MASTER

# Incorporating human perception in computational urban design

## A research with the aim to strengthen computational urban design as a supportive tool in the conceptual design phase of an urban development

van Veghel, Joppe W.

*Award date:*
2022

# Incorporating human perception in computational urban design

**A research with the aim to strengthen computational urban design as a supportive tool in the conceptual design phase of an urban development**

Joppe Willem van Veghel – Master thesis

EINDHOVEN UNIVERSITY OF TECHNOLOGY

## General information:

| | |
|---|---|
| Student name: | Joppe Willem van Veghel |
| Student number: | 1013816 |
| Masters: | Architecture, Building and Planning, track Urban Systems and Real Estate (USRE) |
| | Construction Management Engineering (CME) |
| University: | Eindhoven University of Technology |
| Course Codes | 7Z45M0 (USRE) & 7CC40 (CME) |
| Study Load | 60 ECTS |
| Year of graduation | 2022 |

*Supervising committee*:

| | | | |
|---|---|---|---|
| Aloys Borgers | Main Supervisor | Eindhoven University of Technology | Chair of graduation committee USRE |
| Gamze Dane | Supervisor | Eindhoven University of Technology | |
| Giorgio Agugiaro | Supervisor | Delft University of Technology | |
| Bauke de Vries | | Eindhoven University of Technology | Chair of graduation committee CME |

*This thesis is open to the public and has been carried out in accordance with the rules of the TU/e Code of Scientific Integrity*

# Contents

# Preface

Cities are complex systems, facilitating the day to day live of thousands to millions of individuals. Every individual is moving through this system that consists of transportation networks, houses, offices, open spaces, planned nature and many other elements. How we create our urban system influences how an individual moves through the system, who meets who while moving through the system and what an individual sees and experiences in daily life. Winston Churchill once said in his speech in the House of Lords, October 28, 1943: *"We shape our buildings; thereafter they shape us"*, however it are not just the buildings that shape us. It is the composition of the complete system that shapes us.

It is this influence and importance of the urban system that has fascinated me from the start of my studies. When we construct a new residential building or neighborhood, we are not solely adding new houses to the building stock but we are shaping the life of the new residents. As a result, during my studies, I developed a desire to understand the impact of our urban environment. Because only when we understand the impact of our urban environment thoroughly, we can make the right decision when we make adjustments in it.

Today, we are extracting more and more data from our cities. This urban data, is what can support actors in the field or urban development to understand the existing urban system. However, this urban data also enables us to model the urban system. In addition, when we understand the relation between multiple aspects of the urban system, we can model the interaction between the individual aspects of an urban system. This enables us to better understand the crucial impact of adjustments in our cities.

This opportunity to understand the impact of adjustments in our cities through urban data and models of the urban environment is what has driven me work on my thesis every day in the past year. Too often, adjustments in our urban environment serve the interests of a few stakeholders or address a few aspects of the urban system. Too often, the made choices are not based to serve the day to day life of all humans. I hope that this thesis can contribute to the right choices in the future, choices that are based to serve the people living in our urban environments.

In the past year, I was lucky to enjoy the support of many people involved in my graduation project. Thank you Aloys, Gamze ,Giorgio, Judith and everyone who supported me at Brink for your support and expertise during the process.

This thesis also represents the end of my studies at Eindhoven University of Technology. I would like to grasp this opportunity to thank everyone who has been part of my student life in Eindhoven. It has been a blast!

Finally, I would to specifically thank Fenna and my family for your amazing support and always being there for me during my graduation project and my studies!

## Summary

Existing urban areas are under pressure as there is a need for densification, this comes along with many challenges. In existing urban areas, many different stakeholders are involved. Additionally, further densification of urban areas can have an influence on the wellbeing of humans living in urban areas. Densification can have a negative or positive impact on human wellbeing. As a result, it is extremely important to have a comprehensive overview on the impact of a new urban development project on its stakeholders and the wellbeing of humans.

Computational urban design can be considered as a supportive tool in the development process of new urban areas. It enables fast generation of potential design solutions, in which the impact of a design on multiple design aspects can be calculated and visualized. Computational urban design is specifically strong in the generation of volumetric, conceptual, designs. Furthermore, computational urban design even allows a design to be steered to minimize or maximize impact on a certain design aspect. In complex urban development projects, computational urban design can thus be used to retrieve fast insight on potential design solutions. As a result, computational urban design can contribute to a faster development process. However, current computational urban design tools are not comprehensive as they do not facilitate the inclusion of human wellbeing, even though urban densification brings along risks concerning the wellbeing of humans (Kalantari & Shepley, 2020).

One of the aspects that is related to human wellbeing but not yet included in any computational urban design tool is human perception. In existing literature it was found that specifically perceived beauty, liveliness, and safety influence human wellbeing (Weijs-Perrée et al., 2020; Mouratidis, 2018). In which, momentary subjective wellbeing concerns the influence of emotions and moods (Eid & Diener, 2004) on how humans evaluate their life (Diener, 2000). In order to strengthen computational urban design as a supportive tool in the complex urban development projects, this research explores and demonstrates the incorporation of human perception in computational urban design.

To incorporate human perception in computational urban design, first the relation between the built environment and human perception has been quantified. It was found in existing literature that many elements in the built environment influence human perception. These built environment elements concern both non-volumetric, detailed elements in urban areas and functions of urban spaces, as well as volumetric, predominantly urban morphological, elements. In computational urban design, only volumetric built environment elements are generally included. As a result, only volumetric built environment elements have been studied on the relation with human perception in this research.

The relation between the included volumetric built environment and human perception has been studied and quantified in linear functions using multinomial logit models. The Place Pulse 2.0 (Dubey et al., 2016) dataset has been used as the main choice dataset, including choices between two street view images on human perception. The images in the dataset have been segmented and open built environment data has been used to retrieve data describing the built environment on the location of the images. It was found from the estimated multinomial logit models that there is a difference in the relation between human perception and the volumetric built environment between low density and high density environments. As a result, for each of the three human perception categories, a linear function describing the relation with the volumetric built environment has been formulated for both a low density and a high density environment. It was found from the relations that the share of trees visible in the street view has a strong influence on perceived beauty, liveliness, and safety for both high and low density environments. Furthermore, among others the building

footprint area, building height and relation between the building height and the street width was found to influence human perception. However, these volumetric built environment attributes can only explain a limited part of the preference of humans regarding perceived beauty, liveliness, and safety. Additionally, also non-volumetric built environments have an influence on human perception and human perception is a subjective concept and is therefore hard to generalize. Since computational urban design in its current form does not allow for subjectivity to be included and is specifically strong in generating volumetric urban designs, a limitation on influence of the volumetric built environment on human perception implies a limitation to incorporate human perception in computational urban design. Yet, it should be noted that the found relations do describe a part of the overall relation between human perception and the built environment.

The functions describing the relation between the volumetric built environment and human perception have been incorporated in computational urban design by creating an extension in Grasshopper on an existing computational urban design methodology (García González, 2019). This computational urban design methodology can be considered as a parametric design tool, allowing the user to design urban areas based on data retrieved from existing urban areas. Within this research, a parametrically generated design has been optimized on perceived beauty, liveliness, safety and a combination of the three using the quantified relationships between human perception and the built environment.

The extension has been created in Grasshopper. The created Grasshopper script first imports a generated output scenario. This design is then analyzed on human perception by retrieving the built environment data from the design that has been found to influence human perception. Using the linear relationships that have been found as a result of the conducted analysis on the relation between human perception and the volumetric built environment, a human perception score can be calculated for the design. In addition, design variables have been set to adjust the imported design. Using genetic optimization or simulated annealing through the Galapagos plugin (Rutten, 2013) in Grasshopper, the design can be optimized on perceived beauty, liveliness, or safety. In addition, a multi-objective optimization on all three of the human perception categories based on genetic optimization can be run using the Octopus (Vierlinger et al., 2018) plugin in Grasshopper. Both Galapagos and Octopus optimize the human perception scores by adjusting the design variables. In order to incorporate other design aspects such as the required amount of square meters or a minimum required amount of daylight availability in the buildings, it is possible to set multiple requirements that the optimized design has to meet.

Altogether, this research consists of a first attempt to incorporate human perception in computational urban design. This research has demonstrated a complete process to incorporate human perception in computational urban design. Including an analysis of the relation between human perception and the built environment as well as the creation of a computational urban design extension, that allows for optimizing urban designs on human perception.

In conclusion, it can be stated that it is possible to incorporate human perception in computational urban design, as demonstrated by this research. Furthermore, in this research several chances on improvement are highlighted enabling this research to serve as a base for future improvement. Future research should focus on incorporating more accurate relations between human perception and the built environment, so that one day we can truly state that computational urban design is a comprehensive supportive tool in the urban development process which enables fast and accurate insight on the impact of a potential urban design on its most important stakeholder, humans.

## Samenvatting

Bestaande stedelijke gebieden staan onder druk aangezien het nodig is om deze gebieden te verdichten. Het verdichten van stedelijke gebieden brengt grote uitdagingen met zich mee, in stedelijke gebieden zijn er vele partijen betrokken bij een nieuwe ontwikkeling en de verdichting van stedelijke gebieden kan invloed hebben op het welzijn van mensen die hier leven (Kalantari & Shepley, 2020). Daarom is het van belang om een allesomvattend beeld te hebben van de impact van nieuwe ontwikkelingen op de belangen van betrokken partijen en het welzijn van de mens.

Computational urban design, een container begrip voor parametrisch en generatief stedenbouwkundig ontwerpen, kan als een hulpmiddel worden beschouwd tijdens het ontwikkelproces van nieuwe stedelijke gebieden. Het biedt de mogelijkheid om snel mogelijke ontwerpen te genereren en te toetsen op de impact die het heeft. Computational urban design is voornamelijk sterk in het genereren van conceptuele ontwerpen. Daarnaast biedt computational urban design de mogelijkheid om een ontwerp te genereren dat de impact op een bepaald aspect minimaliseert of maximaliseert. In complexe stedelijke ontwikkelingen, kan computational urban design dus gebruikt worden om snel inzicht te krijgen in mogelijke ontwerpoplossingen. Hiermee kan computational urban design een bijdrage leveren aan een sneller ontwikkelproces. Echter, bestaande computational urban design systemen zijn niet allesomvattend aangezien ze niet het welzijn van mensen meenemen.

Een van de aspecten die invloed heeft op het welzijn van mensen en die nog niet in bestaande computational urban design tools is verwerkt, is menselijke perceptie. Uit bestaande literatuur blijkt dat specifiek de perceptie van schoonheid, levendigheid, en veiligheid van invloed is op het welzijn van mensen (Weijs-Perrée et al., 2020; Mouratidis, 2018). Om computational urban design te versterken als hulpmiddel voor complexe stedelijke ontwikkelingen, focust dit onderzoek zich op het onderzoeken en demonstreren van het verwerken van menselijke perceptie in computational urban design.

Om menselijke perceptie in computational urban design te verwerken, is eerst de relatie tussen de gebouwde omgeving en menselijke perceptie gekwantificeerd. Uit bestaande literatuur blijkt dat vele elementen van de gebouwde omgeving invloed hebben op menselijke perceptie. Deze elementen omvatten zowel elementen gerelateerd aan volumes in de gebouwde omgeving, zoals de stedelijke morfologie, als elementen die niet gerelateerd zijn aan volumes in de gebouwde omgeving, zoals details in de gevels van gebouwen. In computational urban design zijn over het algemeen enkel volume-gerelateerde gebouwde omgevingselementen verwerkt. Hierdoor, omvat dit onderzoek alleen een analyse naar de relatie tussen volume-geralteerde gebouwde omgevingselementen en menselijke perceptie.

