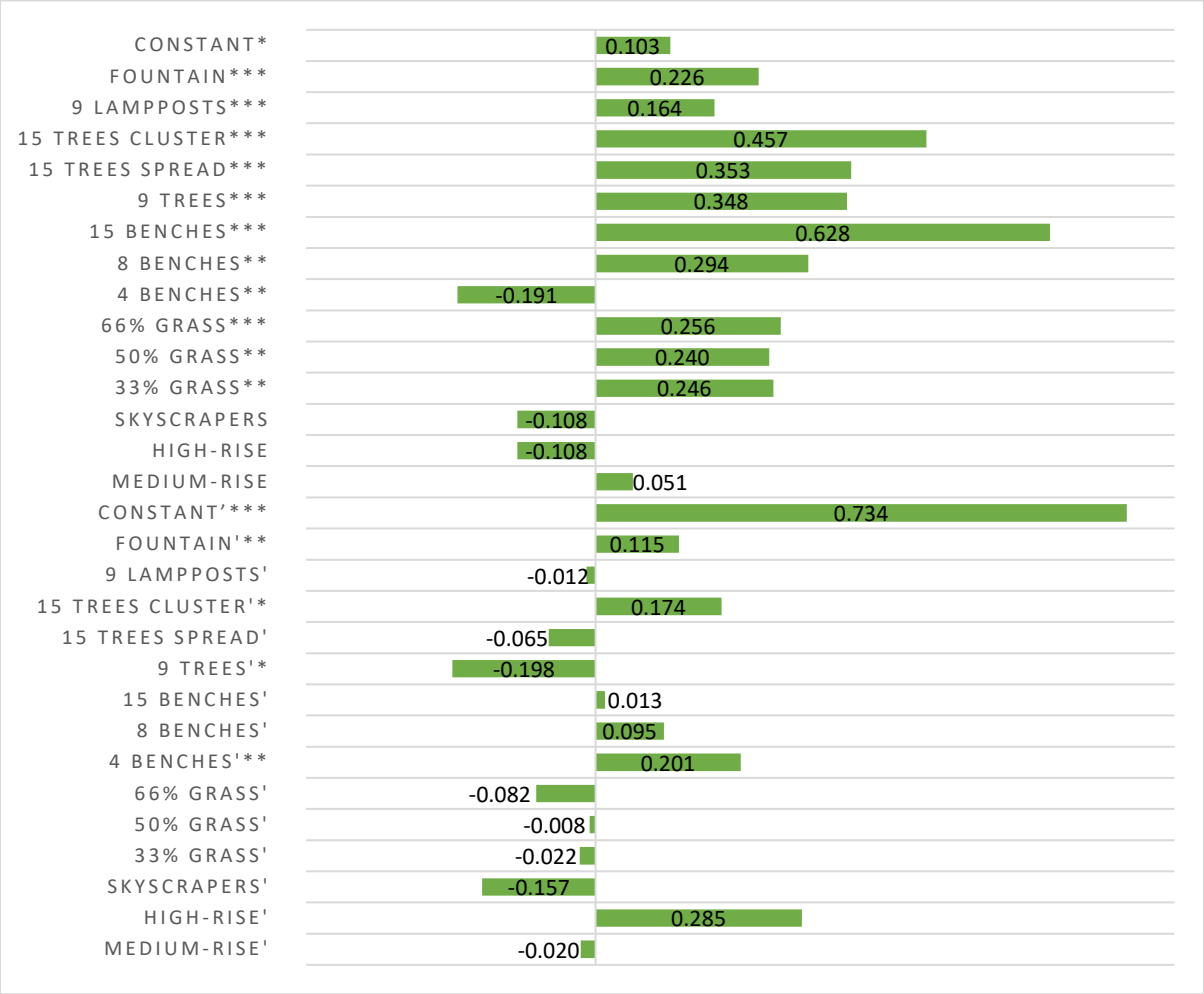


Figure 49: Chart of coefficients from the MNL model comparing presentation modes

Conclusion

The first MNL models incorporating the text and video mode already showed slight differences in choice behavior. These differences are tested in this MNL model. First of all, the model is deemed adequate as the McFadden Rho Square has a value of 0.2. As 4 attribute levels as well as the constant are statistically different, the conclusion can be drawn that the presentation mode does influence the choice behavior in urban design. For this research, a difference was found for the overall comfortability rating, the presence of a fountain, 15 trees

clustered, 9 trees present, and 4 benches present. Therefore, people should be aware that choice behavior might differ when using different modes of presentation. Importantly, as was shown in chapter 4, the datasets did in most cases not statistically differ from each other. Therefore, the found effects are likely related to differences in choice behavior due to presentation mode, and not due to differences within the samples. The literature provided insights into the differences of each presentation mode. For example, using text leads to possible different interpretations of respondents. In addition, the level of information recalling is low. Since the exposure time for text is also low, this does lead to a high level of effectiveness ($\frac{Information\ recalling}{Exposure\ time}$) (Schneiders, 2020). Using videos leads to higher levels of information recalling, as well as less room for interpretation. It is easier for respondents to evaluate choices, and the level of vividness of the material is higher. These intrinsic differences between the presentation modes would predict a difference in choice behavior when comparing the two modes. Therefore, the results of this MNL model are coherent with the literature found.

5.3 Personal characteristics

Additionally, to the previous model, the influence of the personal characteristics can also be measured through an MNL model. Therefore, socio-demographic variables have been added to the model. These socio-demographic variables also require effect coding, of which the coding is visible in Table 19. The advantage of effect coding in this case is that levels which are not interesting for the analysis, such as 'I'd rather not say' can be omitted for that specific variable, while the data for the other variables provided by that particular respondent is still used.

Table 19: Effect coding of socio-demographic variables

Attribute	Level	A	B	C
Gender	Female	1		
	Male	-1		
	I'd rather not say	0		
Age	18 – 34 years	1	0	
	35 – 54 years	0	1	
	55+ years	-1	-1	
Income	Low	1		
	High	-1		
	I'd rather not say	0		
Education level	Low	1		
	High	-1		
	I'd rather not say	0		
Occupation	Not working	1		
	Working	-1		
	I'd rather not say	0		
Household composition	Single	1	0	
	Two-person	0	1	
	Household with children	-1	-1	
	I'd rather not say	0	0	
Living environment	City center	1	0	
	City suburbs	0	1	
	(Small) town or rural	-1	-1	
	I'd rather not say	0	0	
Station plaza visits	Weekly	1	0	
	Monthly	0	1	
	(Almost) never	-1	-1	
Life satisfaction	Dissatisfied	1	0	
	Satisfied	0	1	
	Very satisfied	-1	-1	
Health influence	Unimportant	1	0	
	Neutral	0	1	
	Important	-1	-1	
Background	Yes	1		
	No	-1		
Pre-knowledge	Yes	1		
	No	-1		

First, the McFadden Rho Squared can be computed again with the help of Equation 6:

$$\rho^2 = 1.0 - \frac{LL(\beta)}{LL(0)} = 1.0 - \frac{-892.63026}{-1197.75833} = 0.25$$

In this case, it leads to a value of 0.25, which indicates that the model is deemed adequate.

The MNL model in Table 20 introduces the socio-demographic variable into the model. The estimated parameters in Table 20 directly affect the utility of comfort *(V_c)*.

Table 20: MNL model including socio-demographics

Choice	**Coefficient MNL**	**Sign.**
Constant	0.107	*
Fountain	0.259	***
9 lampposts	0.148	**
15 trees cluster	0.508	***
15 trees spread	0.387	***
9 trees	0.337	***
15 benches	0.662	***
8 benches	0.305	***
4 benches	-0.202	**
66% grass	0.306	***
50% grass	0.272	**
33% grass	0.264	***
Skyscrapers	-0.168	
High-rise	-0.087	
Medium-rise	0.092	
Constant'	0.127	
fountain'	0.134	**
9 lampposts'	-0.009	
15 trees cluster'	0.202	*
15 trees spread'	-0.114	
9 trees'	-0.194	*
15 benches'	-0.043	
8 benches'	0.121	
4 benches'	0.213	**
66% grass'	-0.064	
50% grass'	0.002	
33% grass'	-0.019	
Skyscrapers'	-0.183	*
High-rise'	0.082	
Medium-rise'	0.003	
Female	-0.344	***
Year1834	0.381	***
Year3554	-0.417	***

Low income	-0.056	
Low education	0.104	
Not working	-0.441	
SinglePersonHH	0.232	**
TwoPersonHH	0.069	
CityCenter	0.180	
CItySuburbs	-0.212	**
WeeklyEindhoven	0.188	
MonthlyEindhoven	-0.252	**
WeeklyOther	0.216	**
MonthlyOther	0.232	**
LifeDissatisfaction	-0.371	***
LifeSatisfaction	0.339	***
HealthUnimportant	0.165	
HealthNeutral	-0.232	**
ArchBackground	-0.369	***
Preknowledge	-0.194	**

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

As visible, there are some socio-demographics that are statistically significant. From these coefficients, the following conclusions can be drawn:

- Females are more critical compared to males when considering the overall comfortability. So, the probability of a female rating a scenario as comfortable is smaller than the probability of a male doing so.
- Respondents in the age category of 18 to 34 years old have a higher probability of regarding a scenario comfortable compared to the age category of 35 to 54 years old.
- The education levels are not statistically significant.
- The income levels are not statistically significant.
- The occupation levels are not statistically significant.
- Single person household have a higher probability of viewing a scenario as comfortable.
- There is a lower probability that people living in city suburbs rate a scenario as comfortable.
- Respondents who have reported that they visit the Eindhoven station plaza on a monthly basis have a lower probability of rating a scenario as comfortable.
- Respondents who visit other station plazas weekly or monthly both have a higher probability of rating a scenario as comfortable.
- Respondents who have reported they are dissatisfied with life have a lower probability to rate a scenario as comfortable. On the other hand, respondents who are satisfied with their life have a higher probability of rating a scenario as comfortable.
- Regarding the health influence, respondents who reported a neutral health influence have a lower probability of rating a scenario as comfortable.
- Respondents with a background in architecture or urbanism are more critical compared to respondents without a background in the field. In other words, as respondents with a design background have a lower probability to rate a scenario as comfortable.
- Lastly, respondents who had pre-knowledge gained by filling in both surveys had a lower probability of rating a scenario as comfortable.

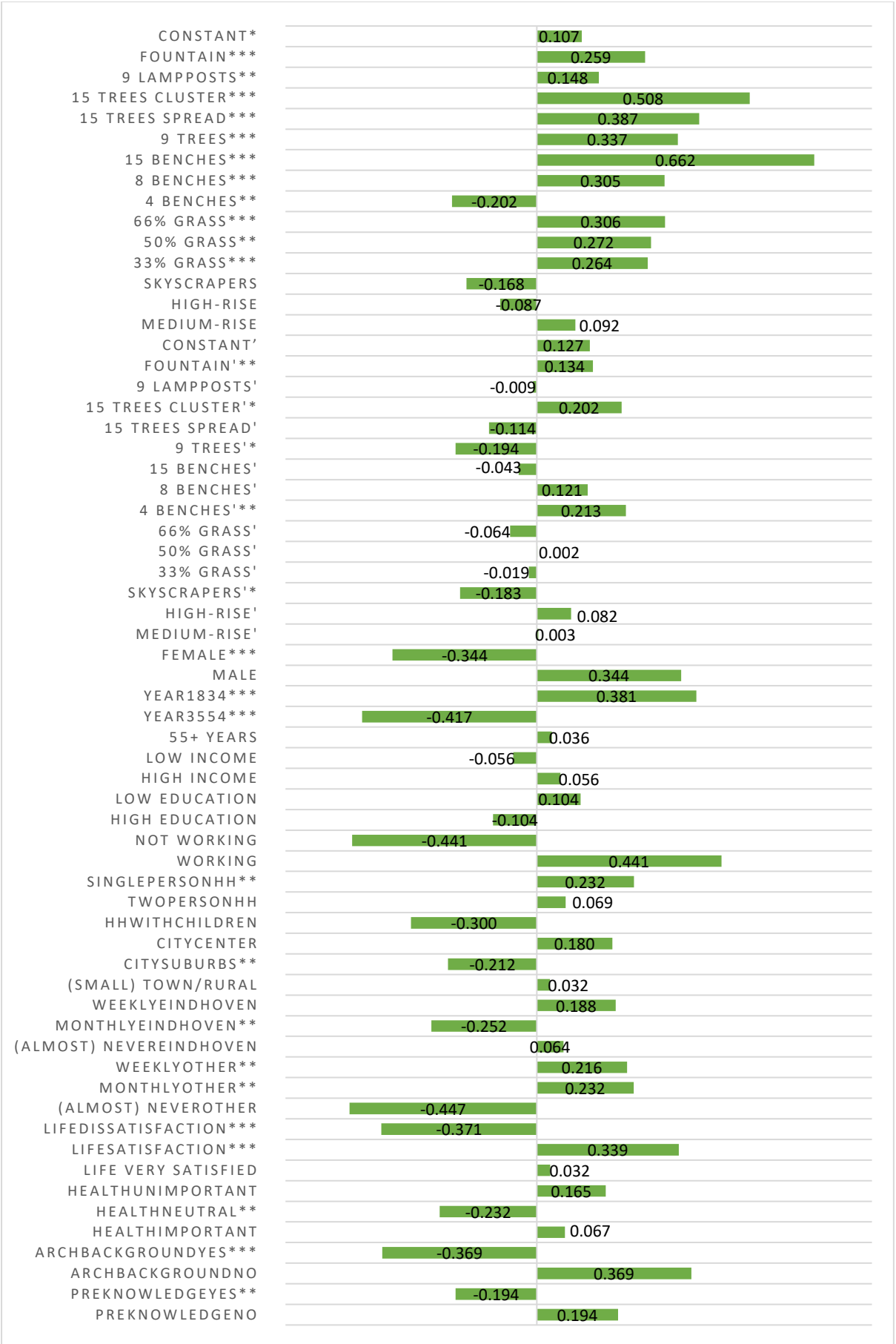


Figure 50: Chart with coefficients from the MNL model with the socio-demographics