De relaties tussen de geïncludeerde volume-gerelateerde gebouwde omgevingsattributen en menselijke perceptie zijn met behulp van multinomial logit models uitgedrukt in lineaire functies. De Place Pulse 2.0 (Dubey et al., 2016) dataset is gebruikt als belangrijkste keuze dataset, de dataset bestaat uit gemaakte keuzes wat betreft menselijke perceptie tussen twee Google Street View foto's. De foto's in de dataset zijn gesegmenteerd en open gebouwde omgevingsdata is gebruikt om data te verzamelen die de gebouwde omgeving omschrijft in de nabijheid van de locatie waar de foto is gemaakt. Uit de analyse blijkt dat in gebieden met een relatief lage dichtheid, er een andere relatie is tussen de gebouwde omgeving en menselijke perceptie dan in gebieden met een hoge dichtheid. Daarom zijn voor alle drie de menselijke perceptiecategorieën twee relaties gekwantificeerd, één voor een omgeving met een relatief lage dichtheid en één voor een omgeving met een relatief hoge dichtheid. Uit de analyse blijkt verder dat het aandeel bomen dat zichtbaar is

in de foto's een sterke invloed heeft op de perceptie van schoonheid, levendigheid, en veiligheid in omgevingen met zowel een relatief lage als hoge dichtheid. Daarnaast hebben onder andere het bebouwde oppervlakte van een gebouw, de gebouwhoogte en de relatie tussen de gebouwhoogte en de straatbreedte een invloed op menselijke perceptie. Echter, vertegenwoordigen de volume-gerelateerde gebouwde omgevingsattributen slechts een deel van de totale invloed van de gebouwde omgeving op menselijke perceptie. Daarnaast hebben ook niet volume-gerelateerde gebouwde omgevingsattributen invloed op menselijke perceptie en is menselijke perceptie subjectief van aard waardoor het lastig te generaliseren is. Omdat computational urban design in haar huidige vorm geen rekening houdt met subjectiviteit en het voornamelijk sterk is in het genereren van conceptuele ontwerpen, betekent een gelimiteerde invloed van volume-gerelateerde gebouwde omgevingselementen op de perceptie van mensen tevens dat de mogelijkheid om menselijke perceptie in computational urban design te verwerken gelimiteerd is.

De functies die de relatie tussen de volume-gerelateerde gebouwde omgeving elementen en menselijke perceptie omschrijven zijn verwerkt in computational urban design door een extensie van een bestaande parametrisch stedenbouwkundig ontwerpmethodologie (García González, 2019) in Grasshopper te creëren. Deze methodologie geeft de gebruiker de mogelijkheid om nieuwe gebieden te ontwerpen op basis van data verkregen uit bestaande stedelijke gebieden. Binnen dit onderzoek zijn parametrisch ontworpen gebieden geoptimaliseerd op de perceptie van schoonheid, levendigheid, veiligheid en een combinatie van deze drie door gebruikt te maken van de gekwantificeerde relaties tussen de volume-gerelateerde gebouwde omgeving en menselijke perceptie.

De gecreëerde extensie importeert eerst een gegeneerd ontwerp. Vervolgens wordt gebouwde omgeving data dat menselijke perceptie beïnvloed uit het ontwerp verzameld. Met behulp van de gevonden relaties tussen de gebouwde omgeving en menselijke perceptie wordt er vervolgens een menselijke perceptiescore berekend voor het ontwerp. Daarnaast zijn er nieuwe ontwerpvariabele gecreëerd die het mogelijk maken om het geïmporteerde ontwerp aan te passen. Door genetische optimalisatie of simulated annealing toe te passen met behulp van de Galapgos plugin (Rutten, 2013) in Grasshopper kan het ontwerp worden geoptimaliseerd op de perceptie van schoonheid, levendigheid en veiligheid. Tijdens het optimaliseren worden de waardes van de ontwerpvariabele automatisch aangepast zodat het ontwerp hoger scoort op de menselijke perceptie. Om ook andere ontwerp aspecten mee te nemen zoals het vereist aantal vierkante meters of de minimum hoeveelheid daglicht is het mogelijk om meerdere voorwaarden te stellen waaraan het geoptimaliseerde ontwerp moet voldoen.

Al met al bestaat dit onderzoek uit een eerste poging om menselijke perceptie te verwerken in computational urban design. Dit onderzoek demonstreert een volledig proces om menselijke perceptie in computational urban design te verwerken, inclusief een analyse tussen menselijke perceptie en de gebouwde omgeving en de creatie van een computational urban design extensie die het mogelijk maakt om stedenbouwkundige ontwerpen te optimaliseren.

Uit dit onderzoek blijkt dat het mogelijk is om menselijke perceptie in computational urban design te verwerken. Desondanks belicht dit onderzoek een aantal mogelijkheden om menselijke perceptie beter en accurater te verwerken in computational urban design. Toekomstig onderzoek zal zich hiervoor moeten focussen op het verwerken van accuratere relaties tussen de gebouwde omgeving en menselijke perceptie in computational urban design, zodat het ooit mogelijk is om te stellen dat computational urban design een allesomvattend ondersteunend middel is in het stedelijk ontwikkelproces.

## Abstract

In most urban areas there is a need for densification. The densification of existing urban areas comes along with risks and influences many different stakeholders and aspects within the existing urban system. In order to manage the influences of potential (re)development projects in an urban context, insight on the impact of potential (re)development projects is needed in an early stage of the development process. Computational Urban Design enables fast generation of conceptual urban designs in an existing urban context. These designs can be optimized to align to certain design aspects and the influence of the generated urban designs on multiple design aspects can be calculated and visualized easily. However, current computational urban design tools do not provide insight or include all relevant design aspects in an existing urban environment. Since cities are built to facilitate the life of humans, the wellbeing of humans can be considered as an important design aspect. Yet, wellbeing of humans is not incorporated in computational urban design. One of the aspects influencing the wellbeing of humans that is not yet incorporated in computational urban design is human perception.

This research demonstrates how human perception can be incorporated in computational urban design. Within this research, first the relation between the built environment and human perception is analysed and quantified using a big data approach, including stated choice data and a multinomial logit analysis. From the analysis it was among others found that the presence of trees, the dimensions of building volumes and the urban morphology influences human perception. The quantified relationships between human perception and the built environment have been implemented in computational urban design by creating an extension on an existing parametric urban design methodology. This extension enables parametrically designed urban designs to be analyzed and optimized on human perception.

As a result of this research, a first methodology has been described and tested that enables the incorporation of human perception in computational urban design. The most important considerations for future research should be to increase the accuracy of the quantified relation between the built environment and human perception. In relation to the applicability in current practice, future works could focus on improving the technical capabilities of the computational urban design methodology by increasing the design freedom, the design generation speed and the comprehensiveness by including more design aspects.

## Keywords

Computational Urban Design, Human Perception, Optimization, Built Environment, Wellbeing

## List of Abbreviations

| | |
|---|---|
| KPI | Key Performance Indicators |
| SWB | Subjective wellbeing |
| TUDPUD | TU Delft Parametric Urban Design Project |
| GSV | Google Street View |
| SA | Simulated annealing |
| GA | Genetic algorithm |

# List of figures

# List of tables

# 1. Introduction

The world population has increased dramatically over the last decades and is expected to keep growing. Additionally, a significant part of the world population lives in urban areas and the share of people living in urban areas is expected to grow (United Nations Department of Economic and Social Affairs Population Division, 2019). On top of that, specifically in The Netherlands, the amount of households in relation to the share of the overall population is growing (Duin et al., 2018) as well as the overall population (Groenemeijer et al., 2020). As a result, there is a high demand for the construction of new dwellings in and around existing urban areas.

Specifically in many densely populated areas and western countries such as The Netherlands, besides a high demand for land for the construction of dwellings due to an increasing population, the pressure on the scarce land is increasing due to additional factors such as shifts towards sustainable energy demands and required space for upgrading the existing infrastructure network. Whereas the current intensive land use already results in challenges regarding the soil, water and biodiversity (PBL, 2021), dealing with these challenges requires more space for natural purposes as well. Therefore, available land for the construction of dwellings in non-urban areas is scarce, shifting the focus from expanding cities to densifying cities (Ministerie van Binnenlandse Zaken en Koningkrijksrelaties, 2020). In addition, building in higher densities has received increased attention due to the advantages that come along with it regarding more sustainable transportation, such as mass transit and the high level of amenities coming along with dense urban areas (Nabielek et al., 2012).

However, densifying existing urban areas comes along with many challenges. Densification for example comes along with the challenge to maintain or improve the livability of the city, in which the livability of a city can among others be expressed in the contribution of the city to the health and wellbeing of humans (Ministerie van Binnenlandse Zaken en Koningkrijksrelaties, 2020) (Nabielek et al., 2012). The livability and wellbeing of humans is affected by many aspects in the overall urban system shaping the built environment. These many individual aspects of the whole city can be affected by one intervention in a dense urban area. Therefore, densifying existing urban areas requires a comprehensive view on its impact on all aspects in the built environment.

In addition to the risks and opportunities coming along with densification in urban areas, more and more responsibilities centered around the densification process are shifting from public authorities towards the market in the Netherlands. As a result, in the real estate and urban development process, market parties such as real estate and urban developers have to take a leading role whereas the public actors have a facilitating role. Nevertheless, in a pro-active manner (Heurkens, 2012). This means that developers have to take up tasks that traditionally would have been taken care of by local public parties to safeguard public interest (Heurkens, 2012). Due to the increase in responsibilities for private parties in the real estate and urban development process, private parties have been given a more comprehensive task. Not only assuring a financially feasible project but also guaranteeing a project that is in line with public interest and thus has a positive impact on the overall urban system.

In order to deal with the high number of complexities and responsibilities that come along with developing an area or building in an urban system, while maintaining or increasing the efficiency of the development process, there is a need for supportive tools providing insight into the effects of new developments on the overall urban system.

Simultaneously, scientific knowledge on the interactions in urban systems increases and the pace in which we retrieve data from the overall urban system is increasing. This increase in knowledge about the interactions in our urban system and the increase in data about what goes in and out of the urban system, in combination with the trend that market parties receive more responsibilities while having to deal with many complexities and challenges, increases the need to model the complete composition of the system.

As with any system, it is modeled before it is constructed. Computational urban design can be considered as designing part of an urban system through modelling the impact of that part on the overall system. Simply stated, computational urban design shifts the design process away from designing geometries into designing based on design variables and desired outcomes. Thus, instead of drawing a cubic block, the computer is asked to generate a cubic geometry with certain dimensions or the computer is asked to create a geometry meeting a certain desired volume. The design variable values can be retrieved by an analysis of the overall urban system and the output of the design can be tested on its impact on overall urban system.

One of the strengths of computational urban design is that it can be used as a supportive tool in the earlier phases of the urban development process. This is the result of the ability of computational urban design to generate designs fast and accurately based on data. In a short period of time, the user has an overview of a potential design that is based on desired outcomes and that is able to indicate the relevant consequences of the design.

Within computational urban design, the ability to include all relevant aspects in one computational urban design tool is of great importance. This means including how the urban environment should influence the wellbeing and behavior of humans but also including the interests of the real estate developer, the interests of residents in the environment and other involved stakeholders. If a computational urban design tool is not comprehensive, it never includes the entire urban system and it will remain to be limited to one or more subsystems.

One of these aspects that are relevant to include in a comprehensive supportive computational urban design tool but that is not yet incorporated is how the urban system shapes us, expressed in terms of the wellbeing of humans. This is especially relevant as current trends in urban developments, including densification and the construction of high-rise buildings in existing urban areas, include risks negatively affecting the wellbeing of humans (Kalantari & Shepley, 2020). Whereas densification can also provide opportunities to contribute to human wellbeing (Mouratidis, 2019a; Kalantari & Shepley, 2020). One of the aspects that influence wellbeing is how humans perceive the built environment (i.e. perceived safety, beauty and liveliness).

Although the perception of humans in relation to wellbeing in the context of the built environment is generally regarded as relevant in urban development, supportive tools such as computational urban design do not include design capabilities relating to the perception of humans. Still, computational urban design is regarded as a promising and strong supportive tool in the urban development process as it allows an urban design to be designed based on its impact on the overall urban system. In line with this, it is important that computational urban design is a comprehensive tool which is able to include all relevant aspects in an urban development. Thus, also able to consider human perception. However, current computational urban design tools are not able to consider this in the design process.

In line to the above, the overall objective of this research is described as:

*Strengthening computational urban design as a supportive tool in the conceptual design phase of an urban development by incorporating human perception in order to improve people's wellbeing.*

Based on this objective, the following research question is formulated:

**How can the perception of humans be included in computational urban design?**

In order to provide an answer to this question, this research has been set up as a first attempt to incorporate human perception in computational urban design. he following sub questions are formulated:

1. *How does human perception relate to wellbeing in the context of the built environment?*
2. *How does the built environment influence human perception?*
3. *How can the relation between the built environment and human perception be quantified so that it can be incorporated in computational urban design?*
4. *How can the quantified relations be incorporated in computational urban design?*

## 1.1. Research design

The global research design has been subdivided based on the sub questions. Sub question one and two will be answered through a literature review, sub question three and four will be answered using a methodology designed for this research. The designed methodology can be split up in two phases, focusing on research question three and four. The first phase uses the results of the literature review to shape a study resulting in finding quantified relations, that can be incorporated in computational urban design, between human perception and the built environment. The second phase uses the quantified relations from phase one and consists of an attempt to incorporate the relations in computational urban design. The methodology used for both phases will be described in the corresponding chapter. Figure 1 provides an overview of the overall research design.

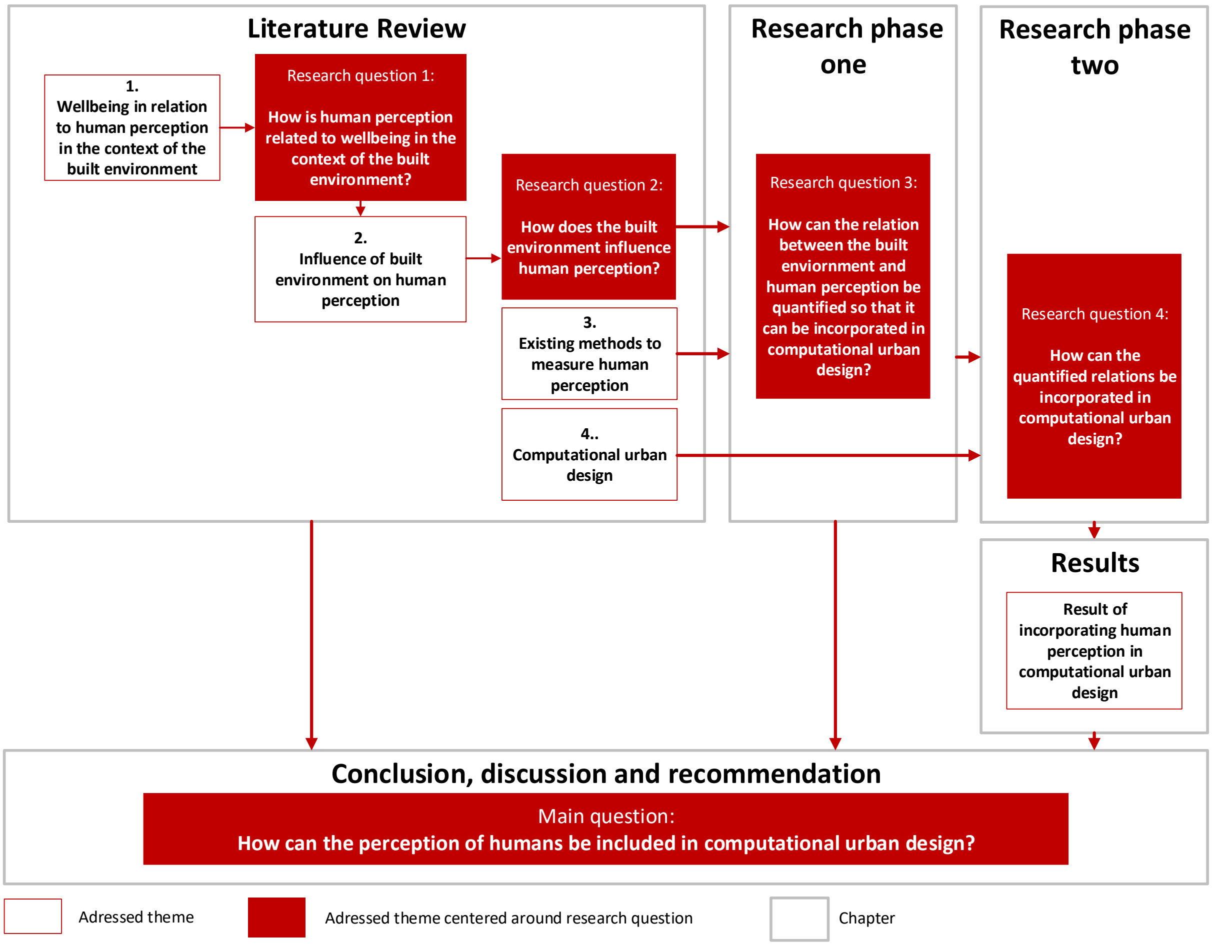



*Figure 1: Global research design*

## 1.2. Scientific and practical relevance

The topic of human perception in relation to human wellbeing and the built environment is an established topic in the field of urban research. Furthermore, the discipline of computational urban design is not a new concept in scientific literature. However, the combination of the two has not received attention in existing literature yet.

Still, in existing scientific literature there have been several successful attempts to include human well-being in computational urban design. For example based on an objective assessment of the designed urban morphology (Zhang & Liu, 2021). However, as the well-being of humans in relation to the built environment includes many subjective elements such as human perception besides objective and quantitative elements (Dodge et al., 2012; Mouratidis, 2018), the wellbeing of humans is not comprehensively taken into account in existing implementations in computational urban design. At least, human perception is not included in computational urban design in a data driven manner. In current practice and often suggested in scientific literature the wellbeing of humans has to be incorporated qualitatively by the user through the abilities of the tool for manual interaction in a hybrid work-flow (Perez-Martinez et al., 2020). Making the overall computational design process less efficient, or neglecting human well-being through human perception in the generation of a completely computational generated design.

In relation to current practice, incorporating human perception in computational urban design is relevant as well. Although computational urban design is not widely applied in current practice, the attention for computational urban design is growing. Especially, as the complexity of our urban environment increases and the attention for human wellbeing in urban areas is growing in relation to today's densification challenges. On top of that, market parties are receiving more responsibilities in the urban development process and are in the need for supportive tools fastening the urban development process and the amount of available data of existing urban environments is growing. This mixture of trends shows how current practice in urban development can benefit from the incorporation of human perception in computational urban design.

Within the urban development process, computational urban design can be used by many stakeholders. It allows the developer to explore potential development opportunities, it allows the municipality to explore opportunities in certain areas but it can also support an urban designer during the design process. As a result, this research does not specifically address one target group within current practice. All the above mentioned stakeholders can benefit from computational urban design and improvements in the capabilities of computational urban design. Above all, this research addresses the capabilities of computational urban design. Therefore, actors active in the field of computational urban design software development might be served best by this research.

## 1.3. Organization of the thesis

In line to the objective of this research, this thesis describes the process from understanding the relations between human perception and the built environment to the creation of a tool that includes human perception in the computational urban design process.

The thesis will therefore start with a literature review, followed by the chapter describing research phase one. In this chapter, first the used methodology for research phase one will be explained. Followed by the data gathering and exploration section after which the data analysis section follows. As conclusion of research phase one, the results from the analysis are reflected upon findings from the literature review. After research phase one, research phase two is addressed. The second research phase chapter starts with the applied methodology for research phase two. Then the implementation of research phase two, being the incorporation of the found relations as a result of research phase one in a computational urban design tool, is described. After research phase two, the results of the overall research are presented in the results chapter. Finally, this thesis ends with a conclusion, discussion and recommendation chapter.

# 2. Literature review

Incorporating human perception in computational urban design covers two main research areas, wellbeing in the built environment and computational urban design. The literature review described in this chapter covers four themes in these two research areas. The first reviewed theme concerns human perception in relation to human wellbeing. The second reviewed theme concerns human perception in relation to the built environment and the third reviewed theme concerns measuring human perception of the built environment using street view images. These three themes all concern the research area of wellbeing in the built environment. The fourth addressed theme in this literature review concerns the overall research area of computational urban design.

## 2.1. Human perception in relation to human wellbeing

The relation between the built environment and well-being has been a topic of interest for many years. In which wellbeing is acknowledged to be related to the built environment (Fathi et al., 2020). Wellbeing is found to be related in many ways with the built environment, of which one of them is how humans perceive the built environment (Mouratidis, 2021; Smith et al., 2015). Therefore, it is important to better understand the relation between human perception and wellbeing in the context of the built environment.

Within this section, the first research question will be addressed. Namely: How is human perception related to human wellbeing in the context of the built environment? Figure 2 shows how this section is contributing to the overall research. In red, the in this section addressed elements in the overall research design are highlighted.