Conclusion

First of all, the model is deemed adequate with a McFadden Rho Square value of 0.25.
Many of the socio-demographics have an influence on the comfortability rating. This holds for gender, age, household composition, living environment, visits to the Eindhoven station plaza or other station plazas, life satisfaction, health influence, a background in architecture, and pre-knowledge.
Comparing the results to the literature found, there are some similarities. First of all, the fact that women tend to be more critical regarding the comfortability rating is coherent with the literature as stated in section 2.5. Research also showed that higher age groups also valued amenities more, as well as nature. In other words, it could be stated that this group is less likely to be comfortable in case of the absence of these facilities. This is also supported by the model, where the youngest age group has the highest probability to be comfortable on the plaza in general. Therefore, these results can also be linked as coherent to the literature. Although literature stated that lower educated people felt more comfortable on plazas and squares, this was not confirmed in this research as the results for these categories are not statistically significant. The same holds for the occupation variable.
Other aspects, such as the frequency of station plaza visits (both Eindhoven and other), and the life satisfaction, also had a significant impact on the probability for rating a scenario as comfortable. Respondents who report visiting the Eindhoven station plaza monthly have a lower probability to rate a scenario as comfortable compared to respondents reporting they visit other station plazas. This makes sense because respondents visiting the Eindhoven station plaza are more familiar with the plaza and probably have a stronger opinion on it.
Respondents who report to have a background in architecture or urbanism are also found to be more critical. As these people have experience with design and the implications of certain choices (e.g. heat island effect), these people could be more critical. Additionally, respondents who had pre-knowledge by filling in the other survey as well were found to be more critical. Lastly, respondents who report a dissatisfaction in life have a lower probability to rate a scenario as comfortable compared to respondents who report a higher level of satisfaction, which might be related to how positive the respondent is at this moment in life.

5.4 Optimal designs

The final questions in the survey gathered data on the optimal attribute levels per attribute according to the respondent, as was visible in Figure 13 and Figure 14. In this question respondents are provided with all attribute levels, after which the most preferred level has to be chosen. The frequencies of the chosen levels can be compared per attribute between text and video, but in this case also the IVE experiment by Dane & Evers (2023) can be involved in the comparison. In the MNL models, the importance of attributes is estimated from comfortability ratings on an entire design scenario, while the results of this section discuss the data retrieved from the final question in the survey that addresses each attribute separately. Therefore, there might be differences when evaluating an attribute in a scenario or when evaluating it on its own.

5.4.1. Frequencies of optimal levels

An overview per attribute is provided in the following sections. Worth noting, the IVE experiment had 43 respondents, which is less than the textual and video experiment had. The respondents of the IVE experiment consisted of graduate students and academics, VR developers, members of the citizen initiatives, representatives of the municipality of Eindhoven and Amsterdam (i.e. participation advisors, area managers, ICT developers, urban designers) and representatives of the Urban Development Initiative. This difference in sample characteristics should be considered when interpreting the results. The most preferred attribute levels according to the MNL model are highlighted in green. Lastly, a statistical

comparison is made between each couple of modes (text-video, text-IVE, video-IVE) by computing the chi-square test statistic and testing it on the critical value.

Grass

Table 21 provides an overview of the most preferred level in case of the grass coverage for the text and video survey, as well as the IVE experiment.

Table 21: Frequencies of chosen optimal grass level by respondents

Grass coverage	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
0 % grass	1	0.9	1	1.0	0	0.0
33% grass	23	2.7	13	12.4	4	9.8
50% grass	50	45.0	33	31.4	12	26.8
66% grass	37	33.3	58	55.2	24	56.1
No preference	-	-	-	-	3	7.3
Total	111	100	105	100	43	100

This is also visualized in Figure 51. In the text variants respondents are more likely to choose the 50% grass coverage as most preferred level, while in the visual presentation modes this shifts towards 66% grass coverage. Remarkably, for all presentation modes the level of 0% grass coverage is not favored at all, with only 2 selections in the entire sample.

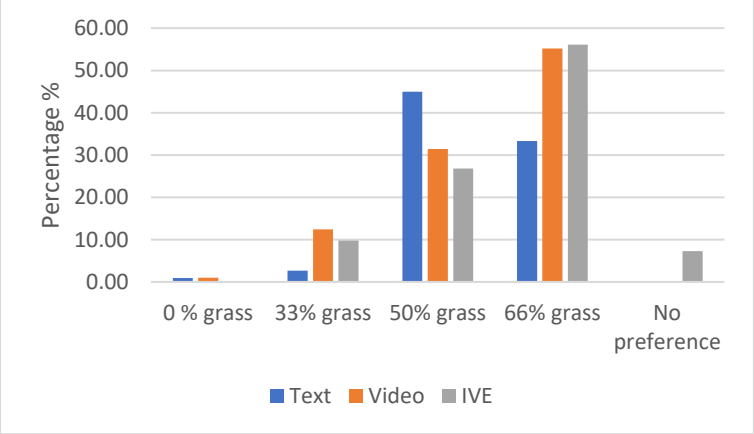


Figure 51: Most preferred grass coverage level per presentation mode

The chi-square test statistic is higher than the critical value when comparing the text to video (10.597) and text to IVE (8.939) choices. This therefore means that there is statistically significant different choice behavior between these modes when assessing the grass levels. There is no statistically significant difference between the video and IVE mode (0.394).

Building height

In Table 22 the frequencies of the chosen optimal building height per presentation mode is visible.

Table 22: Frequencies of chosen optimal building height by respondents

Building height	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Skyscraper	12	10.8	15	14.3	16	36.6
High-rise	14	12.6	20	19.0	17	39.6
Medium-rise	39	35.1	37	35.2	6	14.6
Low-rise	46	41.4	33	31.4	3	7.3
No preference	-	-	-	-	1	2.4
Total	111	100	105	100	43	100

A visualization of this data can be seen in Figure 52. Looking at this chart, a clear difference is seen between mainly the IVE experiment compared to the text and video experiments. In the IVE experiment, respondents preferred the skyscrapers and high-rise respectively more frequently. On the other hand, the text and video variant preferred lower levels of building height, with medium-rise and low-rise being the more frequently chosen levels. For the text variant, the conclusion can even be made that the lower the building height, the better according to the respondents.

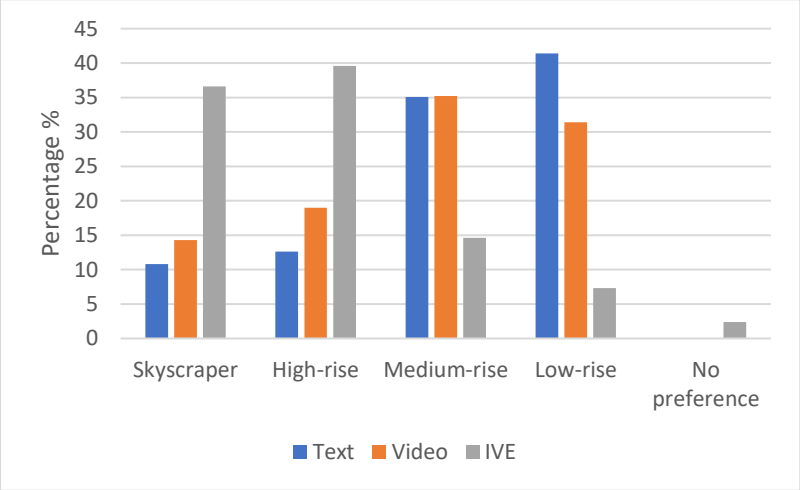


Figure 52: Most preferred building height level per presentation mode

In this case, the chi-square test statistic shows there is a significant difference in choice behavior between the text and IVE mode, and the video and IVE mode. The comparison between text and video provided a chi-square test statistic lower than the critical value, meaning there is no significant difference in choice behavior between these modes.

Number of lampposts

Table 23 provides an overview of the frequencies regarding the most preferred number of lampposts on the Eindhoven station plaza. Here, large differences are apparent between the levels across all presentation modes.

Table 23: Frequencies of chosen optimal number of lampposts by respondents

Lampposts	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
7 lampposts	12	10.8	15	14.3	13	29.3
9 lampposts	99	89.2	90	85.7	28	65.8
No preference	-	-	-	-	2	4.9
Total	111	100	105	100	43	100

Figure 53 visualizes the data on the number of lampposts on a bar chart. Clearly, the presence of 9 lampposts has the biggest preference, which holds for all three presentation modes. However, there is a slightly declining trend when looking at the percentages of 9 lampposts respectively to the increasing visuality of the presentation modes. Since there is only a slight difference of 2 lampposts on an entire plaza, it could be that respondents observe the difference better in text compared to the visual modes.

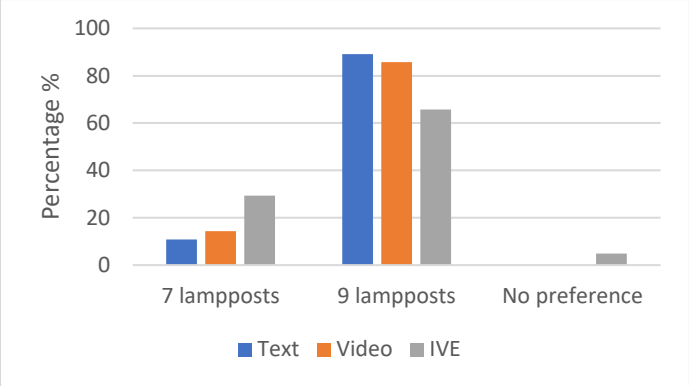


Figure 53: Most preferred number of lampposts per presentation mode

Regarding the lampposts, there is a significant difference in choice behavior between the text and IVE mode, and the video and IVE mode as the chi-square test statistic is higher than the critical value. On the contrary, there is no significant difference between the text and video mode.

Fountain presence/absence

Table 24 provides the frequencies that indicate the optimal fountain presence level on the Eindhoven station plaza. Similarly to the number of lampposts, a clear distinction is seen in the percentages representing the different levels.

Table 24: Frequencies of chosen fountain presence level by respondents

Fountain	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Present	86	77.5	79	75.2	31	73.3
Absent	25	22.5	26	24.8	9	19.5
No preference	-	-	-	-	3	7.3
Total	111	100	105	100	43	100

Figure 54 provides a clear view on the data, stating the clear preference for a fountain being present on the Eindhoven station plaza. Furthermore, the differences between the presentation modes are negligible.

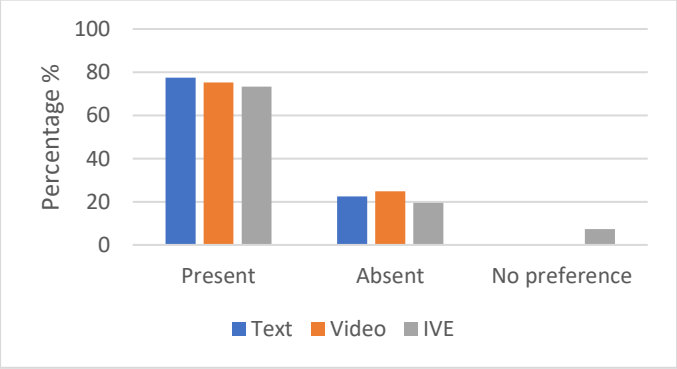


Figure 54: Most preferred level of fountain presence per presentation mode

A chi-square test could not prove a significant difference in choice behavior between the different modes regarding the presence or absence of a fountain.