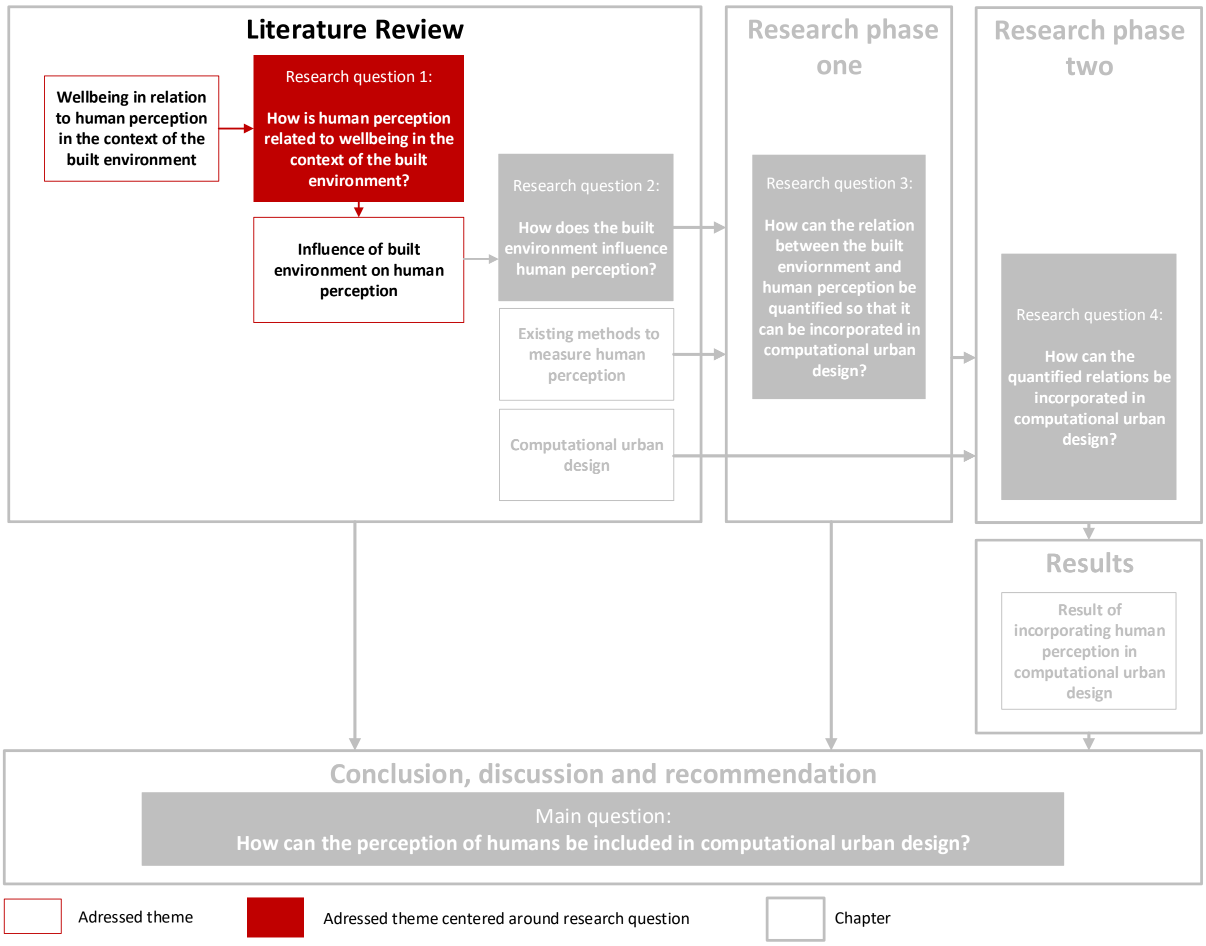



*Figure 2: Literature review section 2.1. within overall research design*

As a starting point, the definition of human perception and wellbeing as found in the literature is described below. After the description of the definitions, the relation between human perception and wellbeing in the context of the built environment is described based on existing literature.

### 2.1.1. Definition of Human perception

Human perception can be considered as one of the six layers in the Layered Reference Model of the Brain along with among others sensation and memory (Wang et al., 2006). How humans perceive their environment thus fundamentally influences an individual's cognitive system. This cognitive system on its hand influences how humans behave, how they feel and how they move through the built environment.

Wang (2006) formulates the following definition for perception in relation to the Layered Reference Model of the Brain: *"Perception is a set of internal sensational cognitive processes of the brain at the subconscious cognitive function layer that detects, relates, interprets, and searches internal cognitive information in the mind* (Wang et al., 2006, p.126)*"*

The importance of an individual's perception cannot be underestimated, as almost all cognitive life functions of humans rely on perception and human perception influences an individual's behaviour (Ferguson & Bargh, 2004) and even personality (Wang, 2007). In relation to this, it is no surprise that someone's perception of the built environment can influence his or her wellbeing. In order to better understand this interaction, it is first important to formulate the definition of wellbeing in existing literature.

### 2.1.2. Definition of wellbeing

Wellbeing can be seen as a balance point between the resources and challenges an individual faces (Dodge et al., 2012). More specifically, "Stable wellbeing is when individuals have the psychological, social and physical resources they need to meet a particular psychological, social and/or physical challenge. "When individuals have more challenges than resources, the see-saw dips, along with their wellbeing, and vice-versa" (Dodge et al., 2012). Wellbeing can be measured in subjective terms in which people cognitively and affectively evaluate their life (Diener, 2000). This approach on measuring wellbeing is referred to in existing literature as subjective wellbeing. Subjective wellbeing is centered around the question, what is the good life? As a result, it is argued that if people evaluate their life well, they are living a good life. In relation to wellbeing in general, subjective wellbeing can thus be considered as a personal evaluation of an individual if he or she is able to balance between his or her available resources and challenges. Figure 3 visualizes the relation between wellbeing and subjective wellbeing.

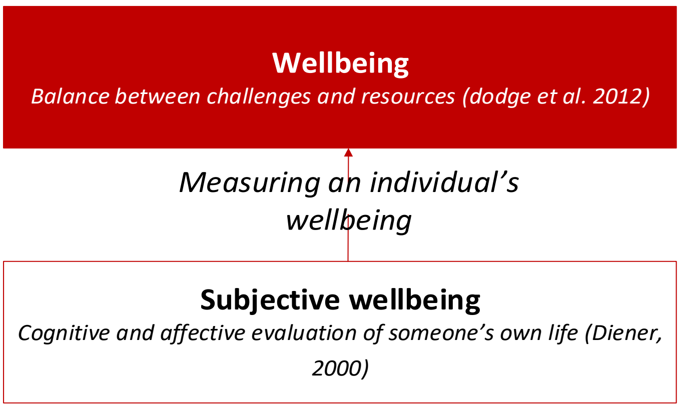



*Figure 3: Definition of wellbeing, distinction between objective and subjective wellbeing.*

### Definition subjective wellbeing

Subjective wellbeing (SWB) can be expressed in momentary terms and in long terms. Emotions and moods concern the momentary terms whereas general life satisfaction concerns the long term (Eid & Diener, 2004). Long term subjective wellbeing positively influences momentary subjective wellbeing (Weijs-Perrée et al., 2019). In relation to the built environment, the built environment directly influences the momentary wellbeing (Weijs-Perrée et al., 2020; Mouratidis, 2018). Long term subjective wellbeing is also indirectly influenced by the built environment (Weijs-Perrée et al., 2020), this can partially be explained by the finding that the built environment directly influences someone's health (Mouratidis, 2018). Figure 4 visualizes how momentary subjective wellbeing is related to subjective wellbeing and wellbeing in general.

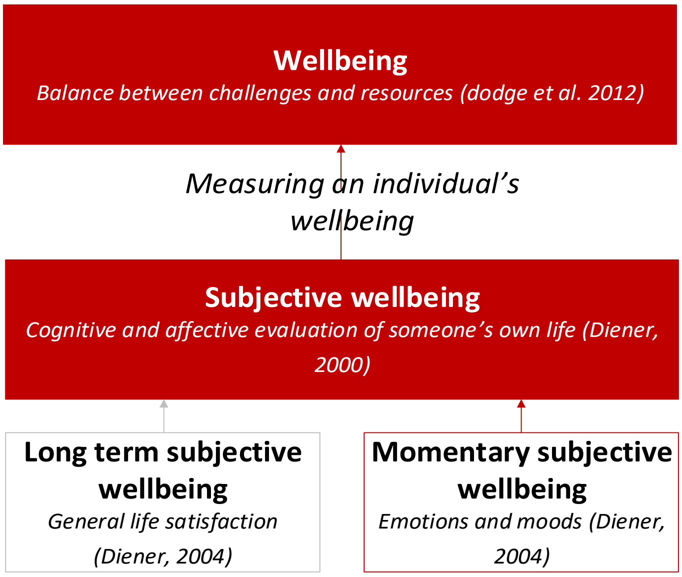



*Figure 4: Definition of subjective wellbeing*

### 2.1.3. Human perception in relation to subjective wellbeing

Human perception in the context of the built environment is ought to be influenced by sociodemographic characteristics as well as urban physical characteristics (Mouratidis, 2018). Here, in relation to momentary SWB and long term SWB, momentary SWB is mostly influenced by how humans perceive the urban space. Momentary SWB can be further split up into four dimensions: happiness, sense of security, sense of comfort and annoyance (Birenboim, 2018). In relation to these four dimensions of momentary SWB and based on existing literature, perceived safety is ought to influence happiness and sense of security. In addition, perceived beauty is ought to influence comfort. Furthermore, the ambience and therefore among others perceived liveliness is ought to influence the overall momentary SWB (Weijs-Perrée et al., 2020). Weijs-Perrée et al. (2020) indeed found perceived safety to influence happiness, sense of security and annoyance. Also, atmosphere is found to influence momentary SWB through happiness. Although, the exact definition of atmosphere was not specified, it is ought to relate to ambience. Whereas ambience can be expressed in among others perceived liveliness and perceived beauty (Redi et al., 2018). Although Weijs-Perrée et al. (2020) did not find a significant relation between perceived beauty and one of the four dimensions of SWB, other literature does indicate that perceived beauty is able to influence SWB (Mouratidis, 2018)(Weijs-Perrée et al., 2020) or more in general the perceived environmental quality (Bonaiuto et al., 2003).

Therefore, the following three human perceptual attributes are proposed for further study on its relation to the public space of the built environment in this research: Perceived beauty, perceived liveliness and perceived safety. Figure 5 visualizes the described relations.

### Definition of perceived beauty, liveliness, and safety

The three human perceptual categories differ in the roots of their definition. The definition of liveliness, being "the quality of being interesting and exciting" (Cambridge University Press, n.d.) can be considered as a cognitive concept. This, since the concepts 'interesting' and 'exciting' are cognitive concepts. Therefore closely related to human perception, which is also a cognitive concept. As a result, perceived liveliness by definition does not differ from actual liveliness. The same reasoning can be applied to perceived beauty, of which the definition is: "the quality of being pleasing, especially to look at, or someone or something that gives great pleasure, especially when you look at it" (Cambridge University Press, n.d.). This definition of beauty can also be considered as a cognitive concept that is closely related to perception, which makes beauty not much different from perceived beauty either. However, perceived safety on the other hand is a different concept then actual safety, being defined by: "a state in which or a place where you are safe and not in danger or at risk" (Cambridge University Press, n.d.). Perceived safety does not concern someone's actual safety but how he or she perceives his or her safety.

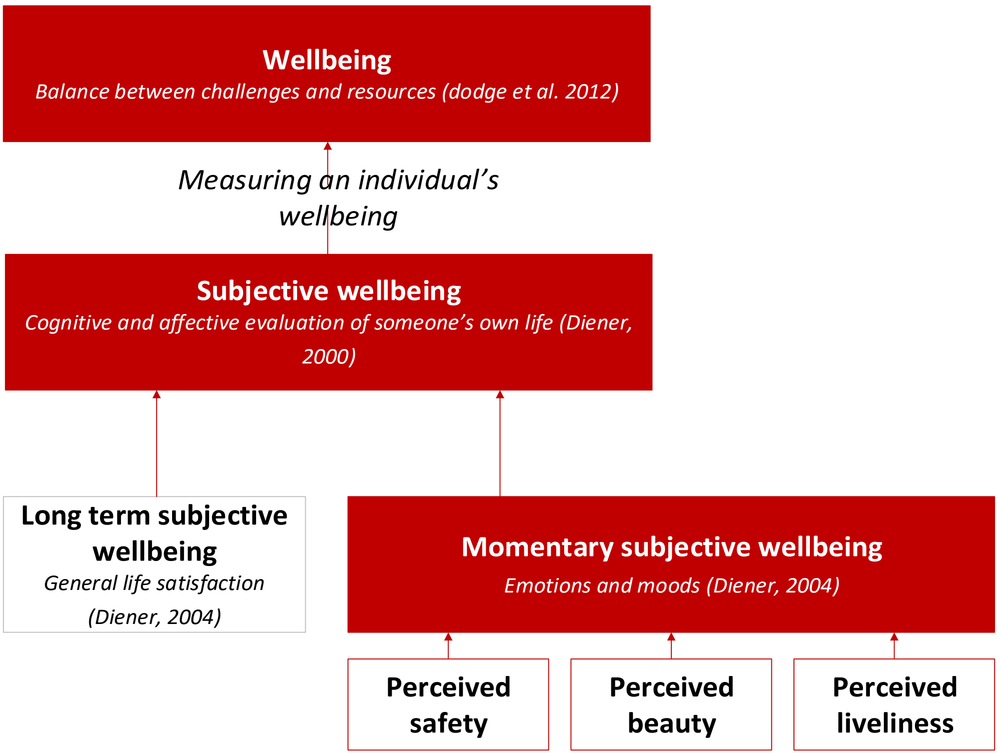



*Figure 5: Human perceptual attributes found to have a relation with momentary subjective wellbeing*

### Inter-relation between perceived beauty, liveliness, and safety

Perceived beauty, liveliness, and safety can be studied individually on its relation with the built environment, however these human perception categories have been found to be related to each other as well in the context of the built environment. Studies including measuring human perception in the built environment through street view image comparisons found a positive correlation between perceived liveliness and perceived beauty (Zhang et al., 2018). Furthermore, perceived safety is found to correlate with perceived liveliness (Verma et al., 2020; Zhang et al., 2018) and perceived liveliness positively correlates with perceived beauty (Verma et al., 2020; Zhang et al., 2018). In addition to the found statistical relation, multiple theories can be considered concerning the relation between multiple human perception categories in relation to the built environment. For example, a more lively environment including the presence of people significantly contributes to the perceived safety in general (De Nadai et al., 2016; Jansson, 2019) and specifically to the perceived safety after dark (Rahm et al., 2021) as more people on the streets can lead to more social control and a higher perceived safety (Zhang et al., 2018).

### 2.1.4. Conclusion literature review human perception in relation to wellbeing

Existing literature on human perception, wellbeing and the relation between the two indicate that there is a relation between human perception and wellbeing in the context of the built environment. Perceived beauty, liveliness, and safety of the built environment all directly or indirectly are able to influence someone's subjective wellbeing and therefore someone's overall wellbeing. The scheme in Figure 5 visualizes how human perception is related to human wellbeing in the context of the built environment.

## 2.2. Human perception in relation to the built environment

This section describes the in the literature found relations between the built environment and human perception. The findings of this section therefore address the second research question: How does the built environment influence human perception? Figure 6 shows how this section is contributing to the overall research. In red, the in this section addressed elements in the overall research design are highlighted.

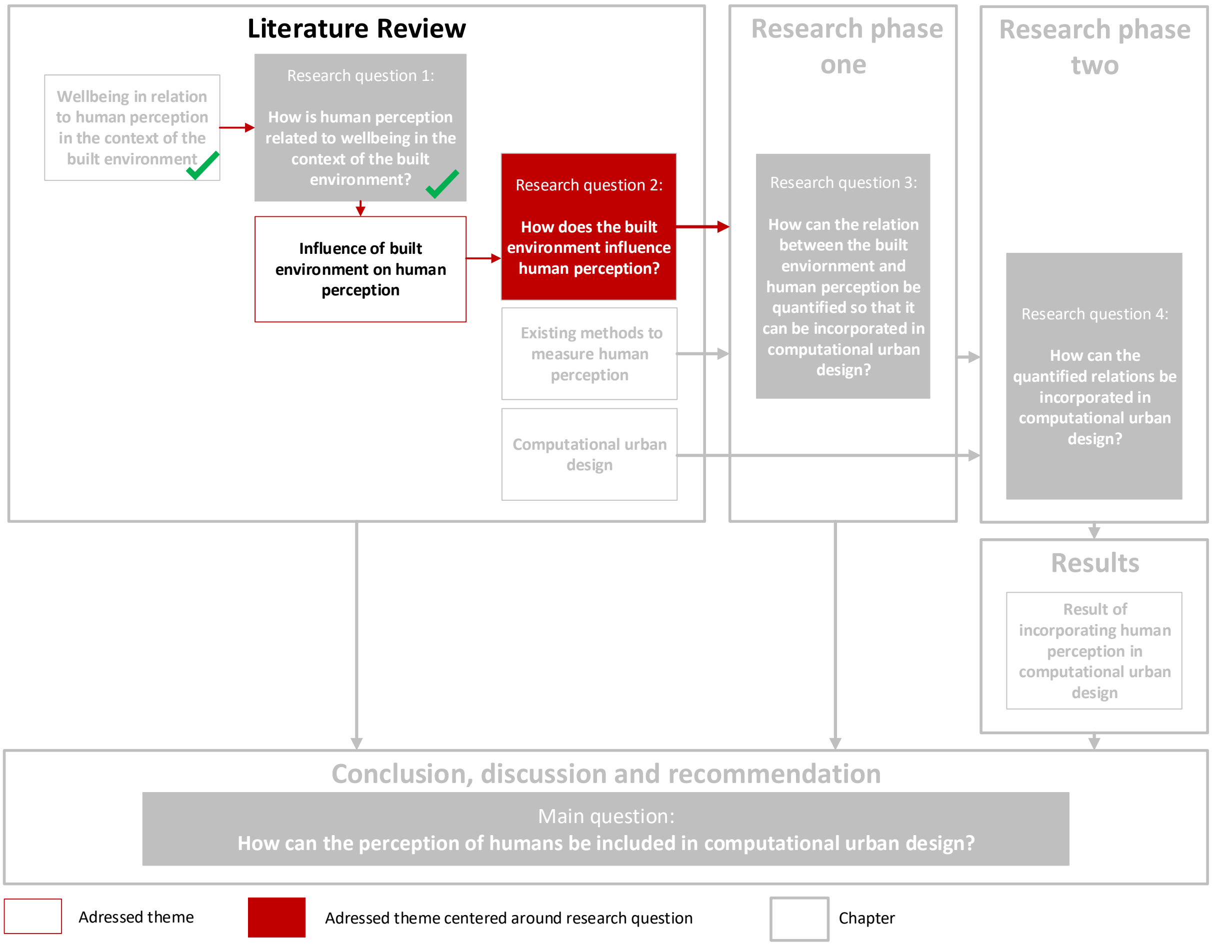



*Figure 6: Literature review section 2.2. in relation to the overall research design*

First the topic of human perception in relation to the built environment will be introduced in relation to the goal of this research. Second, the in the literature found relations between perceived beauty, liveliness, and safety and the built environment will be described. Third, the subjectivity of human perception will briefly be described. Finally, the overall literature review will be presented in tabular form in the conclusion of this section.

### 2.2.1. Human perception in relation to the built environment within this research

In relation to the goal of this research, incorporating human perception in a computational urban design focusing on conceptual designs that solely contain volumes, specifically the relation between volumetric elements of the built environment and human perception is relevant. Whereas the relation between non-volumetric elements of the built environment and human perception are in relation to the goal of this research less relevant. Figure 7 illustrates the difference of what in this research is considered as volumetric and non-volumetric. Here it can be seen that the volumetric elements, concern the main shape of the building, street and trees whereas the non-volumetric elements concern elements such as building function and façade objects.

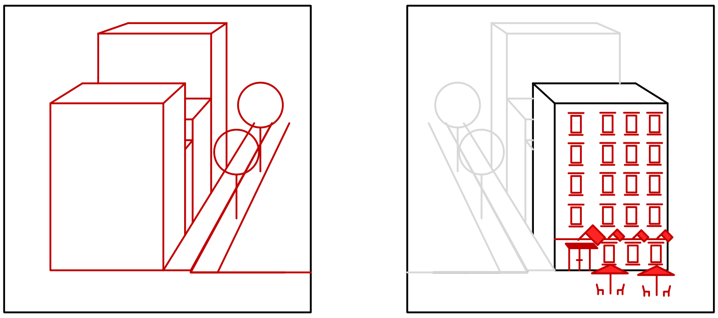


*Figure 7: On the left, the volumetric built environment elements are highlighted in red. On the right, the non-volumetric elements are highlighted in red.*

Furthermore, every individual perceives something different. Although, taking the common opinion of the mass, it is generally possible to find the shared perception of something. In the remainder of this thesis, this common opinion will be referred to using the term "objective aspect of the relation between human perception and the built environment", whereas the variation in perception between individuals will be referred to using the term "subjective aspect of the relation between human perception and the built environment". Since the goal of this research is to incorporate human perception in computational urban design using a simplistic understandable and general approach, specifically the objective aspect of the relation between human perception and the built environment is considered to be relevant in relation to this research.

However, this literature review does not only focus on the volumetric built environment. Also, this literature review will briefly cover the subjective aspect on the relation between human perception and the built environment. The reason for this is that solely the volumetric built environment and solely the objective aspect of the relation between human perception and the built environment does not capture the full relation between the built environment and the objective aspect of human perception. A better understanding of the overall relation between the built environment and human perception contributes to an understanding of the extent to which a computational urban design tool created for designing conceptual urban designs is able to include human perception.

### Human perception in relation to the built environment in general

Concerning the general relation between human perception and the built environment, several important remarks can be made based on existing literature. First of all, specifically in relation to human perception of computationally created urban designs, the level of abstractness or completeness of the urban organization influences the brain activity and perception of humans in relation to the urban environment (Hakak et al., 2016). In other words, people perceive a purely volumetric urban design differently from an urban design containing several details of urban objects. Here, more detailed designs generally attract more attention of the viewer (Hakak et al., 2016). Retrieving accurate insights on human perception of an area using a conceptual design would therefore not be likely to result in accurate insights of human perception of an actual realized area. However, the other way around, this does not mean that insight retrieved on human perception based on actual environments or detailed computationally generated designs does not result in accurate insights on volumetric influences on human perception.

Furthermore, concerning buildings specifically, buildings have been found as being the dominant factor for imageability of an image (Tao et al., 2022). Thus, regardless of the way buildings influence a specific human perception category, how humans perceive a building seems to be crucial for how they remember a view or environment.

## 2.2.2. Perceived Beauty

Perceived beauty is generally considered as a very subjective topic. However, existing literature does mention several findings on the common perception of what humans perceive as beautiful or not.

### Volumetric built environment characteristics

Regarding the volumetric built environment characteristics, tall residential buildings are found to be negatively associated with beauty whereas tall office buildings and landmarks are exceptions on this (Quercia et al., 2014a). This is in line with a study conducted by Karimimoshaver & Winkemann (2018) who found that landmarks in the skyline generally have a positive impact on people's perception of beauty of the skyline. Furthermore, not per definition relating to building height, the presence of buildings in the street view is found to negatively relate to perceived beauty (Rossetti et al., 2019). High buildings and landmarks in the skylines can thus have a positive influence on the perceived beauty of a skyline view but on a street level the presence of buildings generally negatively influences perceived beauty.

Concerning vegetation in the built environment in relation to perceived beauty, greenery on general positively contributes to perceived beauty (Joglekar et al., 2020; Quercia et al., 2014a; Rossetti et al., 2019; Weber et al., 2008; Zhang et al., 2018). Quercia et al. (2014) even mention the amount of greenery as the most influential positive factor in relation to beauty. Gardens, yards, trees and grass are found to be related to beautiful street scenes (Joglekar et al., 2020), (Zhang et al., 2018). Additionally, also buildings with incorporated vegetation are in aesthetical terms generally preferred over buildings without incorporated vegetation (White & Gatersleben, 2011).

Furthermore, broader streets are negatively related with beauty, whereas small paths are positively related with beauty (Joglekar et al., 2020). Concerning the view from the street, less sky present in the street view tends to correspond to more beautiful scenes (Joglekar et al., 2020; Rossetti et al., 2019). This combination of less sky view and smaller roads could indicate a preference for more enclosure concerning perceived beauty. Since greenery positively influences perceived beauty whereas the presence of buildings in the street view negatively influences perceived beauty, this feeling of enclosure thus is preferably facilitated by vegetation rather than buildings. Which is in line with findings from Weber (2008).