Number of benches

In Table 25, the frequencies regarding the number of benches on the plaza is visible. In this case, for the IVE experiment all respondents had a preference regarding their optimal level, something which is not the case for the other variables.

Table 25: Frequencies of chosen optimal number of benches by respondents

Benches	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
No benches	0	0.0	0	0.0	1	2.4
4 benches	4	3.6	2	1.9	5	12.2
8 benches	50	45.0	35	33.3	25	58.5
15 benches	57	51.4	68	64.8	12	26.8
No preference	-	-	-	-	0	0.0
Total	111	100	105	100	43	100

Figure 55 visualizes the data, showing a clear trend in an increasing preference for an increase in the number of benches. Remarkably, respondents in all presentation modes do not prefer the absence of benches, as well as the presence of few (4) benches. In addition, in the IVE experiment the most optimal level is 8 benches, meaning for this presentation mode respondents do not prefer the highest number of benches.

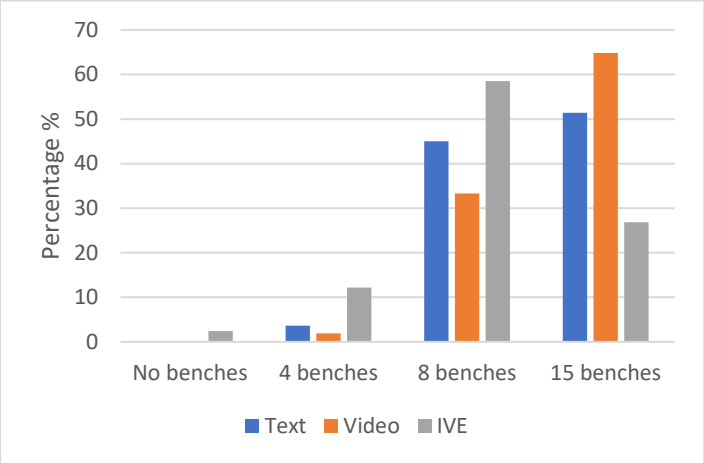


Figure 55: Most preferred number of benches per presentation mode

The chi-square test proves statistically different choices for the text and IVE mode, and the video and IVE mode as the chi-square test statistic is higher than the critical value. There is no statistically different choice behavior when comparing the text to video mode.

Number of trees

The number of trees also has a distinct difference in the preferences, as is visible in

Table 26.

Table 26: Frequencies of chosen optimal number of trees by respondents

Number of trees	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
26 trees	-	-	-	-	22	51.2
15 trees	106	95.5	102	97.1	12	26.8
9 trees	5	4.5	2	1.9	3	7.6
0 trees	0	0.0	1	1.0	6	14.6
No preference	-	-	-	-	0	0.0
Total	111	100	105	100	43	100

Figure 56 visualizes the data in a bar chart. For this variable, a difference in the attribute levels is seen. For the surveys including the text and video variant, it was required to merge the number and grouping of trees in order to fit the experimental design, whereas the IVE experiment had an additional level. However, still trends are visible. Respondents hardly prefer the lower levels of number of trees. Thus, for all 3 presentation modes, respondents prefer the highest number of trees possible. Worth noting, the MNL model did prove that the presence of 9 trees had the biggest positive impact on comfortability for the video mode. This shows a contrast with the results from

Table 26. This shows there is a difference in how respondents perceive a design scenario compared to assessing a variable one by one. Additionally remarkable, whereas in the text variant and video variant (almost) no one prefers ‘no trees’ on the plaza, the percentage is somewhat higher for the IVE experiment.

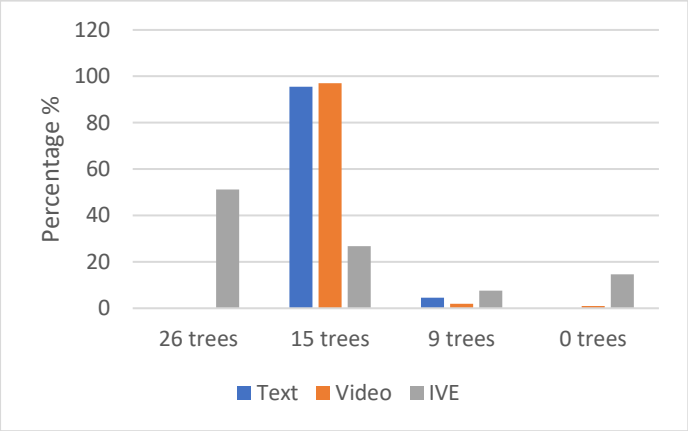


Figure 56: Most preferred number of trees per presentation mode

No statistical difference in choice behavior was found for the number of trees per presentation mode when computing the chi-square test statistic. In this case, the category of 26 trees in the IVE mode was merged with the 15 trees to compute a variable ‘maximum number of trees’.

Grouping of trees

Lastly, Table 27 shows the frequencies of the choices made on the grouping of trees in the different presentation modes. Regarding this variable, some differences are apparent.

Table 27: Frequencies of chosen optimal grouping of trees level by respondents

Grouping of trees	Text		Video		IVE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Clustered	37	33.3	69	65.7	23	53.7
Spread	74	66.7	35	33.3	14	31.7
No trees	0	0.0	1	1.0	5	12.2
No preference	-	-	-	-	1	2.4
Total	111	100	105	100	43	100

This becomes more visible in Figure 57, where the spreading of trees is preferred in case of the text variant, and clustering of trees is preferred in the visual variants (video and IVE). A possible reason for this is again the imagination of respondents in the text variant compared to the other modes, in combination with levels that are clearly distinctive from each other. In addition, there is a difference when comparing the MNL model to Table 27, as was also visible for the number of trees.

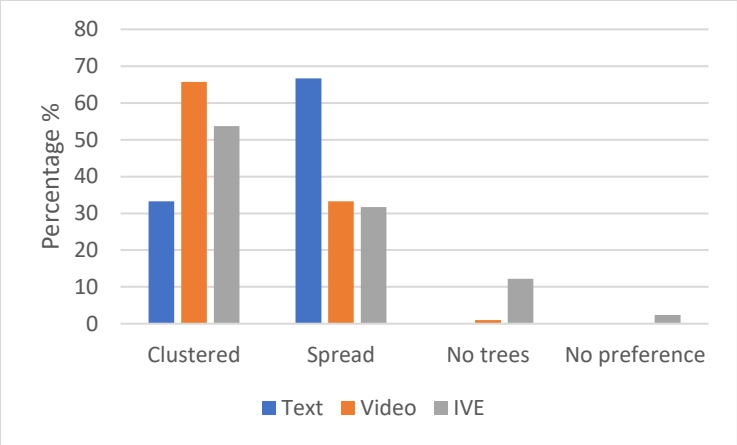


Figure 57: Most preferred level of tree grouping per presentation mode

In this case there is a statistical difference between the text and video mode, and the text and IVE mode as the chi-square test statistic is higher than the critical value. There is no statistical difference found for the comparison between video and IVE.

5.4.2. Conclusion

First of all, caution must be taken in the conclusions as the IVE had a different sample compared to the text and video experiment, which might lead to the different results possibly tracing back to this. To conclude, as visible in Table 28, there are some minor differences in the choices of most preferred attribute levels. Regarding the grass coverage, respondents using the visual presentation modes seem to have a higher chance of selecting the highest level of grass coverage as their favorite. Also, the preferred building height raises with the visuality of the presentation modes, with a contrast of low-rise in the text variant compared to the high-rise in the IVE experiment. The number of lampposts and presence of a fountain does

not lead to any differences. In the text and video variant, respondents preferred the highest number of benches (15), compared to the 8 benches in the IVE experiment. Then, in all presentation modes the highest available number of trees was preferred. To end, the use of visual presentation modes seemed to lead to a different preference of respondents for the clustered grouping of trees. The text variant had more respondents preferring the spreading of trees.

Table 28: Summary of most preferred attribute levels per presentation mode

	Text	Video	IVE
Grass coverage	50% grass	66% grass	66% grass
Building height	Low-rise	Medium-rise	High-rise
Lampposts	9 lampposts	9 lampposts	9 lampposts
Fountain	Present	Present	Present
Benches	15 benches	15 benches	8 benches
Number of trees	15 trees	15 trees	Max. trees
Grouping of trees	Spread	Clustered	Clustered

Table 29 shows whether the choices for different optimal levels shown in Table 28 are statistically different when comparing the different presentation modes. This indicates there are 10 comparisons in which the choice behavior is statistically different.

Table 29: Statistical difference in choice behavior between modes

	Text-video	Text-IVE	Video-IVE
Grass coverage	Yes	Yes	No
Building height	No	Yes	Yes
Lampposts	No	Yes	Yes
Fountain	No	No	No
Benches	No	Yes	Yes
Number of trees	No	No	No
Grouping of trees	Yes	Yes	No

Apparently, there are some differences, mainly between the text variant and the IVE mode. In the textual survey, respondents have to imagine the scenarios that are presented, which might differ from what was presented in the video or IVE mode. The visual presentation modes provide this imagery, leaving no room for interpretations and therefore differences between respondents. On the other hand, there are also relatively many similarities between all three presentation modes. For example, higher grass coverage levels are preferred, as well as more lampposts, the presence of a fountain, more benches and more trees. To compare these presentation modes, the environments used were as similar as possible. However, more differences in choice behavior could possibly be found if the full potential of the modes is used. Lastly, worth noting, for the number of trees and the grouping of trees, a difference was found for the chosen most optimal design levels and the actual results from the MNL model. This could indicate a difference in choice behavior when respondents have to assess a complete design scenario compared to when assessing only one attribute.

6. Conclusion, discussion and recommendations

This chapter contains the final learning curves through this research, as well as what remains to be learned. It reflects on the research questions stated in chapter 1. Furthermore, the weaknesses and limitations are discussed through a critical evaluation, which is followed by the strengths and the possible applications of this study. Lastly, a recommendation for future research is provided.

6.1 Conclusion

Choice behavior, regarding a comfortability rating, is different when presenting designs of the Eindhoven station plaza in textual form or in video form. For the overall comfortability rating, and four attribute levels (the presence of a fountain, 15 trees clustered, 9 trees present, and 4 benches present) a statistically significant difference was found. In the text mode, respondents are more likely to rate a scenario as comfortable compared to the video mode.

In urban design, there is few research performed examining choice behavior for different presentation modes. Especially the use of videos on a bigger scale is relatively new. Therefore, the objective of this research was to get insights in these possible differences. This led to the following main research question:

"To what extent is there a difference in individual choice behavior considering comfortability in textual scenarios and video-based scenarios for a healthy public space design?"

To answer this question, a literature review was conducted into the different presentation modes, the strengths and weaknesses of these modes, the built environment attributes, and other socio-demographic characteristics that could play a role in choice behavior. Literature showed a difference in importance of attributes. For example, the presence of greenery as well as the presence of amenities has a positive effect on comfort. Also the presence of water and lampposts on a plaza contribute to comfort. This led to the creation of 32 different scenarios, both in text and video. Using these scenarios, a stated preference experiment was conducted, in which respondents had to rate the scenarios on overall level of comfortability, and the comfortability level per attribute level in that particular scenario.

The literature study, including the study of the CoHeSIVE research team, led to 6 attributes being used; the presence or absence of a fountain, the number of lampposts, the number and grouping of trees, the amount of grass coverage, the building height of the surrounding buildings, and the number of benches (Dane & Evers, 2023). Additionally, the effects of gender, age, household composition, occupation, education level, urbanization level of living environment, station plaza visits, life satisfaction, health influence of plazas, education background and possible pre-knowledge were investigated.

Regarding the importance of the attributes, the conclusion is drawn that the presence of 15 benches had the biggest influence on the comfortability rating. This was found in the model containing the data from the textual survey, the video survey, and the model containing all data. Also, the number and grouping of trees had a big impact on the comfortability rating. These results are coherent to the literature found. The effect of the number of lampposts on the comfortability rating was lowest of the significant results. The results for building height were almost all statistically insignificant. Where comfortability contributes to health, also the choice for certain attribute levels (e.g. additional greenery) contributes to health. The models

proved that respondents prefer attribute levels that are linked with both comfort and health. This was seen in the choice for greenery over pavement, the presence of the maximum number of benches and lampposts, and the presence of a fountain. The model containing the text data performed best with a McFadden Rho Square of 0.22, followed by a McFadden Rho Square of 0.18 by the video data model. Due to the differences in presentation modes, it was expected that the model containing the video mode would perform best as videos are superior in vividness of the material and leave less room for interpretations (compared to text). The MNL model that compared the choice behavior between the two modes, proved differences in choice behavior for the overall comfort rating, the presence of a fountain, 15 trees clustered, 9 trees present, and 4 benches present.