Regarding the composition of the urban elements, sense of order in urban form has been considered as a key aesthetic aspect for a long time (Karimi, 2012). An uniform arrangement was found to be perceived as more beautiful, both in relation to buildings and vegetation and mainly concerning their height in rough geometric terms (Weber et al., 2008). This is more or less in line with the finding that beautiful scenes are of low to medium complexity (Joglekar et al., 2020).

#### Non volumetric built environment characteristics

The presence of vehicles is negatively associated with beauty (Quercia et al., 2014a; Rossetti et al., 2019). Additionally the façade design is likely to have an influence on perceived beauty since a study towards the pleasantness, a broader term then just perceived beauty, of facades shows significant differences between the pleasantness of façades in relation to the geometrical shapes of the windows in the facades (Naghibi Rad et al., 2019). Thus, elements of street life and façade design have been found to influence perceived beauty on a street level, in addition to the found volumetric built environment elements.

### 2.2.3. Perceived Liveliness

There is fewer attention within scientific literature on perceived liveliness in relation to the built environment. This could be the consequence of its definition, capturing the terms 'interesting' and 'exciting', as literature could focus more on these terms rather than on perceived liveliness. There is quite some literature available on the relation between the visual engagement of someone with the built environment and the characteristics of the built environmental context he or she finds him- or herself. More visual engagement with the built environment can be considered as a higher level of interest of that person in its environment. In other words, more engagement could indicate a livelier environment considering the definition of liveliness. This reasoning has also been applied in a study of Al Mushayt (2021) on the influence of the street interface, being defined as "the spaces between urban and architectural dimensions on the ground floors of buildings forming collective spaces" (Al Mushayt et al., 2021), on the liveliness of that street. Therefore, also eye-tracking studies describing these relations have been included in the literature review on perceived liveliness in relation to the built environment.

#### Volumetric built environment characteristics

First of all, considering the direct found relation between perceived liveliness and the built environment, greenery is ought to negatively influence liveliness whereas infrastructure and vehicles generally seem to positively influence liveliness (Zhang et al., 2018., Verma et al., 2020). However, these conclusions have been drawn in studies based on the Place Pulse 2.0 dataset (Dubey et al., 2016) containing choices predominantly including urban street views however also including rural street views. As rural environments generally include more greenery, a closer look at the relation between greenery and perceived liveliness based on solely urban street views would provide a more accurate insight in this relation. Especially trees can increase detailing and the level of shading in streets which positively relate to perceived liveliness (Mehta, 2007).

Considering perceived liveliness in relation to crowd density, the perception of volumetric built environment characteristics such as greenness, openness, enclosure, walkability and imageability is not related to crowd density (Tao et al., 2022). Although, actual walkability and specifically denser road networks are positively related to the concentration of people on the street (Zhang et al., 2019).

The subdivision of the building mass along a street in segments making up visually distinctive buildings or building parts have a significant influence in the visual engagement with pedestrians. More plinths, defined as a morphological segment in the building mass, cause pedestrians to have a longer visual engagement with the ground floor of the building mass (Simpson et al., 2022).

#### Non volumetric built environment characteristics

Concerning non volumetric built environment characteristics in relation to perceived liveliness, variety in the business on the street and number of independently owned stores are important for supporting perceived liveliness. Detailing in the form of personalization, decoration of urban objects are also found to positively influence perceived liveliness (Mehta, 2007). Additionally, commercial and public seating both positively influence perceived liveliness (Mehta, 2007).

Regarding the façade of a building, irregularities in the facades are generally considered as more interesting and exciting (Chamilothori et al., 2019), two fundamental concepts of liveliness. Also, permeability of the façade positively influences perceived liveliness (Mehta, 2007), both visual permeability and physical permeability (Al Mushayt et al., 2021). Furthermore, more detailed and complex designs are generally perceived as more interesting (Lu et al., 2021). Specifically regarding urban green space, the complexity level of the landscape significantly correlates with eye movement (Liu et al., 2021) also possibly indicating a relation between design complexity in an urban environment and level of interest.

Finally the presence of life on the streets also influences perceived liveliness. Presence of social activities (Al Mushayt et al., 2021), facilitated by community gathering places (Mehta, 2007) positively influence perceived liveliness of a street. In line to this, mixed use streets are perceived as more lively as well (Al Mushayt et al., 2021).

### 2.2.4. Perceived safety

As mentioned earlier in the literature review, perceived safety is a fundamental different term then safety. A likely result is that, in relation to perceived beauty and perceived liveliness, perceived safety received most attention of all included human perception categories concerning the relation to the built environment.

#### Volumetric built environment characteristics

First of all, the general presence of a building in the street view is found to negatively influence perceive safety. The presence of greenery and specifically trees (Jansson, 2019)(Harvey et al., 2015)(Mouratidis, 2019b) and grass (Zhang et al., 2018) positively influence perceived safety. Regarding the size of vegetation, specifically vegetation higher than 2.5 meter positively influences perceived safety (Li et al., 2015). Furthermore, the presence of a sidewalk, a road and a path were found to relate to a higher perceived safety (Zhang et al., 2018). Additionally, the separation of walking infrastructure from the road (Byoung-Suk et al., 2004) and the width of the sidewalk (Al Mushayt et al., 2021) both positively influence perceived safety.

Urban form was found to influence perceived safety in a study conducted on the important factors to the perceived safety of street users on a main street (Jansson, 2019). Urban form here contained a broad perspective on the built environment. Specifically, the presence of open space and sight as well as refuges are positively related to perceived safety (Rahm et al., 2021; Loewen et al., 1993). These findings are confirmed by Jansson (2019), mentioning that the subdivision of the place or area is also positively related to perceived safety. On top of that, concerning the subdivision of building plots, many individual buildings are found to positively relate to perceived safety (Harvey et al., 2015)

Concerning the building - street relation, the building height – street width ratio, was also found to be significantly related to perceived safety (Alkhresheh, 2007; Harvey et al., 2015). This is in line with the findings that the feeling of enclosure positively relates to perceived safety (Harvey et al., 2015; Stamps, 2005). The feeling of enclosure on its hand negatively correlates with the depth of a street, the visible area, open sides and a visible horizon (Stamps, 2005). The negative influence of a visible horizon on the feeling of enclosure, which on its hand positively influences perceived safety, is in accordance with the finding that the presence of sky in a street view negatively influences perceived safety. Finally, Individual street width and building height on the other hand are not found to influence perceived safety (Harvey et al., 2015). Additionally, Mouratidis (2019) mentions that density as well as street-wall continuity does not relate to perceived safety.

### Non volumetric built environment characteristics

Concerning the non-volumetric built environment characteristics in relation to perceived safety, detailing of objects in an urban context, the pavement design (Lee & Kim, 2021) has a positive influence on how safe a street is perceived. In relation to the building facades, the presence of windows (Iglesias et al., 2013), entrances (Shaffer & Anderson, 1985) and active frontages (Heffernan et al., 2014) all have a positive influence on perceived safety. Active frontages are defined by the presence of doors and windows, the depth & relief of the façade surface and the material quality of the façade. Active frontages could be related to the feeling of social security on the streets, also contributing to perceived safety (Jansson, 2019). In line to the positive influence of social security in general, the presence of other people (Iglesias et al., 2013; Jansson, 2019) positively influence perceived safety of people. However, the presence of an unpleasant crowd can also negatively influence perceived safety, for example in the case of unsupervised youth (Austin et al., 2002). Regarding the presence of people, an exponential effect that might occur, as the presence of other people significantly influences the perceived safety, it is important that people are present in the street view to stimulate perceived safety. However, the presence of people in a space is among others influenced by how safe people perceive that space. Furthermore, the presence of moving objects such as a vehicle positively influences perceived safety as found by Iglesias et al. (2013).

Urban functions are also related to perceived safety. The presence of shops (Jiang et al., 2018; Iglesias et al., 2013) and a frontage function (Iglesias et al., 2013) variation are positively related to perceived safety in a street view. However, concerning the neighborhood function, perception of crime is lower in residential sub-urban neighborhoods in relation to mixed-use neighborhoods (Foster et al., 2013).

Additionally, the maintenance and tidiness of streets and buildings influence the perceived safety. Deteriorating buildings (Austin et al., 2002) or deprivation of buildings negatively influence perceived safety (Mouratidis, 2019b). Also trash on streets (Austin et al., 2002) has been found to negatively influence perceived safety whereas clean streets (Jiang et al., 2018), although limited, have a positive influence on perceived safety. Finally, well maintained and incorporated greenery results in a higher sense of security (Shaffer & Anderson, 1985). Furthermore, concerning vegetation and natural elements, the influence of greenery on perceived safety was found to differ between day and night. During day greenery could positively contribute to perceived safety however during night, unmaintained and dense green, negatively influences perceived safety (Rahm et al., 2021). This is supported by the finding that the lightness of the scene and specifically the overall presence of light was found to influence perceived safety significantly (Loewen et al., 1993).

### 2.2.5. Subjective influence on perception

Although, as described above, many common characteristics of the built environment can be found to have an influence on human perception, subjectivity plays a major role in the perception of humans. People with depressive symptoms for example perceive their neighborhood less positive (Latkin & Curry, 2003). Furthermore, men perceive their neighborhood as safer (Austin et al., 2002). Finally, if someone recognizes a certain image, shape or view in an urban environment based on his or her personal background his or her view is attracted by it. For example someone who is religious, recognizes a religious symbol and pays less attention to other details (Vinnikov et al., 2021).

### 2.2.6. Conclusion relation human perception – built environment

In conclusion, existing literature mentions multiple built environment elements to influence perceived beauty, safety and liveliness. These elements can be classified in volumetric and non-volumetric built environment elements. Furthermore, different categories can be found within this classification. Volumetric built environment elements that influence human perception can be categorized in the categories: Building, Vegetation, Street and Urban morphology. Non-volumetric built environment elements that influence human perception can be categorized in the categories: Urban objects detailing, Building façade, Street life and Maintenance. Table 1 below provides an overview of the in the literature found indications on the relation between individual built environment elements and each of the three human perception categories. This Table has been subdivided based on the above mentioned classification and categories. From Table 1 it can be seen that the literature mentions quite some relations between the volumetric built environment and perceived beauty and safety whereas perceived liveliness seems to be influenced mostly by non-volumetric built environment elements. Based on Table 1 and the finding in the literature that buildings are strong influential elements for imageability, buildings, vegetation and urban morphological built environment all are interesting to include in this research.

*Table 1: Literature matrix on relation between built environment attribute and human perception category*

| Built environment element category | Built environment element | Beauty | Liveliness | Safety |
|---|---|---|---|---|
| **Volumetric built environment characteristics** | | | | |
| Building | Building height residential | - (Quercia et al., 2014b) | | |
| | Landmarks in skyline | + (Karimimoshaver & Winkemann, 2018) | | |
| | Visible buildings | -(Rossetti et al., 2019) | | -(Zhang et al., 2018) |
| Vegetation | Visible greenery | +(Joglekar et al., 2020; Quercia et al., 2014b; Rossetti et al., 2019; Weber, 2008; Zhang et al., 2018) | -(Verma et al., 2020; Zhang et al., 2018) + (Mehta, 2007) | +(Harvey et al., 2015; Jansson, 2019; Mouratidis, 2019b; Zhang et al., 2018) |
| Street | Street width | -(Joglekar et al., 2020) | | |
| | Sidewalk width | | +(Al Mushayt et al., 2021; Mehta, 2007) | +(Al Mushayt et al., 2021) |
| | Visible sidewalk | | | +(Zhang et al., 2018) |
| | Visible road | | | +(Zhang et al., 2018) |
| | Visible path | | | +(Zhang et al., 2018) |
| | Walking path seperation | | | +(Byoung-Suk et al., 2004) |
| Urban morphology | Order/ uniformity | +(Karimi, 2012; Weber, 2008) | | |

| | | | | |
|---|---|---|---|---|
| | Finer division of building masses | | +(Simpson et al., 2022) | +(Harvey et al., 2015; Jansson, 2019) |
| | Dense street network & refuges | | +(Zhang et al., 2019) | +(Loewen et al., 1993; Rahm et al., 2021) |
| | Presence of open space and sight | | | +(Loewen et al., 1993; Rahm et al., 2021) |
| | Street depth | | | -(Stamps, 2005) |
| | Open street sides | | | -(Stamps, 2005) |
| | Visible sky & horizon in street view | - (Joglekar et al., 2020; Rossetti et al., 2019) | | -(Stamps, 2005; Zhang et al., 2018) |
| | Building height/ street width ratio | | | +(Harvey et al., 2015) |
| **Non volumetric built environment characteristics** | | | | |
| Urban objects detailing | Decoration | | +(Mehta, 2007) | |
| | Urban seating | | +(Al Mushayt et al., 2021; Mehta, 2007) | |
| | Pavement design | | | +/-(Lee & Kim, 2021) |
| | Presence of vehicles | -(Quercia et al., 2014a; Rossetti et al., 2019) | | +(Iglesias et al., 2013) |
| | Greenery complexity | | +(Liu et al., 2021) | |
| Building facade | Façade design irregularities | | +(Chamilothori et al., 2019) | |
| | Façade detail and complexity | | +(Al Mushayt et al., 2021; Lu et al., 2021) | |
| | Ground floor façade visual permeability | | +(Al Mushayt et al., 2021; Mehta, 2007) | +(Heffernan et al., 2014; Iglesias et al., 2013; Shaffer & Anderson, 1985) |
| | Ground floor façade physical permeability | | +(Al Mushayt et al., 2021) | +(Heffernan et al., 2014; Iglesias et al., 2013; Shaffer & Anderson, 1985) |
| | Façade geometries | +/- (Naghibi Rad et al., 2019) | | |
| | Frontage function variation | | +(Al Mushayt et al., 2021) | +(Heffernan et al., 2014; Iglesias et al., 2013) |
| Street life | Presence of people | | | +(Iglesias et al., 2013; Jansson, 2019) |
| | Presence of social activities | | +(Al Mushayt et al., 2021) | |
| | Unsupervised youth | | | -(Austin et al., 2002) |
| | Presence of shops | | | +(Jiang et al., 2018) |
| | Community gathering places | | +(Mehta, 2007) | |
| | Mixed use streets | | +(Al Mushayt et al., 2021) | |
| | Mixed use neighborhoods | | | -(Foster et al., 2013) |
| Maintenance | Deteriorating & deprived buildings | | | -(Austin et al., 2002; Mouratidis, 2019b) |
| | Maintenance of greenery | | | +(Shaffer & Anderson, 1985) |
| | Street lighting | | | +(Loewen et al., 1993) |
| | Trash on streets | | | -(Austin et al., 2002; Jiang et al., 2018) |

## 2.3. Measuring human perception using choice data and street view images

There are many ways in which human interaction, including perception, with the built environment can be studied, e.g., by including virtual environments (Birenboim et al., 2021; Echevarria Sanchez et al., 2017; Johnson et al., 2010; Lee & Kim, 2021; Leite et al., 2019; Lu et al., 2021), real images and videos (Alhasoun & Gonzalez, 2019; Chen et al., 2022; Ye et al., 2019), and the tracking of real behavior (Al Mushayt et al., 2021; Batool et al., 2020; Liu et al., 2021). Every method has its disadvantages and advantages. This section describes several methods, the understanding of these methods contributes to the designing of the methodology in research phase one. Figure 8 visualizes how this section therefore contributes to the overall research design by highlighting its role in the overall research design.

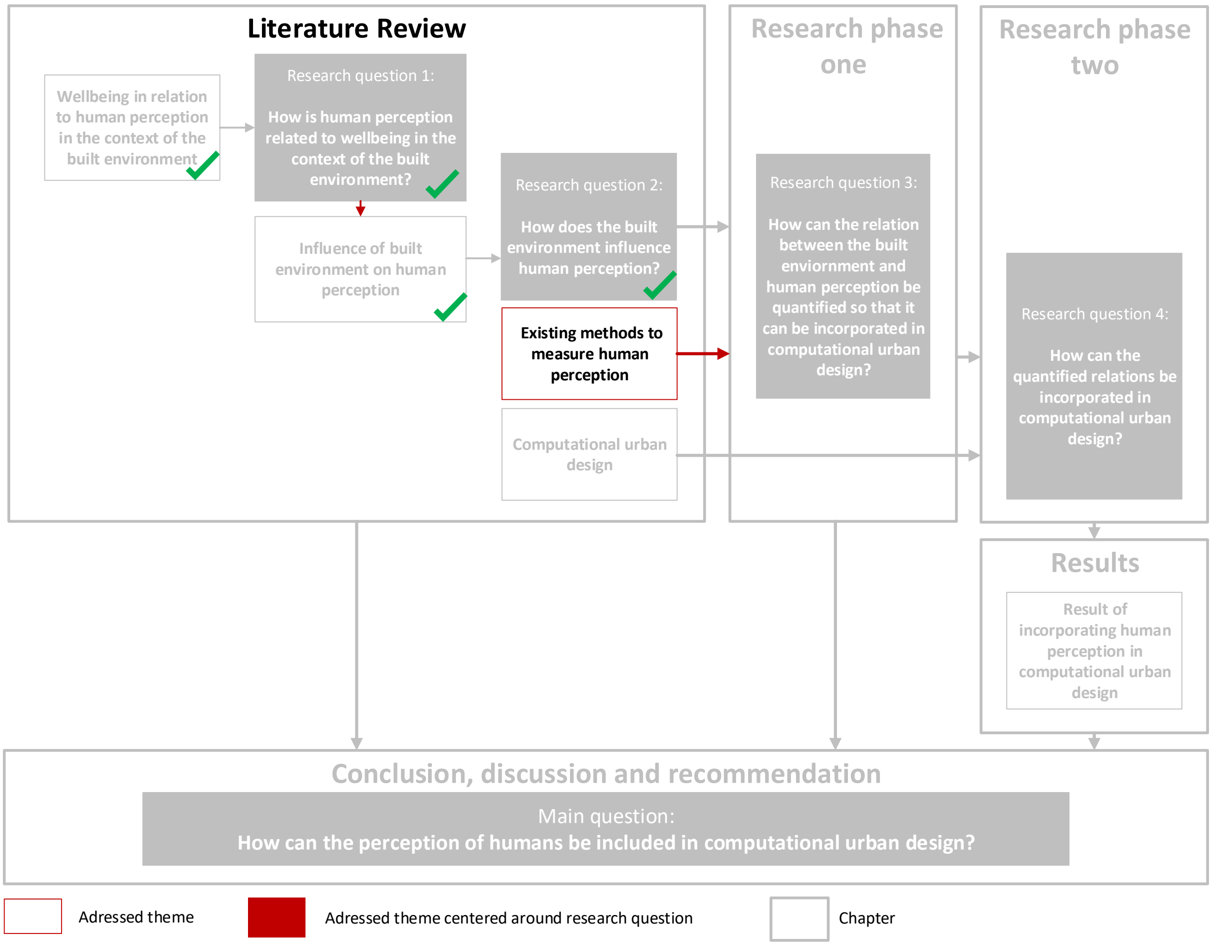



*Figure 8: Literature review section 2.3. in relation to the overall research design*

Concerning virtual reality, differences in perception can be found between virtual environments and actual environments (Johnson et al., 2010). In relation to this, one can imagine that if a virtual environment is more realistic, the difference in perception with a real image becomes smaller. Furthermore, virtual environments can be customized so that the research can be controlled better. Immersive virtual environments can even extend the visual view with other perceptions and experiences related to the environment of a certain view. However, more customization and more realistic virtual environments also lead to an increase in required effort and costs (Birenboim et al., 2019).

The most realistic environments are the actual environments, but these environments cannot be controlled. Whereas these environments cannot be controlled, human sense monitoring techniques do allow for measuring human activities and senses when people are present in or moving through an urban environment. This results in useful insights on the interaction between humans and the built environment (Al Mushayt et al., 2021; Simpson et al., 2022). However, although people's tracked senses and reactions are likely to be related to their perception, these insights do not reveal how humans perceive an environment.

Therefore, if a study concerns perception rather than experience or interaction, realistic images generally are a relative low cost but accurate mean to measure human perception of a group of respondents. Especially as gaining accurate insights in human perception requires images used for measuring human perception to be as realistic as possible so that the difference in perception between actual and visualized environments is minimized. Street view images could fulfill this need for accessible realistic images of the built environment. Whereas virtual environments or actual environments used to be the only means for presenting built environment scenes to respondents, the accessibility of street view images has increased rapidly over the past decade providing researchers with a lot of accurate visual data on existing environments that can be presented in a low-cost manner to respondents. The use of street view images has resulted in usable and interesting results (Biljecki & Ito, 2021). As a result this technique has received an increase in attention in scientific literature (Biljecki & Ito, 2021). Finally, due to the extensive availability of street view images, researchers are able to select relevant images in order to control the test data. However, as the complete street view image of an actual environment is never fully controllable, large datasets are preferred to retrieve insights on human perception in relation to the built environment.

### Finding human perception rating street view images

One of the large datasets that has been used in existing literature to study the relation between the built environment and human perception is the Place Pulse 2.0 dataset (Dubey et al., 2016). This dataset contained enough images and choices so that a deep learning model could be trained on it, enabling new street view images to be rated on human perception (Zhang et al., 2018). However, within this study, the deep learning model predicting human perception scores of new images solely uses image segmentation data to predict the human perception score. This means that only percentages of major built environment elements visible in the images were used to predict how people perceive that image, not including many of the in this literature found relevant built environment elements, such as absolute height and distance values.

The size and availability of the Place Pulse 2.0 dataset along with the generally considered usefulness of real street view images in relation to studying human perception make the Place Pulse 2.0 dataset very interesting for the scope of this research. Additionally, using image segmentation to recover analyzable data on a street view image provides useful insights on human perception (Zhang et al., 2018). Notwithstanding that many relevant built environment elements cannot be captured using solely image segmentation.

## 2.4. Computational urban design

Within this section of the literature review, existing literature on computational urban design is pointed out. In scientific literature, computational urban design has received an increase in attention over the past decade. This section will start with the definition used in this thesis when referring to computational urban design, followed with a brief overview of the development and current implementation of computational urban design in existing literature. Figure 9 shows how this section contributes to the overall research. In red, the in this section addressed elements in the overall research design are highlighted.