The effects of the socio-demographics were not illogical, proving mostly that what was found in the literature study. Examples of this are the level of criticality, that was higher for both females and people of an older age category. Also, older respondents, as well as respondents with children, prefer amenities more. Respondents with a background in architecture and urbanism were also found to have a lower probability to rate a scenario as comfortable. This was also suggested in the literature, as this group might have more knowledge on for example the heat island effect and implications of design decisions. Lastly, respondents with pre-knowledge (for example by filling in both surveys) were also more critical regarding the comfortability rating.

Furthermore, the literature study suggested 3 interesting modes to compare: text, video, and immersive virtual environments. For that, the data gathered by workshops from CoHeSIVE (Dane & Evers, 2023) was used to compare the most optimal design scenarios between these three presentation modes. This study concluded that there is a slight difference in preferred optimal attribute levels. For example, the text survey concluded that respondents prefer a situation in which the trees on the plaza are spread, whereas the visual modes (video and IVE) suggested that respondents prefer a clustering of trees. A chi-square test, which tested for statistical differences between text-video, text-IVE, and video-IVe, proved a statistical difference in choice behavior in 10 out of the 21 cases. An interesting statistically different choice is the choice for low-rise in text, and high-rise in IVE. This might be influenced by interpretations of people by the absence of visuals. Also, the video mode, which does of course show visuals, resulted in higher buildings as well compared to text. This is therefore an interesting attribute to examine further.

Concluding, the research answered the main research questions by proving a difference in choice behavior between the presentation modes. Respondents in the text survey were more likely to regard a scenario as comfortable compared to the video survey. The attribute that was found to have the largest effect on the comfortability rating was the presence of 15 benches. Furthermore, when comparing the most optimal attribute levels between the text mode, video mode and IVE mode, statistically different choices were found in 10 out of the 21 cases.
This research should aware people that the choice of a certain presentation mode could lead to different outcomes. Progressing technologies lead to possibilities to implement textual, video, and immersive environment-based scenarios in the participatory process. In these participatory processes, one must consider the advantages and disadvantages of each presentation method, while also considering that the results can differ. It is hard to draw conclusions on what mode is better, and which mode to use in which situation. There are many other factors that are not part of this thesis, such as investments costs, time intensiveness and required personnel. However, the model containing the text mode performed best in this case. This mode also offers highest potential to reach a big public, has a low exposure time, and generally lower costs. Therefore, in an initial design stage where a big public is allowed to

provide feedback on an area, the text mode is still a good option. In section 6.2 however, it is discussed why it is hard to draw such conclusions in hindsight of this research.
Lastly, this research also added to existing literature, for example by confirming the importance of benches and trees in a public space such as an urban plaza. Also adding the socio-demographic characteristics lead to similar effects compared to literature. However, it also tried to seek answer to the unexplored territories of the field, using different presentation modes to show design scenarios to the bigger public. It has therefore proven that choice behavior in urban design is influenced by the presentation mode.

6.2 Discussion

As mentioned, there were 5 differences found in choice behavior in the MNL model. Differences were found for the overall comfortability, the presence of a fountain, 15 trees clustered, 9 trees present, and 4 benches present. Literature accounted for differences between the presentation modes. From these differences, some can be related to preferences, while others are more related to production and efforts. Regarding the differences related to preferences, the text mode reports to have a low exposure time, but also a low level of information recalling. Text also leaves room for interpretations as there is no concrete visual of the situation. Video and IVE report to have a higher level of information recalling, higher level of vividness of the material, higher entertainment value, and more ease to evaluate choices. Since the sample size was similar for most socio-demographics, the differences can be related to the differences in the presentation modes. A suspicion is that most of the differences in preferences are related to the interpretation of respondents. However, it would be interesting to conduct the research with more distinction in the attribute levels. For example, the difference between 7 and 9 lampposts was not always clearly visible. Similarly, 4 and 8 benches, and 9 and 15 trees could be more emphasized.
The research performed in this thesis has some limitations. First of all, the literature research performed can be extended. As such, there are definitely more and other relevant studies that may not have been included in this thesis (Fonseca et al., 2021).
Secondly, the set of built environment attributes used is limited. A limiting reason is the capability to be modelled in a virtual environment, as well as the load a respondent can bear. In this case, 6 variables and an overall comfort rating were included, which when rating 8 design scenarios already leads to 56 ratings (besides all socio-demographics, and final preferences). As such, there was a sort of trade-off between the number of participants and the number of design scenarios presented in the survey. Since the number of participants was expected to be below 250 participants, the number of design scenarios per participant had to be relatively high in order to perform the statistical analysis. This was also due to the experiment design leading to 32 different profiles/design scenarios. However, the survey length in the end is considered a limitation as multiple respondents reported it to be quite a burden. Also, the eventual gathered number of respondents could be higher. In total, this research gathered 216 useful cases, divided over 111 for the text survey and 105 for the video survey. Finally, in order to perform an adequate statistical analysis, the number of respondents could be higher.
Practically, the distribution of the presented profiles would ideally be better distributed. In this case, there was a difference in the number of times a certain profile was shown to the respondent. In case there are many respondents, this is not too relevant. However, in this case, with limited respondents, it was preferred to have a more equal distribution. This was due to a limitation in LimeSurvey.
Looking at the scenario creation, there is also the assumption that the aesthetically best-looking option was chosen. Within Lumion, there were numerous options regarding all

variables, so various types of trees, lampposts, benches, grass, fountain. The choices made in this research may influence the preferences of the respondents, who might prefer other looks. Additionally, the color attraction in urban design might influence the results, meaning that the implementation of other colors could have influenced the results (Gorzaldini, 2016).
Coherent to the scenario creation is the location that was used in this research, the station plaza on the center side of Eindhoven. Therefore, one should be careful to generalize results to other areas or other public spaces. Choices made could be location-specific and may not hold for other locations.
Another limitation of the research is the natural preference of mode of presentation. Naturally, some respondents will process text differently than videos. Some people engage better with a verbal description, compared to other people who prefer visual stimuli (Mokas et al. 2019). This might also have a possible influence on their preference for certain design alternatives. Also, dynamic aspects aren't taken into consideration yet. People's preferences might change depending on for example weather conditions, or day/night-time. Logically, the number of lampposts is an example of an attribute that would be more visible in a nighttime scenario. Therefore, in case a static situation is provided to the participants, it might not be representative for all situations in real life, and thus this should be carefully considered when drawing conclusions.
Considering the data usage some conclusions can also be drawn in hindsight. First of all, the data gathered by the additional questions (Figure 11 and Figure 12), that inquire the comfortability rating of individual attribute levels in a design scenario, was not used for the analysis. This increased the survey size significantly, which is regrettable.
Regarding the data transformation to the two choices (comfortable or not comfortable), may not have resulted in the most efficient method to use the data. In this thesis, every design scenario presented to a respondent was only evaluated once in the MNL model. As such, in the current situation every scenario was evaluated by the respondents on a 1-10 preference scale, while this scale was reduced to a 'comfortable' vs 'non-comfortable' choice, ignoring smaller differences in preferences and resulting in 8 choice sets per individual. However, a different situation could have been created in which each evaluated scenario was compared to another scenario evaluated by a respondent, meaning that for every comparison the scenario with the highest comfortability rating was chosen. In that way, the data is more efficiently used as 28 combinations can be made in case a respondent rates 8 design scenarios.
Reflecting, the question itself could also be rephrased to whether a design scenario is considered comfortable or not. This would prevent the data from consisting of a range of comfortability ratings. Currently, the ratings are therefore also generalized to 'comfortable' or 'not comfortable', meaning that for example a rating of 10 is considered the same as a rating of 6 in this thesis.
Lastly, it is hard to draw conclusions on the best presentation mode. This research merely compares presentation modes in as similar scenarios as possible. As the IVE model by CoHeSIVE was used as a basis, the videos were made as comparable as possible. However, videos also have the opportunity to be superior in visuals, as it is easier to implement different textures, different dynamic effects such as moving people, and sound. Therefore, additional research is required that examines the full potential of each presentation mode. The higher McFadden Rho Square for the text mode would indicate that the mode is still a good option. Especially reaching larger numbers of respondents against lower costs, combined with a lower burden for the respondents. Video, and especially IVE, are modes which require higher efforts to be created. However, these modes contain as mentioned a higher potential to show for example dynamic effects, textures and sound, which weren't incorporated in this research.

Besides some limitations, also some risks are applicable to the research. First of all, a sufficient number of respondents is required for statistically significant results. The modes of textual scenarios and VR scenarios can be put in an online survey and can be shared both online and physically.
The method itself also creates a very time intensive process, as the experimental design leads to a minimum requirement regarding the number of profiles in the experiment. Still a high number of profiles was needed for an efficient experimental design, which also leads to high video production efforts. On the other hand, the method enables the researcher to evaluate relatively many attributes while trying to minimize the load on the respondent.

6.3 Recommendations

The results should aware people that the use of different presentation modes leads to different results. For instance, in the participatory design process, rather than creating designs in one mode, one could consider creating the designs in multiple modes and compare the results of these experiments for the optimal outcome. However, this would mean a more time and costs extensive process, in which also more respondents are required to statistically compare the results. The text mode still proves to be a relevant mode, also by having the better McFadden Rho Square compared to videos in this thesis. In combination with the lower costs, efforts and burden for the respondents, this is still a good mode to reach a vast public to examine their opinions. In case the design has advanced and has a smaller scope, visuals could add to the interpretations. The relevance of the video and IVE mode is also shown by the difference in preferences for the most preferred attribute levels. An example is the building height, where respondents in the text mode prefer the low-rise, while people in the IVE mode prefer the high-rise. Therefore, it is important to find a balance between the modes, and not only rely on one mode.
There are also still a lot of aspects that are undiscovered and require more research in order to gain additional insights. First of all, regarding the scenario creation, the rendering of the videos as well as the handling of the software was relatively slow. For future research, it is advised to arrange a laptop with a better processor to reduce the time spent on the creation of the video scenarios.
Further research could include several other aspects that were omitted in this experiment. This could refer to the use of dynamic environments, including movements of people as well as dynamic day and night-time environments. Coming back to the rendering process, introducing these factors would also negatively influence the speed of rendering as well as software handling.
After the creation of the scenarios, the survey was implemented. In hindsight, the survey was relatively extensive. This also became apparent by the number of respondents that quit the survey fast. This was also caused by a lagging progress bar in LimeSurvey, which very pessimistically showed progress in the survey. After a few comments on the first day from respondents, this bar was removed, and the successful response rate rose. However, in the future the size of the survey could still be reduced, as the load on the respondent was still substantial. Therefore, it is advised to use less than 8 videos that take 1 minute each. In addition, people in the text variant mentioned getting bored by the presentation of 8 textual scenarios and having to rate 7 aspects per scenario. In combination, less questions could be asked and as explained in section 6.2, the question could be rephrased to ‘Comfortable’ or ‘Not comfortable’.
Additionally, in order to perform an adequate analysis, the IVE experiment could be extended. Optimistically, the IVE model could also be altered in such a way that the same experiment

could be done in the environment, rather than only choosing your most preferred attribute level. This would however require very high efforts, and probably isn't efficient. Gathering more respondents for the IVE experiment is also very time intensive.

Concluding, the results should be interpreted in the way that different presentation modes could lead to different outcomes regarding satisfaction with comfortability, and the importance of attributes. On the other hand, it is not possible to draw conclusions on what presentation mode is better, or which presentation mode to use in what situation. However, a suggestion can be provided. The text mode model performed well and is still a very efficient mode to gather the opinions of a vast public. For smaller workshops and more detailed discussions, visuals could help the process and eliminate the different interpretations of respondents. Therefore, decision makers should be aware that the choice of presentation mode could influence the results. As such, the choice could also be made to create scenarios in different presentation modes (as was done in this research) and generalize the results afterwards to the most preferred scenarios.

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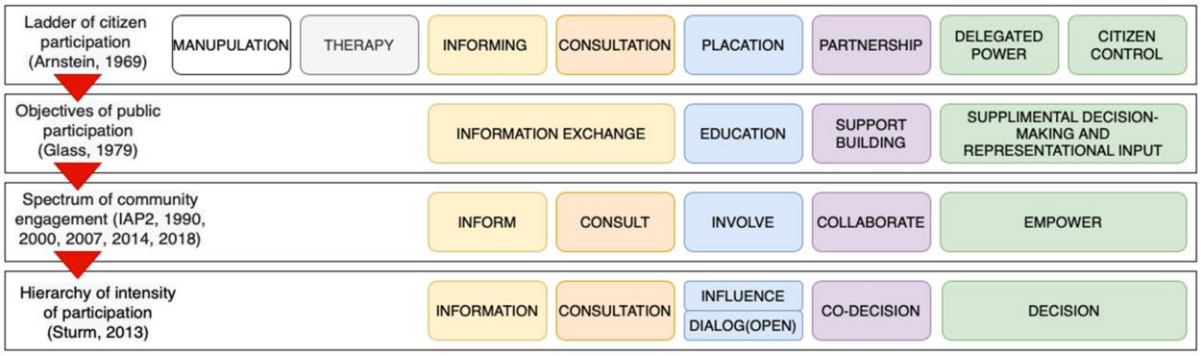
APPENDIX A – Development of the public participation concept (Geekiyanage et al., 2021)



APPENDIX B – Spectrum of Public participation by the International Association for Public Participation (2018).

IAP2 Spectrum of Public Participation

IAP2's Spectrum of Public Participation was designed to assist with the selection of the level of participation that defines the public's role in any public participation process. The Spectrum is used internationally, and it is found in public participation plans around the world.

INCREASING IMPACT ON THE DECISION

	INFORM	CONSULT	INVOLVE	COLLABORATE	EMPOWER
PUBLIC PARTICIPATION GOAL	To provide the public with balanced and objective information to assist them in understanding the problem, alternatives, opportunities and/or solutions.	To obtain public feedback on analysis, alternatives and/or decisions.	To work directly with the public throughout the process to ensure that public concerns and aspirations are consistently understood and considered.	To partner with the public in each aspect of the decision including the development of alternatives and the identification of the preferred solution.	To place final decision making in the hands of the public.
PROMISE TO THE PUBLIC	We will keep you informed.	We will keep you informed, listen to and acknowledge concerns and aspirations, and provide feedback on how public input influenced the decision.	We will work with you to ensure that your concerns and aspirations are directly reflected in the alternatives developed and provide feedback on how public input influenced the decision.	We will look to you for advice and innovation in formulating solutions and incorporate your advice and recommendations into the decisions to the maximum extent possible.	We will implement what you decide.

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APPENDIX C – Survey English

PART 1: Personal information

Q1: What is your gender?

- o Male
- o Female
- o Other
- o I'd rather not say

Q2: What is your age group?

- o < 25 years
- o 25-34 years
- o 35-44 years
- o 45-54 years
- o 55-64
- o ≥ 65 years
- o I'd rather not say

Q3: What is your monthly income range?

- o Lower than €1000 net per month
- o Between €1001 and €2000 net per month
- o Between €2001 and €3000 net per month
- o Higher than €3000 net per month
- o I'd rather not say

Q4: What is the highest level of education you have completed?

- o Secondary education (VMBO/HAVO/VWO)
- o Secondary vocational education (MBO)
- o Higher vocational education (HBO)/Bachelor degree (WO)
- o WO Master/PhD
- o I'd rather not say

Q5: What is your main occupation?

- o Student
- o Working part-time
- o Working full-time
- o Retired
- o Other
- o I'd rather not say

Q6: What is your household composition?

- o Single-person household
- o Two-person household with partner
- o Household with children
- o Other
- o I'd rather not say

Q7: What is the urbanization level of your living environment?

o City center
o City suburbs
o (small) Town
o Rural
o I'd rather not say

Q8: How often do you visit (e.g. passing by) the current urban public space used in this case study; the station plaza of Eindhoven?

o Daily
o Weekly
o 1-2 per month
o Less than once per month
o Never
o I'd rather not say

Q9: How often do you visit (e.g. passing by) other urban public space such as plazas in Dutch cities?

o Daily
o Weekly
o 1-2 per month
o Less than once per month
o Never
o I'd rather not say

Q10: How satisfied are you with your current life?

Very dissatisfied O O O O O Very satisfied

O I'd rather not say

Q11: How important do you think the influence of using (urban) station plazas is on your health?

Very unimportant O O O O O Very important

O I'd rather not say

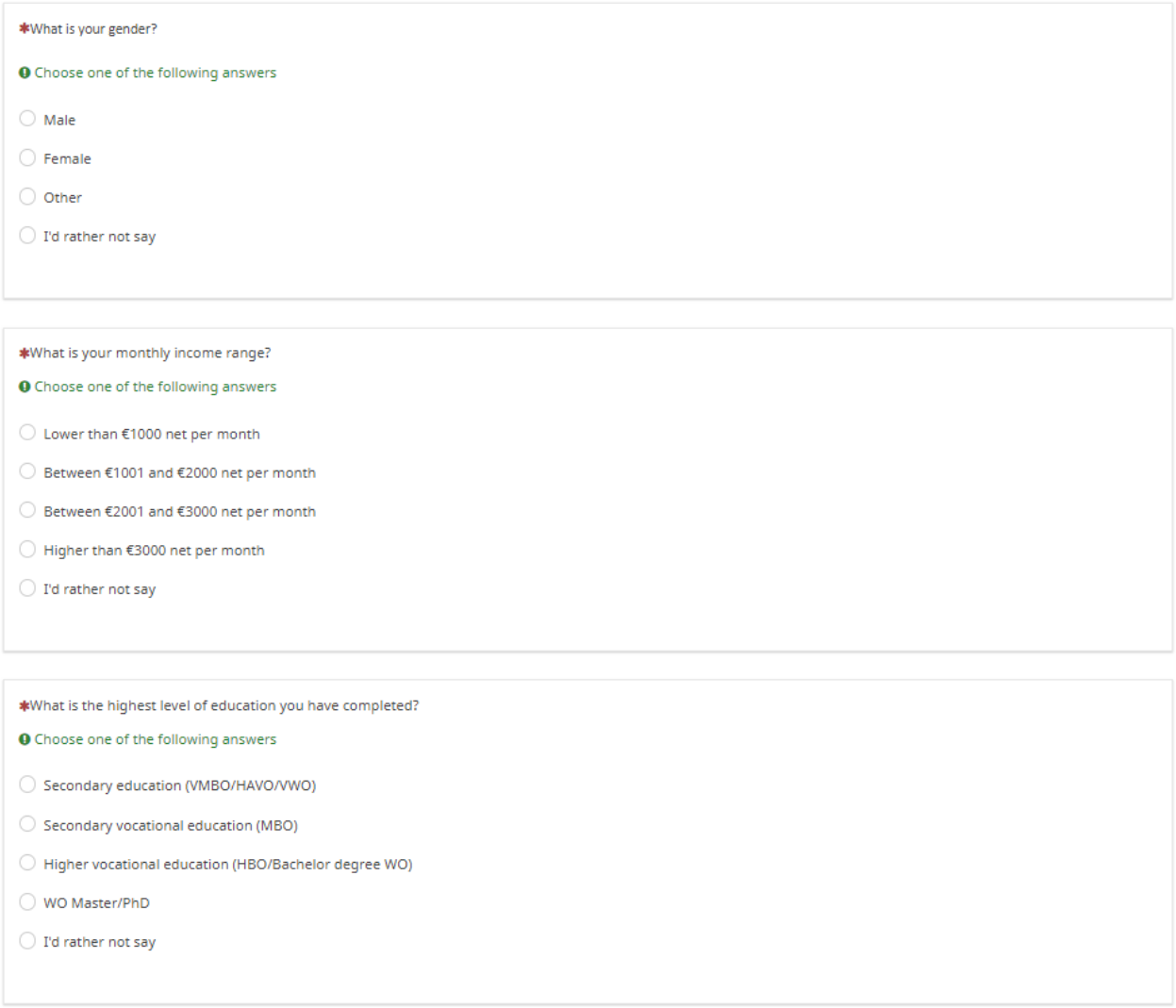
Q12: Do you have an architectural/urban design background?

o Yes
o No

APPENDIX D – Experiment Design generated by SAS Software (SAS Software, 2023)

Run	x1	x2	x3	x4	x5	x6
1	1	2	3	3	3	4
2	1	1	4	2	2	4
3	1	2	2	3	4	4
4	1	1	3	4	4	3
5	1	2	2	2	4	1
6	1	2	3	2	3	1
7	2	2	1	2	4	3
8	2	2	1	3	4	2
9	2	1	3	2	2	2
10	2	2	4	2	3	3
11	2	2	3	1	1	1
12	2	2	2	1	2	1
13	1	1	4	3	2	1
14	1	1	2	4	3	3
15	2	1	1	4	3	1
16	2	2	3	4	1	4
17	2	1	4	1	4	4
18	2	1	2	3	1	3
19	1	2	4	4	1	2
20	2	2	2	4	2	4
21	2	1	1	1	3	4
22	2	1	2	2	1	2
23	2	1	4	4	4	1
24	1	1	1	2	1	4
25	1	1	3	1	4	2
26	1	2	1	1	2	3
27	1	2	1	4	2	2
28	1	1	1	3	1	1
29	1	2	4	1	1	3
30	2	2	4	3	3	2
31	2	1	3	3	2	3
32	1	1	2	1	3	2

APPENDIX E – Presentation of questions on personal characteristics in LimeSurvey



*What is your gender?

Choose one of the following answers

- Male
- Female
- Other
- I'd rather not say

*What is your monthly income range?

Choose one of the following answers

- Lower than €1000 net per month
- Between €1001 and €2000 net per month
- Between €2001 and €3000 net per month
- Higher than €3000 net per month
- I'd rather not say

*What is the highest level of education you have completed?

Choose one of the following answers

- Secondary education (VMBO/HAVO/VWO)
- Secondary vocational education (MBO)
- Higher vocational education (HBO/Bachelor degree WO)
- WO Master/PhD
- I'd rather not say

APPENDIX F – Data storage

First of all, the data is stored within LimeSurvey as the survey is active. Before deactivation of the survey, all response data should be exported as these will not be available after deactivation. These exported data files are stored on SURFDrive. This is an association by Dutch educational and research institutes, where data can safely be stored.

APPENDIX G – Data transformation

In this part, the python script used for transforming the wide format data set to a long format dataset is discussed, as this transformation is required for the analysis. It does so by addressing the separate parts of the script individually. Since there are two databases (one for the textual scenario survey and one for the video scenario survey), there are two python codes that only differ on certain column names. These scripts are very similar and only vary on some directory names and referrals to the correct documents, and therefore in this chapter only one of the scripts is covered.

First of all, the file containing the entire database is located in order for the script to run on the file. The first step is then to eliminate all cases where respondents did not reach the end of the survey. In many cases, these respondents only opened the survey and did not reach past the socio-demographic questions of the survey. In the script, the column 'lastpage' is located and deleted if it is below or equal to 41. This is visible in Figure 58.

```
import pandas as pd
import numpy as np

path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/Tekst pk compleet.csv'
data = pd.read_csv(path_to_file, sep=';', dtype=str)


#removal of incomplete responses through "lastpage"
data["lastpage"] = data["lastpage"].astype(float)
data = data.loc[data["lastpage"] >= 41]
print(data)
```

Figure 58: Removal of cases that did not reach the end of the survey

Secondly, the relevant columns for the personal data were selected and saved in another file. This is visible in Figure 59. In order to have a complete dataset in the end, the dataset has to be separated on personal data (socio-demographics in the survey) and the choice data (scenario rating in the survey). In the end, these files are merged with a file that includes all profiles and the attribute levels used per profile. This data does not yet need to be converted to long format, as this is automatically done while merging in the end of the script.

```
#selecting relevant columns and separate data
    #Personal data incl. remarks selection (b4)
data2 = data.iloc[:,np.r_[0,2,7:19:1,250:259:1]]
data2.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata2.csv', index=False)
print('Selection_of_personal_data._Results_saved_in_tekstdata2')
```

Figure 59: Selecting personal data in the data set and saving it in another file.

Similarly, the choice data is selected and saved in another file. Since every column has the same name, Excel has a tendency to rename the column by adding a number to it. However, in this case the columns should have the exact same name as the data should be combined under one column. Therefore, in Figure 60 it is visible that the column names are 'forced' upon the document.

```
    #Choice data selection (and forcing the names of the columns)
data3 = data.iloc[:,np.r_[0,26:250:1]]
data3.set_axis(['id', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
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'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height'], axis=1, inplace=True)
data3.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final//Tekst/tekstdata3.csv', index=False)
print('Selection_of_choice-data._Results_saved_in_data3')

)
```

Figure 60: Selecting choice data and saving it in another file

As the data was in wide format when exported from LimeSurvey, that means the 32 profiles were next to each other horizontally. In Figure 61, it is visible that for each different profile the correct columns are selected when there is data present. In other words, the script assesses all 32 profiles, and only takes the profiles which were rated by the respondent, leaving 8 rows with rated profiles which are now in long format. Again in this case, it is also important to include the respondent id and profile number, as in the end all files will be merged based on these characteristics.

```
count=int(1)
while (count<=32):
    if (count == 1):
        df = data3.iloc[:,np.r_[0,1:8:1]]
    elif (count == 2):
        df = data3.iloc[:,np.r_[0,8:15:1]]
    elif (count == 3):
        df = data3.iloc[:,np.r_[0,15:22:1]]
    elif (count == 4):
        df = data3.iloc[:,np.r_[0,22:29:1]]
    elif (count == 5):
        df = data3.iloc[:,np.r_[0,29:36:1]]
    elif (count == 6):
        df = data3.iloc[:,np.r_[0,36:43:1]]
    elif (count == 7):
        df = data3.iloc[:,np.r_[0,43:50:1]]
    elif (count == 8):
        df = data3.iloc[:,np.r_[0,50:57:1]]
    elif (count == 9):
        df = data3.iloc[:,np.r_[0,57:64:1]]
    elif (count == 10):
        df = data3.iloc[:,np.r_[0,64:71:1]]
    elif (count == 11):
        df = data3.iloc[:,np.r_[0,71:78:1]]
    elif (count == 12):
        df = data3.iloc[:,np.r_[0,78:85:1]]
    elif (count == 13):
        df = data3.iloc[:,np.r_[0,85:92:1]]
    elif (count == 14):
        df = data3.iloc[:,np.r_[0,92:99:1]]
    elif (count == 15):
        df = data3.iloc[:,np.r_[0,99:106:1]]
    elif (count == 16):
        df = data3.iloc[:,np.r_[0,106:113:1]]
    elif (count == 17):
        df = data3.iloc[:,np.r_[0,113:120:1]]
    elif (count == 18):
        df = data3.iloc[:,np.r_[0,120:127:1]]
    elif (count == 19):
        df = data3.iloc[:,np.r_[0,127:134:1]]
```

```
    elif (count == 20):
        df = data3.iloc[:,np.r_[0,134:141:1]]
    elif (count == 21):
        df = data3.iloc[:,np.r_[0,141:148:1]]
    elif (count == 22):
        df = data3.iloc[:,np.r_[0,148:155:1]]
    elif (count == 23):
        df = data3.iloc[:,np.r_[0,155:162:1]]
    elif (count == 24):
        df = data3.iloc[:,np.r_[0,162:169:1]]
    elif (count == 25):
        df = data3.iloc[:,np.r_[0,169:176:1]]
    elif (count == 26):
        df = data3.iloc[:,np.r_[0,176:183:1]]
    elif (count == 27):
        df = data3.iloc[:,np.r_[0,183:190:1]]
    elif (count == 28):
        df = data3.iloc[:,np.r_[0,190:197:1]]
    elif (count == 29):
        df = data3.iloc[:,np.r_[0,197:204:1]]
    elif (count == 30):
        df = data3.iloc[:,np.r_[0,204:211:1]]
    elif (count == 31):
        df = data3.iloc[:,np.r_[0,211:218:1]]
    elif (count == 32):
        df = data3.iloc[:,np.r_[0,218:225:1]]
    print(df)

    df.dropna(inplace=True)
    print(df)
    df["profile"]=count
    print(df)

    if (count==1):
        data4 = df
    else: data4 = pd.concat([data4, df], axis=0)
    count = count+1

data4["id"]=data4["id"].astype(int)
data4=data4.sort_values(["id","profile"], ascending=True)
print(data4)

data4.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata4.csv',
index=False)print('Selection_of_choice-data._Results_saved_in_tekstdata4'
```

Figure 61: Selecting rated profiles and including id and profile number in the file

As mentioned, to finish with a complete dataset, the separated files should be merged again. In Figure 62 the previously selected choice data with 8 rated profiles are merged with the file containing the actual attribute levels in these profiles. This is essential for the eventual analysis, as solely evaluating ratings of profiles does not include any information on the content of these profiles. Therefore, in this case these files are merged on the column 'profile', meaning that if the profile of the choice data set is coherent with the profile in the file containing the attribute levels, it merges these rows.

```
#merge lf choicedata with scenario attributelvls
path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/Experiment design.csv'
mergefile = pd.read_csv(path_to_file, sep=';', dtype=str)
data4 = data4.astype(str)
print (mergefile)
print (data4)
data5 = pd.merge(data4, mergefile, how='left', on=["profile"])

data5.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata5.csv', index=False)
print('Merger_complete_Results_saved_in_tekstdata5')
```

Figure 62: Merging the long format choice data with the corresponding attribute levels

Lastly, the recently created file with the rated profiles and corresponding attribute levels, should be merged again with the personal data. This is done on the column 'id', as this characteristic is still present in both to be merged files, which is seen in Figure 63. In the end, this leaves a file in which the data is in long format, and in which the attribute levels corresponding to the profiles are included.

```
#merge lf choicedata with pers. data (b6)
path_to_file = "C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata2.csv"
mergefile = pd.read_csv(path_to_file, sep=',', dtype=str)
data5 = data5.astype(str)
print (mergefile)
print(data5)
data6 = pd.merge(data5, mergefile, how='left', on=["id"])

data6.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata6.csv', index=False)
print('Merger_complete_Results_saved_in_tekstdata6')
```

Figure 63: Merging the personal data with the rated profiles and attribute levels.

Appendix H – Full python script for text survey database

```
import pandas as pd
import numpy as np

path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/Tekst pk compleet.csv'
data = pd.read_csv(path_to_file, sep=';', dtype=str)


#removal of incomplete responses through "lastpage"
data["lastpage"] = data["lastpage"].astype(float)
data = data.loc[data["lastpage"] >= 41]
print(data)


#selecting relevant columns and separate data
    #Personal data incl. remarks selection (b4)
data2 = data.iloc[:,np.r_[0,2,7:19:1,250:259:1]]
data2.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata2.csv', index=False)
print('Selection_of_personal_data._Results_saved_in_tekstdata2')


    #Choice data selection (and forcing the names of the columns)
data3 = data.iloc[:,np.r_[0,26:250:1]]
data3.set_axis(['id', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height
```

```
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height'], axis=1, inplace=True)
data3.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final//Tekst/tekstdata3.csv', index=False)
print('Selection_of_choice-data._Results_saved_in_data3')

count=int(1)
while (count<=32):
    if (count == 1):
        df = data3.iloc[:,np.r_[0,1:8:1]]
    elif (count == 2):
        df = data3.iloc[:,np.r_[0,8:15:1]]
    elif (count == 3):
        df = data3.iloc[:,np.r_[0,15:22:1]]
    elif (count == 4):
        df = data3.iloc[:,np.r_[0,22:29:1]]
    elif (count == 5):
        df = data3.iloc[:,np.r_[0,29:36:1]]
    elif (count == 6):
        df = data3.iloc[:,np.r_[0,36:43:1]]
    elif (count == 7):
        df = data3.iloc[:,np.r_[0,43:50:1]]
    elif (count == 8):
        df = data3.iloc[:,np.r_[0,50:57:1]]
    elif (count == 9):
        df = data3.iloc[:,np.r_[0,57:64:1]]
    elif (count == 10):
        df = data3.iloc[:,np.r_[0,64:71:1]]
    elif (count == 11):
        df = data3.iloc[:,np.r_[0,71:78:1]]
    elif (count == 12):
        df = data3.iloc[:,np.r_[0,78:85:1]]
    elif (count == 13):
        df = data3.iloc[:,np.r_[0,85:92:1]]
    elif (count == 14):
        df = data3.iloc[:,np.r_[0,92:99:1]]
    elif (count == 15):
        df = data3.iloc[:,np.r_[0,99:106:1]]
    elif (count == 16):
        df = data3.iloc[:,np.r_[0,106:113:1]]
    elif (count == 17):
```

```
        df = data3.iloc[:,np.r_[0,113:120:1]]
    elif (count == 18):
        df = data3.iloc[:,np.r_[0,120:127:1]]
    elif (count == 19):
        df = data3.iloc[:,np.r_[0,127:134:1]]
    elif (count == 20):
        df = data3.iloc[:,np.r_[0,134:141:1]]
    elif (count == 21):
        df = data3.iloc[:,np.r_[0,141:148:1]]
    elif (count == 22):
        df = data3.iloc[:,np.r_[0,148:155:1]]
    elif (count == 23):
        df = data3.iloc[:,np.r_[0,155:162:1]]
    elif (count == 24):
        df = data3.iloc[:,np.r_[0,162:169:1]]
    elif (count == 25):
        df = data3.iloc[:,np.r_[0,169:176:1]]
    elif (count == 26):
        df = data3.iloc[:,np.r_[0,176:183:1]]
    elif (count == 27):
        df = data3.iloc[:,np.r_[0,183:190:1]]
    elif (count == 28):
        df = data3.iloc[:,np.r_[0,190:197:1]]
    elif (count == 29):
        df = data3.iloc[:,np.r_[0,197:204:1]]
    elif (count == 30):
        df = data3.iloc[:,np.r_[0,204:211:1]]
    elif (count == 31):
        df = data3.iloc[:,np.r_[0,211:218:1]]
    elif (count == 32):
        df = data3.iloc[:,np.r_[0,218:225:1]]
    print(df)

    df.dropna(inplace=True)
    print(df)
    df["profile"]=count
    print(df)

    if (count==1):
        data4 = df
    else: data4 = pd.concat([data4, df], axis=0)
    count = count+1

data4["id"]=data4["id"].astype(int)
data4=data4.sort_values(["id","profile"], ascending=True)
print(data4)
```

```
data4.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata4.csv', index=False)
print('Selection_of_choice-data._Results_saved_in_tekstdata4')


#merge lf choicedata with scenario attributelvls
path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/Experiment design.csv'
mergefile = pd.read_csv(path_to_file, sep=';', dtype=str)
data4 = data4.astype(str)
print (mergefile)
print (data4)
data5 = pd.merge(data4, mergefile, how='left', on=["profile"])

data5.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata5.csv', index=False)
print('Merger_complete_Results_saved_in_tekstdata5')


#merge lf choicedata with pers. data (b6)
path_to_file = "C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata2.csv"
mergefile = pd.read_csv(path_to_file, sep=',', dtype=str)
data5 = data5.astype(str)
print (mergefile)
print(data5)
data6 = pd.merge(data5, mergefile, how='left', on=["id"])

data6.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Tekst/tekstdata6.csv', index=False)
print('Merger_complete_Results_saved_in_tekstdata6')
```

Appendix I – Full python script for video survey database

```
import pandas as pd
import numpy as np

path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/Video pk compleet.csv'
data = pd.read_csv(path_to_file, sep=';', dtype=str)


#removal of incomplete responses through "lastpage"
data["lastpage"] = data["lastpage"].astype(float)
data = data.loc[data["lastpage"] >= 41]
print(data)


#selecting relevant columns and separate data
    #Personal data incl. remarks selection (b4)
data2 = data.iloc[:,np.r_[0,2,7:19:1,250:259:1]]
data2.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata2.csv', index=False)
print('Selection_of_personal_data._Results_saved_in_videodata2')


    #Choice data selection (and forcing the names of the columns)
data3 = data.iloc[:,np.r_[0,26:250:1]]
data3.set_axis(['id', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height
```

```
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height', 'comf','fountain',
'lamp','trees','bench','grass','height'], axis=1, inplace=True)
data3.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata3.csv', index=False)
print('Selection_of_choice-data._Results_saved_in_videodata3')

count=int(1)
while (count<=32):
    if (count == 1):
        df = data3.iloc[:,np.r_[0,1:8:1]]
    elif (count == 2):
        df = data3.iloc[:,np.r_[0,8:15:1]]
    elif (count == 3):
        df = data3.iloc[:,np.r_[0,15:22:1]]
    elif (count == 4):
        df = data3.iloc[:,np.r_[0,22:29:1]]
    elif (count == 5):
        df = data3.iloc[:,np.r_[0,29:36:1]]
    elif (count == 6):
        df = data3.iloc[:,np.r_[0,36:43:1]]
    elif (count == 7):
        df = data3.iloc[:,np.r_[0,43:50:1]]
    elif (count == 8):
        df = data3.iloc[:,np.r_[0,50:57:1]]
    elif (count == 9):
        df = data3.iloc[:,np.r_[0,57:64:1]]
    elif (count == 10):
        df = data3.iloc[:,np.r_[0,64:71:1]]
    elif (count == 11):
        df = data3.iloc[:,np.r_[0,71:78:1]]
    elif (count == 12):
        df = data3.iloc[:,np.r_[0,78:85:1]]
    elif (count == 13):
        df = data3.iloc[:,np.r_[0,85:92:1]]
    elif (count == 14):
        df = data3.iloc[:,np.r_[0,92:99:1]]
    elif (count == 15):
        df = data3.iloc[:,np.r_[0,99:106:1]]
    elif (count == 16):
        df = data3.iloc[:,np.r_[0,106:113:1]]
    elif (count == 17):
```

```
        df = data3.iloc[:,np.r_[0,113:120:1]]
    elif (count == 18):
        df = data3.iloc[:,np.r_[0,120:127:1]]
    elif (count == 19):
        df = data3.iloc[:,np.r_[0,127:134:1]]
    elif (count == 20):
        df = data3.iloc[:,np.r_[0,134:141:1]]
    elif (count == 21):
        df = data3.iloc[:,np.r_[0,141:148:1]]
    elif (count == 22):
        df = data3.iloc[:,np.r_[0,148:155:1]]
    elif (count == 23):
        df = data3.iloc[:,np.r_[0,155:162:1]]
    elif (count == 24):
        df = data3.iloc[:,np.r_[0,162:169:1]]
    elif (count == 25):
        df = data3.iloc[:,np.r_[0,169:176:1]]
    elif (count == 26):
        df = data3.iloc[:,np.r_[0,176:183:1]]
    elif (count == 27):
        df = data3.iloc[:,np.r_[0,183:190:1]]
    elif (count == 28):
        df = data3.iloc[:,np.r_[0,190:197:1]]
    elif (count == 29):
        df = data3.iloc[:,np.r_[0,197:204:1]]
    elif (count == 30):
        df = data3.iloc[:,np.r_[0,204:211:1]]
    elif (count == 31):
        df = data3.iloc[:,np.r_[0,211:218:1]]
    elif (count == 32):
        df = data3.iloc[:,np.r_[0,218:225:1]]
    print(df)

    df.dropna(inplace=True)
    print(df)
    df["profile"]=count
    print(df)

    if (count==1):
        data4 = df
    else: data4 = pd.concat([data4, df], axis=0)
    count = count+1

data4["id"]=data4["id"].astype(int)
data4=data4.sort_values(["id","profile"], ascending=True)
print(data4)
```

```
data4.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata4.csv', index=False)
print('Selection_of_choice-data._Results_saved_in_videodata4')


#merge lf choicedata with scenario attributelvls
path_to_file = 'C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/Experiment design.csv'
mergefile = pd.read_csv(path_to_file, sep=';', dtype=str)
data4 = data4.astype(str)
print (mergefile)
print (data4)
data5 = pd.merge(data4, mergefile, how='left', on=["profile"])

data5.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata5.csv', index=False)
print('Merger_complete_Results_saved_in_videodata5')


#merge lf choicedata with pers. data (b6)
path_to_file = "C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata2.csv"
mergefile = pd.read_csv(path_to_file, sep=',', dtype=str)
data5 = data5.astype(str)
print (mergefile)
print(data5)
data6 = pd.merge(data5, mergefile, how='left', on=["id"])

data6.to_csv('C:/Users/s167474/OneDrive - TU Eindhoven/Graduation/9.
Thesis/Data/final/Video/videodata6.csv', index=False)
print('Merger_complete_Results_saved_in_videodata6')
```

Appendix J – Text database

Variable	Level	Frequency	Percent (%)	Cumulative percent (%)
Age	18 – 24 years	25	22.5	22.5
	25 – 34 years	28	25.2	47.7
	35 – 44 years	10	9.0	56.7
	45 – 54 years	16	14.4	71.1
	55 – 64 years	14	12.6	83.8
	≥ 65 years	18	16.2	100.0
Gender	Male	65	58.6	58.6
	Female	46	41.4	100.0
Income	Lower than €1000 net per month	16	14.4	14.4
	Between €1001 and €2000 net per month	23	20.7	35.1
	Between €2001 and €3000 net per month	43	38.7	73.8
	Higher than €3000 net per month	20	18.0	91.9
	I'd rather not say	9	8.1	100.0
Education Level	Secondary education (VMBO/HAVO/VWO)	18	16.2	16.2
	Secondary vocational education (MBO)	21	18.9	35.1
	Higher vocational education (HBO/Bachelor WO)	52	46.8	82.0
	WO Master/PhD	20	18.0	100.0
Occupation	Student	26	23.4	23.4
	Working part-time	18	16.2	39.6
	Working full-time	46	41.4	81.0
	Retired	16	14.4	95.5
	Other	5	4.5	100.0
Household Composition	Single-person household	20	18.0	18.0
	Two-person household with partner	47	42.3	60.3
	Household with children	25	22.5	82.9
	Other	19	17.1	100.0
Living Environment	City center	26	23.4	23.4
	City suburbs	43	38.7	62.1
	(Small) Town	35	31.5	93.7
	Rural	7	6.3	100.0

Station plaza visits Eindhoven	Daily	7	6.3	6.3
	Weekly	17	15.3	21.6
	1 -2 times per month	22	19.8	41.4
	Less than once per month	25	22.5	63.9
	(Almost) never	40	36.1	100.0
Other station plaza visits	Daily	7	6.3	6.3
	Weekly	24	21.6	27.9
	1 -2 times per month	30	27.0	54.9
	Less than once per month	36	32.5	87.4
	(Almost) never	14	12.6	100.0
Life satisfaction	Very dissatisfied	0	0	0
	Dissatisfied	4	3.6	3.6
	Neutral	11	9.9	13.5
	Satisfied	69	62.2	75.7
	Very satisfied	27	24.3	100.0
Influence of station plaza on health	Very unimportant	5	4.5	4.5
	Unimportant	15	13.5	18.0
	Neutral	42	37.8	55.8
	Important	40	36.1	91.9
	Very important	9	8.1	100.0
Background in architecture/urbanism	Yes	33	29.7	29.7
	No	78	70.3	100.0
Preknowledge	Yes	20	18.0	18.0
	No	91	82.0	82.0

Appendix K – Video database

Variable	Level	Frequency	Percent (%)	Cumulative percent (%)
Age	18 – 24 years	30	28.6	28.6
	25 – 34 years	27	25.7	54.3
	35 – 44 years	11	10.5	64.8
	45 – 54 years	12	11.4	76.2
	55 – 64 years	11	10.5	86.7
	≥ 65 years	14	13.3	100.0
Gender	Male	53	50.5	50.5
	Female	51	48.6	99.0
	Other	1	1.0	100.0
Income	Lower than €1000 net per month	23	21.9	21.9
	Between €1001 and €2000 net per month	21	20.0	41.9
	Between €2001 and €3000 net per month	31	29.5	71.4
	Higher than €3000 net per month	21	20.0	91.4
	I'd rather not say	9	8.6	100.0
Education Level	Secondary education (VMBO/HAVO/VWO)	19	18.1	18.1
	Secondary vocational education (MBO)	14	13.3	31.4
	Higher vocational education (HBO/Bachelor WO)	54	51.4	82.8
	WO Master/PhD	17	16.2	99.0
	I'd rather not say	1	1.0	100.0
Occupation	Student	29	27.6	27.6
	Working part-time	19	18.1	45.7
	Working full-time	38	36.2	81.9
	Retired	13	12.4	94.3
	Other	5	4.8	99.0
	I'd rather not say	1	1.0	100.0
Household Composition	Single-person household	21	20.0	20.0
	Two-person household with partner	41	39.0	59.0
	Household with children	23	21.9	81.0
	Other	20	19.0	100.0
Living Environment	City center	30	28.6	28.6

	City suburbs	40	38.1	66.7
	(Small) Town	31	29.5	96.2
	Rural	3	2.9	99.0
	I'd rather not say	1	1.0	100.0
Station plaza visits Eindhoven	Daily	6	5.7	5.7
	Weekly	16	15.2	20.9
	1 -2 times per month	15	14.3	35.2
	Less than once per month	21	20.0	55.2
	(Almost) never	47	44.8	100.0
Other station plaza visits	Daily	9	8.6	8.6
	Weekly	32	30.5	39.1
	1 -2 times per month	25	23.8	62.9
	Less than once per month	22	21.0	83.9
	(Almost) never	17	16.1	100.0
Life satisfaction	Very dissatisfied	1	1.0	1.0
	Dissatisfied	3	2.8	3.8
	Neutral	13	12.4	16.2
	Satisfied	61	58.1	74.3
	Very satisfied	27	25.7	100.0
Influence of station plaza on health	Very unimportant	0	0	0
	Unimportant	13	12.4	12.4
	Neutral	49	46.7	59.1
	Important	35	33.3	92.4
	Very important	8	7.6	100.0
Background in architecture/urbanism	Yes	22	21.0	21.0
	No	83	79.0	100.0
Preknowledge	Yes	13	12.4	12.4
	No	92	87.6	100.0

Appendix L – NLOGIT code and output

```
|-> RESET

=====================================================
      /\    /  /     ___  __    /   ____
     /  \  /  /     /  /  /__   /    /
    /    \/  /__   /__/  /__/  /    /
=====================================================

O-----------------------------------------------------------O
| NLOGIT 6  (tm)              Jan 25, 2024, 07:07:57PM      |
| Econometric Software, Inc.  Copyright 1986-2016           |
| Plainview, New York 11803   www.nlogit.com                |
| Registered to Yannick Pagie                               |
|              TU Eindhoven                                 |
| Registration Number:  0817-0017673-6NSL                   |
O-----------------------------------------------------------O
-------Initializing NLOGIT Version 6 (Sep 7, 2016)---------
-----------------------------------------------------------

|-> IMPORT;FILE="C:\Users\s167474\OneDrive - TU Eindhoven\Graduation\9.
Thesis\Data\final\Final data correctly recoded comma.csv"$
Last observation read from data file was    3456
|-> reset$
|-> Read; File=C:\Users\s167474\OneDrive - TU Eindhoven\Graduation\9.
Thesis\Data\final\Final data correctly recoded comma.csv $
Last observation read from data file was    3456
|-> Reject ; Mode=-1 $    ? exclude the data for Mode=-1
|-> NLOGIT
    ;lhs = Choice, Nalt
    ;rhs = constant, foun, lamp, treesc15, treess15, trees9, bench15, bench8,
bench4, grass66, grass50, grass33, skyscrap, highrise, mediumri
    $
Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .4798220D+03

------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function      -479.82199
Estimation based on N =    888, K =  15
Inf.Cr.AIC  =    989.6 AIC/N =    1.114
--------------------------------------
           Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=   888, skipped    0 obs
--------+---------------------------------------------------------------------
        |                 Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+---------------------------------------------------------------------
CONSTANT|     .83745***      .08350    10.03  .0000      .67379   1.00110
    FOUN|     .34097***      .08049     4.24  .0000      .18321    .49873
    LAMP|     .15192*        .08195     1.85  .0637     -.00869    .31254
TREESC15|     .63092***      .15282     4.13  .0000      .33140    .93044
TREESS15|     .28824**       .14018     2.06  .0398      .01350    .56298
  TREES9|     .14965         .13899     1.08  .2816     -.12277    .42207
```

```
 BENCH15|     .64091***      .15455     4.15  .0000      .33800    .94382
  BENCH8|     .38874***      .14734     2.64  .0083      .09996    .67751
  BENCH4|     .00973         .13607      .07  .9430     -.25696    .27643
 GRASS66|     .17375         .13707     1.27  .2050     -.09491    .44241
 GRASS50|     .23208         .15082     1.54  .1238     -.06351    .52768
 GRASS33|     .22384         .14175     1.58  .1143     -.05398    .50166
SKYSCRAP|    -.26482*        .13594    -1.95  .0514     -.53125    .00161
HIGHRISE|    -.07592         .13635     -.56  .5776     -.34316    .19131
MEDIUMRI|     .03101         .13902      .22  .8235     -.24147    .30348
--------+-------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2024 at 07:12:37 PM
-----------------------------------------------------------------------------

|-> Include ; Mode=-1 $    ? include the data for Mode=-1
|-> Reject ; Mode=1 $      ? exclude the data for Mode=1
|-> NLOGIT
    ;lhs = Choice, Nalt
    ;rhs = constant, foun, lamp, treesc15, treess15, trees9, bench15, bench8,
bench4, grass66, grass50, grass33, skyscrap, highrise, mediumri
    $
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=    .4753237D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function       -475.32369
Estimation based on N =    840, K =  15
Inf.Cr.AIC  =    980.6 AIC/N =    1.167
--------------------------------------
           Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=   840, skipped    0 obs
--------+--------------------------------------------------------------------
        |                   Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
CONSTANT|    -.63086***      .08105    -7.78  .0000     -.78971   -.47202
    FOUN|     .11009         .08073     1.36  .1727     -.04813    .26832
    LAMP|     .17681**        .08129     2.18  .0296      .01748    .33613
TREESC15|     .28305**        .13633     2.08  .0379      .01585    .55025
TREESS15|     .41777***      .13898     3.01  .0026      .14538    .69016
  TREES9|     .54546***      .14796     3.69  .0002      .25546    .83546
 BENCH15|     .61496***      .15187     4.05  .0001      .31730    .91262
  BENCH8|     .19955         .14312     1.39  .1632     -.08095    .48006
  BENCH4|    -.39138***      .13506    -2.90  .0038     -.65609   -.12668
 GRASS66|     .33814**        .14086     2.40  .0164      .06207    .61422
 GRASS50|     .24815*         .13822     1.80  .0726     -.02276    .51907
 GRASS33|     .26725*         .13889     1.92  .0543     -.00498    .53947
SKYSCRAP|     .04834         .14085      .34  .7314     -.22773    .32441
HIGHRISE|    -.13290         .13109    -1.01  .3107     -.38983    .12403
MEDIUMRI|     .07181         .14332      .50  .6163     -.20909    .35270
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2024 at 07:13:20 PM
-----------------------------------------------------------------------------

|-> Include ; Mode=1 $    ? include the data for Mode=-1
|-> NLOGIT
    ;lhs = Choice, Nalt
```

```
    ;rhs = constant, foun, lamp, treesc15, treess15, trees9, bench15, bench8,
bench4, grass66, grass50, grass33, skyscrap, highrise, mediumri
    $
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=    .1055729D+04

------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function     -1055.72887
Estimation based on N =   1728, K =  15
Inf.Cr.AIC  =   2141.5 AIC/N =    1.239
--------------------------------------
            Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
               Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=  1728, skipped    0 obs
--------+---------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+---------------------------------------------------------------------
CONSTANT|     .09083*        .05245     1.73  .0833     -.01196    .19362
    FOUN|     .21767***      .05312     4.10  .0000      .11355    .32178
    LAMP|     .17106***      .05314     3.22  .0013      .06690    .27522
TREESC15|     .43757***      .09062     4.83  .0000      .25995    .61519
TREESS15|     .36748***      .08843     4.16  .0000      .19416    .54080
  TREES9|     .31920***      .09074     3.52  .0004      .14135    .49705
 BENCH15|     .51660***      .09462     5.46  .0000      .33114    .70206
  BENCH8|     .26266***      .09172     2.86  .0042      .08290    .44242
  BENCH4|    -.12274         .08928    -1.37  .1692     -.29772    .05224
 GRASS66|     .30139***      .08953     3.37  .0008      .12591    .47687
 GRASS50|     .19746**       .09252     2.13  .0328      .01612    .37880
 GRASS33|     .22242**       .09041     2.46  .0139      .04522    .39963
SKYSCRAP|    -.07298         .09069     -.80  .4210     -.25073    .10477
HIGHRISE|    -.00266         .08829     -.03  .9760     -.17571    .17040
MEDIUMRI|     .03537         .09223      .38  .7014     -.14541    .21614
--------+---------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2024 at 07:13:49 PM
------------------------------------------------------------------------------

|-> Create                    ? create variables to measure differences between
the two modes
    ; Mcon=constant*Mode
    ; Mfoun=foun*Mode
    ; Mlamp=lamp*Mode
    ; Mtrc15=treesc15*Mode
    ; Mtrs15=treess15*Mode
    ; Mtr9=trees9*Mode
    ; Mbn15=bench15*Mode
    ; Mbn8=bench8*Mode
    ; Mbn4=bench4*Mode
    ; Mgr66=grass66*Mode
    ; Mgr50=grass50*Mode
    ; Mgr33=grass33*Mode
    ; Msky=skyscrap*Mode
    ; Mhigh=highrise*Mode
    ; Mmed=mediumri*Mode
    $
|-> NLOGIT
    ;lhs = Choice, Nalt
```

```
    ;rhs = constant, foun, lamp, treesc15, treess15, trees9, bench15, bench8,
bench4, grass66, grass50, grass33, skyscrap, highrise, mediumri ,
    Mcon,     Mfoun,Mlamp,Mtrc15,    Mtrs15,    Mtr9,     Mbn15,    Mbn8,     Mbn4,     M
gr66,    Mgr50,    Mgr33,    Msky,     Mhigh,     Mmed
    $
Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .9551457D+03

--------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function       -955.14568
Estimation based on N =   1728, K =  30
Inf.Cr.AIC  =   1970.3 AIC/N =    1.140
--------------------------------------
           Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=  1728, skipped    0 obs
--------+-----------------------------------------------------------------------
        |                   Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+-----------------------------------------------------------------------
CONSTANT|     .10329*        .05818     1.78  .0758     -.01074    .21733
    FOUN|     .22553***      .05700     3.96  .0001      .11381    .33725
    LAMP|     .16436***      .05771     2.85  .0044      .05125    .27748
TREESC15|     .45699***      .10240     4.46  .0000      .25630    .65768
TREESS15|     .35300***      .09870     3.58  .0003      .15956    .54645
  TREES9|     .34755***      .10150     3.42  .0006      .14861    .54650
 BENCH15|     .62793***      .10834     5.80  .0000      .41559    .84028
  BENCH8|     .29415***      .10270     2.86  .0042      .09285    .49544
  BENCH4|    -.19082**       .09586    -1.99  .0465     -.37870   -.00294
 GRASS66|     .25595***      .09827     2.60  .0092      .06333    .44856
 GRASS50|     .24012**       .10229     2.35  .0189      .03964    .44060
 GRASS33|     .24554**       .09923     2.47  .0133      .05107    .44002
SKYSCRAP|    -.10824         .09788    -1.11  .2688     -.30007    .08359
HIGHRISE|    -.10441         .09457    -1.10  .2696     -.28977    .08095
MEDIUMRI|     .05141         .09983      .51  .6066     -.14426    .24707
    MCON|     .73415***      .05818    12.62  .0000      .62012    .84819
   MFOUN|     .11544**       .05700     2.03  .0428      .00372    .22716
   MLAMP|    -.01244         .05771     -.22  .8293     -.12555    .10067
  MTRC15|     .17394*        .10240     1.70  .0894     -.02675    .37463
  MTRS15|    -.06477         .09870     -.66  .5117     -.25821    .12868
    MTR9|    -.19790*        .10150    -1.95  .0512     -.39685    .00104
   MBN15|     .01297         .10834      .12  .9047     -.19937    .22531
    MBN8|     .09459         .10270      .92  .3570     -.10670    .29588
    MBN4|     .20056**       .09586     2.09  .0364      .01268    .38844
   MGR66|    -.08220         .09827     -.84  .4029     -.27481    .11041
   MGR50|    -.00803         .10229     -.08  .9374     -.20852    .19245
   MGR33|    -.02170         .09923     -.22  .8269     -.21618    .17277
    MSKY|    -.15658         .09788    -1.60  .1096     -.34841    .03525
   MHIGH|     .02849         .09457      .30  .7632     -.15687    .21384
    MMED|    -.02040         .09983     -.20  .8381     -.21607    .17527
--------+-----------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2024 at 07:14:31 PM
--------------------------------------------------------------------------------

|-> create                        ? set all personal characteristics to 0 for
second alternative
    ; gender=  (2-altid)*gender
    ; year1834=(2-altid)*year1834
```

```
    ; year3554=(2-altid)*year3554
    ; income=  (2-altid)*income
    ; educatio=(2-altid)*educatio
    ; occupati=(2-altid)*occupati
    ; singlep= (2-altid)*singlep
    ; twopp=   (2-altid)*twopp
    ; citycent=(2-altid)*citycent
    ; citysub= (2-altid)*citysub
    ; weeklyei=(2-altid)*weeklyei
    ; monthlye=(2-altid)*monthlye
    ; weeklyot=(2-altid)*weeklyot
    ; monthlyo=(2-altid)*monthlyo
    ; lifediss=(2-altid)*lifediss
    ; lifesati=(2-altid)*lifesati
    ; healthun=(2-altid)*healthun
    ; healthne=(2-altid)*healthne
    ; backgrou=(2-altid)*backgrou
    ; preknow= (2-altid)*preknow
    $
|-> NLOGIT
    ;lhs = Choice, Nalt
    ;rhs = constant, foun, lamp, treesc15, treess15, trees9, bench15, bench8,
bench4, grass66, grass50, grass33, skyscrap, highrise, mediumri ,
    Mcon,     Mfoun,Mlamp,Mtrc15,   Mtrs15,   Mtr9,    Mbn15,   Mbn8,    Mbn4,    M
gr66,   Mgr50,   Mgr33,   Msky,     Mhigh,    Mmed,
    gender, year1834, year3554, income,
educatio,occupati,singlep,twopp,citycent,citysub,weeklyei,monthlye,weeklyot,monthly
o,lifediss,lifesati,
    healthun,healthne,backgrou,preknow
    $
Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=    .8926303D+03

------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function       -892.63026
Estimation based on N =   1728, K =  50
Inf.Cr.AIC  =   1885.3 AIC/N =    1.091
--------------------------------------
           Log likelihood R-sqrd R2Adj
ASCs  only  model must be fit separately
              Use NLOGIT ;...;RHS=ONE$
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
--------------------------------------
Response data are given as ind. choices
Number of obs.=  1728, skipped    0 obs
--------+---------------------------------------------------------------------
        |                 Standard            Prob.      95% Confidence
  CHOICE|  Coefficient       Error       z    |z|>Z*         Interval
--------+---------------------------------------------------------------------
CONSTANT|     .10708*        .06315     1.70  .0900     -.01669    .23086
    FOUN|     .25851***      .05971     4.33  .0000      .14147    .37555
    LAMP|     .14824**       .06013     2.47  .0137      .03040    .26609
TREESC15|     .50808***      .10733     4.73  .0000      .29771    .71844
TREESS15|     .38741***      .10246     3.78  .0002      .18660    .58823
  TREES9|     .33680***      .10646     3.16  .0016      .12814    .54546
 BENCH15|     .66216***      .11339     5.84  .0000      .43993    .88440
  BENCH8|     .30506***      .10668     2.86  .0042      .09596    .51416
  BENCH4|    -.20249**       .10052    -2.01  .0440     -.39951   -.00547
 GRASS66|     .30591***      .10272     2.98  .0029      .10457    .50725
 GRASS50|     .27244**       .10732     2.54  .0111      .06210    .48279
 GRASS33|     .26448***      .10266     2.58  .0100      .06327    .46570
SKYSCRAP|    -.16815         .10238    -1.64  .1005     -.36882    .03252
HIGHRISE|    -.08735         .09893     -.88  .3773     -.28124    .10655
```

```
MEDIUMRI|     .09214         .10453      .88  .3781     -.11273    .29700
    MCON|     .12684         .12410     1.02  .3068     -.11640    .37007
   MFOUN|     .13373**        .05954     2.25  .0247      .01703    .25043
   MLAMP|    -.00886         .06008     -.15  .8828     -.12662    .10890
  MTRC15|     .20227*         .10718     1.89  .0591     -.00780    .41235
  MTRS15|    -.11400         .10276    -1.11  .2673     -.31541    .08741
    MTR9|    -.19424*         .10601    -1.83  .0669     -.40203    .01354
   MBN15|    -.04325         .11321     -.38  .7025     -.26513    .17864
    MBN8|     .12147         .10725     1.13  .2574     -.08875    .33168
    MBN4|     .21260**        .10090     2.11  .0351      .01484    .41036
   MGR66|    -.06353         .10284     -.62  .5368     -.26510    .13804
   MGR50|     .00153         .10740      .01  .9886     -.20898    .21203
   MGR33|    -.01897         .10287     -.18  .8537     -.22059    .18265
    MSKY|    -.18304*         .10192    -1.80  .0725     -.38280    .01672
   MHIGH|     .08179         .09924      .82  .4098     -.11271    .27630
    MMED|     .00343         .10446      .03  .9738     -.20132    .20818
  GENDER|    -.34445***       .06655    -5.18  .0000     -.47488   -.21401
YEAR1834|     .38096***       .09426     4.04  .0001      .19620    .56571
YEAR3554|    -.41715***       .11000    -3.79  .0001     -.63275   -.20156
  INCOME|    -.05609         .08188     -.68  .4934     -.21658    .10440
EDUCATIO|     .10434         .07058     1.48  .1393     -.03399    .24267
OCCUPATI|    -.04408         .08076     -.55  .5852     -.20237    .11420
 SINGLEP|     .23180**        .09975     2.32  .0201      .03630    .42730
   TWOPP|     .06855         .08754      .78  .4336     -.10303    .24014
CITYCENT|     .18014         .11033     1.63  .1025     -.03611    .39639
 CITYSUB|    -.21182**        .08696    -2.44  .0149     -.38226   -.04138
WEEKLYEI|     .18838         .15165     1.24  .2142     -.10885    .48562
MONTHLYE|    -.25189**        .10034    -2.51  .0121     -.44855   -.05522
WEEKLYOT|     .21561**        .10120     2.13  .0331      .01725    .41396
MONTHLYO|     .23161**        .09573     2.42  .0155      .04399    .41923
LIFEDISS|    -.37101***       .11825    -3.14  .0017     -.60276   -.13925
LIFESATI|     .33878***       .08573     3.95  .0001      .17075    .50681
HEALTHUN|     .16459         .11633     1.41  .1571     -.06340    .39259
HEALTHNE|    -.23181**        .09013    -2.57  .0101     -.40846   -.05516
BACKGROU|    -.36886***       .10911    -3.38  .0007     -.58271   -.15501
 PREKNOW|    -.19401**        .09006    -2.15  .0312     -.37052   -.01749
--------+------------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2024 at 07:15:05 PM
-------------------------------------------------------------------------------
```