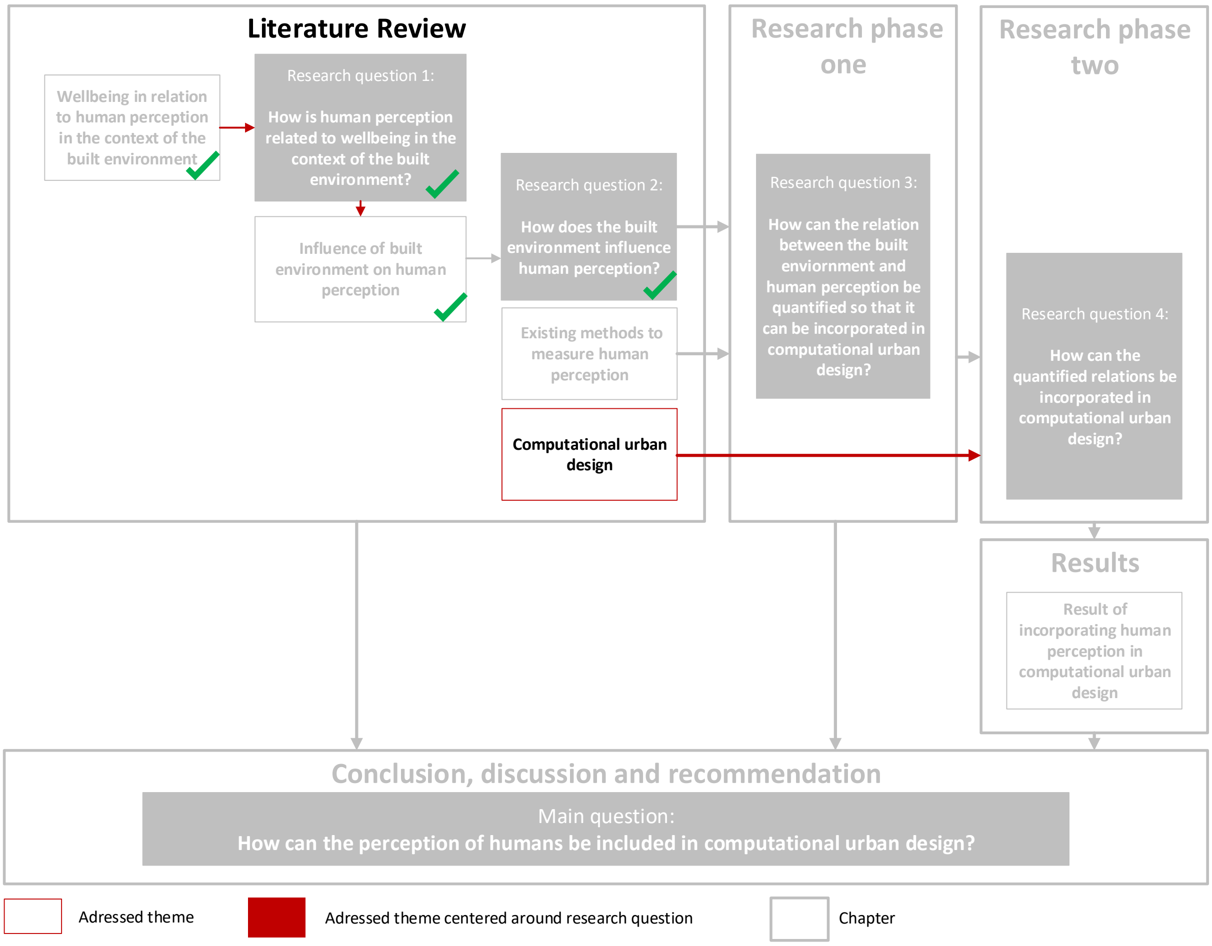



*Figure 9: Literature review section 2.4. in relation to the overall research design*

### 2.4.1. Definitions in computational urban design

Within existing literature, different terms exist when we are talking about using the computer to create a design based on non-geometric user input. When referring to this principle, generative, parametric and computational design are common terms. However, these terms are different from each other.

Within the discipline of architecture, the following understanding can be given to the term parametric design: "Parametric design can be understood as the process of developing a computer model or description of a design problem. This representation is based on relationships between objects controlled by variables. Making changes to the variables results in alternative models..." (Hudson, 2010). By designing the relations based on design variables rather than the final design, the eventual design can be generated by inserting values for the design parameters.

Generative design shifts the focus away from the designer. Meaning that the design variables are not set by the designer but, partly, by the computer. The evaluation of the design is also not done by the designer but by constraints, inserted by the designer, that test whether alternatives fulfill the design goals (Pauwels, 2020). Generative systems thus automatically generate designs based on the desired output of the user, whereas parametric systems require the user to generate designs based on pre-designed relations and adjustable design parameters. In common generative designs systems the following optimization algorithms are generally applied to come to a design that meets the requirements by a user (de Boissieu, 2021) :

- Gradient methods. Gradient methods optimize a design by adjusting the input value step by step until the design is not improved anymore.
- Simulated Annealing. Simulated annealing is an optimization approach inspired by the annealing process applied in the metal industry. It comes down to the principle that a designs space is initially explored in large steps, after which better outputs are sought using small steps. The optimization algorithm does not abort when a design output initially results in a weaker result. Therefore, the algorithm does not stop when a local optimum is found.
- Genetic algorithm. Genetic algorithms create populations of designs, then a selection of the design population that performs the best is used and combined to form the next population of design. This process continues until no better designs can be found anymore.

Within this thesis computational design will be referred to as the container concept for both parametric and generative urban design. As will become clear later in this thesis, both parametric and generative principles have been applied in the developed tool. Therefore, in this thesis the term computational urban design will be used on general.

On top of that, several terms can be found in relation to computational urban design in existing literature. First of all, the term parameter is generally used to refer to the input variable that can be adjusted and therefore enabling the flexibility in the design. Second, as computationally generated designs are parameter or data driven designs, the output quality of the designs are generally expressed using a value that is referred to by the term key performance indicator (KPI).

### 2.4.2. Development of computational urban design

Different studies in the past decade identified computational design specifically useful as a supportive tool in the exploration process of the development of urban areas (ÇalıŞKan, 2017; Fusero et al., 2013; Nagy et al., 2018; Steinø et al., 2013; Y. Zhang & Liu, 2021). Computational urban design is namely able to contribute to a more efficient urban development and design process by generating conceptual designs fast while taking into account the interest of many stakeholders (Steinø et al., 2013) and the complexity of the existing urban environment (Nagy et al., 2018; Wilson et al., 2019).

Although, it is acknowledged in the literature that computational urban design is mainly a supportive tool enabling support in the design process, many implementations of computational urban design in scientific literature concern specific design problems. Additionally, the targeted design problems do not cover the complete spectrum of relevant disciplines in urban design. Table 2 provides an overview of several papers focused on a specific application of computational urban design. Although there is more existing literature on the application of computational urban design, Table 2 represents the main application topics that can be found in the literature.

*Table 2: Main application topics found in literature on computational urban design*

| year | Reference paper | Main KPI's | Theme | Focus |
|---|---|---|---|---|
| 2012 | (Rakha & Reinhart, 2012) | Objective walkability | Infrastructure | Urban fabric |
| 2018 | (Nagy et al., 2018) | Profitability and sustainability | Economic/financial, building physical | Urban fabric |
| 2013 | (Vidmar & Koželj, 2013) | Meeting the planning regulations or not | Planning regulations | Building volumes |
| 2021 | (Chi et al., 2021) | Temperature | Building physics | Urban objects |
| 2022 | (Çalışkan & Barut, 2022) | Context integration | Urban morphology | Urban fabric |
| 2022 | (Di Filippo et al., 2021) | Solar radiation | Building physics | Building volumes |

Based on the indications retrieved from existing literature, the literature on the one hand mentions that the strength of computational urban design is its potential contribution in the design process, facilitating among others the stakeholder involvement and management during the design process. However, on the other hand, existing literature tends to focus on quite specific themes such as infrastructure, economic/financial, building physical and urban morphology. Human perception for example is never considered in computational urban design in the existing literature. In addition, if multiple KPI's are included in papers concerning computational urban design, it are generally just a few. For example profitability and sustainability (Nagy et al., 2018). Therefore, two main problems in existing literature may be identified. First of all, the lack of incorporating different KPI's in one computational urban design tool. Second, wellbeing related topics such as human perception are not considered as KPI's at all in computational urban design tools. As a consequence, the set of implemented design performance indicators implemented and studied in existing literature lack comprehensiveness.

### 2.4.3. Challenges of including human perceptual subjective parameters in computational urban design

As computational urban design is data driven, the relations between human perception and the built environment will also have to be quantified for it to be taken into account. In addition, in order to quantify a subjective concept such as human perception, it should be generalized as well. However, generating final designs that are based on generalized subjective relations is not favorable since a very general design is ought to have negative consequences for the wellbeing of humans (Altomonte et al., 2020). When computational urban design is specifically used as tool for exploration, retrieving fast insight in development options is required. In this stage, too generic designs are not yet a problem as these are not final designs. However, another challenge that can occur here, is the question to which very generic built environment elements that are present in a conceptual design are able to influence human perception. It is of importance that careful attention is given to this challenge while studying the relations between human perception and the built environment. Based on this, further conclusions can be drawn on this challenge.

A potential development goes through many different design phases. A design from a later design phase generally is more detailed, therefore the question may arise to which extent the human perception of a conceptual design is relevant when the design is processed through the different phases. A study done on the difference in human gaze in 3D virtual environments of a design from an early design phase and a design from a later design phase demonstrates that people indeed explore the designs differently and in a more engaged manner for the more detailed design from a later design phase. Furthermore, the interaction with the design in a more detailed design is more intensive (Lu et al., 2021).

## 2.5. Conclusion literature review

Within the literature review, existing literature covering the research areas of wellbeing in the built environment and computational urban design have been addressed. The main objective of the literature review, is to formulate answers to sub question one and two, being respectively: (i) How is human perception related to wellbeing in the context of the built environment? (ii) How does the built environment influence human perception?

Starting with the answer on sub question one. Within the literature, it was found that the built environment has a significant impact on people's wellbeing. People's wellbeing can be considered objectively and subjectively. Subjective wellbeing can further be categorized as momentary subjective wellbeing and long term subjective wellbeing. How humans perceive the built environment mostly influences momentary subjective wellbeing. Specifically perceived beauty, liveliness, and safety all influence human wellbeing through momentary subjective wellbeing, as accumulation of momentary subjective wellbeing influences the overall subjective wellbeing.

Concerning sub question two, the built environment on its hand was found to influence perceived beauty, liveliness, and safety. The built environment elements that influence each of the three human perception categories have been classified as either a volumetric or a non-volumetric built environment element. Within this research, only volumetric built environment elements can be included however it is important to understand the overall relation between the built environment and each of the three human perception categories. This is important, in order to put a computational urban design tool that incorporates human perception and the insights that can be retrieved from it in context of its potential and the overall relation between human perception and the built environment.

Furthermore, the following conclusion can be drawn on existing literature addressing the topic of computational urban design: In current literature the application of computational urban design, being considered as a container term for both parametric and generative urban design, generally does not focus on topics that do not include easy quantifiable relationships. In other words, most current applications of computational urban design tools focus on the generation of volumes using explicit mathematical or physical relations. Human perception can be made quantifiable so that it can be incorporated in computational urban design through the common perception of the mass, however the subjective aspect of human perception always leaves space for inaccuracy in how an individual perceives the built environment. As a result, in contradiction to for example the incorporated relations calculating amount of daylight accessing a space, the incorporated relations calculating a human perception score will never calculate the exact score as perceived by an individual.

Lastly, existing methodologies on measuring human perception in relation to the built environment show potential for finding accurate results. Specifically the use of street view images has found to be an interesting, relative accurate and relative low cost method for measuring human perception in relation to the built environment.

# 3. Implementation Research Phase One

Research phase one addresses research question 3: How can the relation between the built environment and human perception be quantified so that it can be incorporated in computational urban design? In order to do so, several steps have been taken, together resulting in quantified relationships that can be incorporated in computational urban design. First, the applied methodology is explained. Next, the data gathering process is described and finally the applied analysis is described. This chapter ends with a conclusion. As illustrated in Figure 10, the results from the literature review have been used to shape the methodology of research phase one whereas the output of research phase one will be used to shape research phase two.

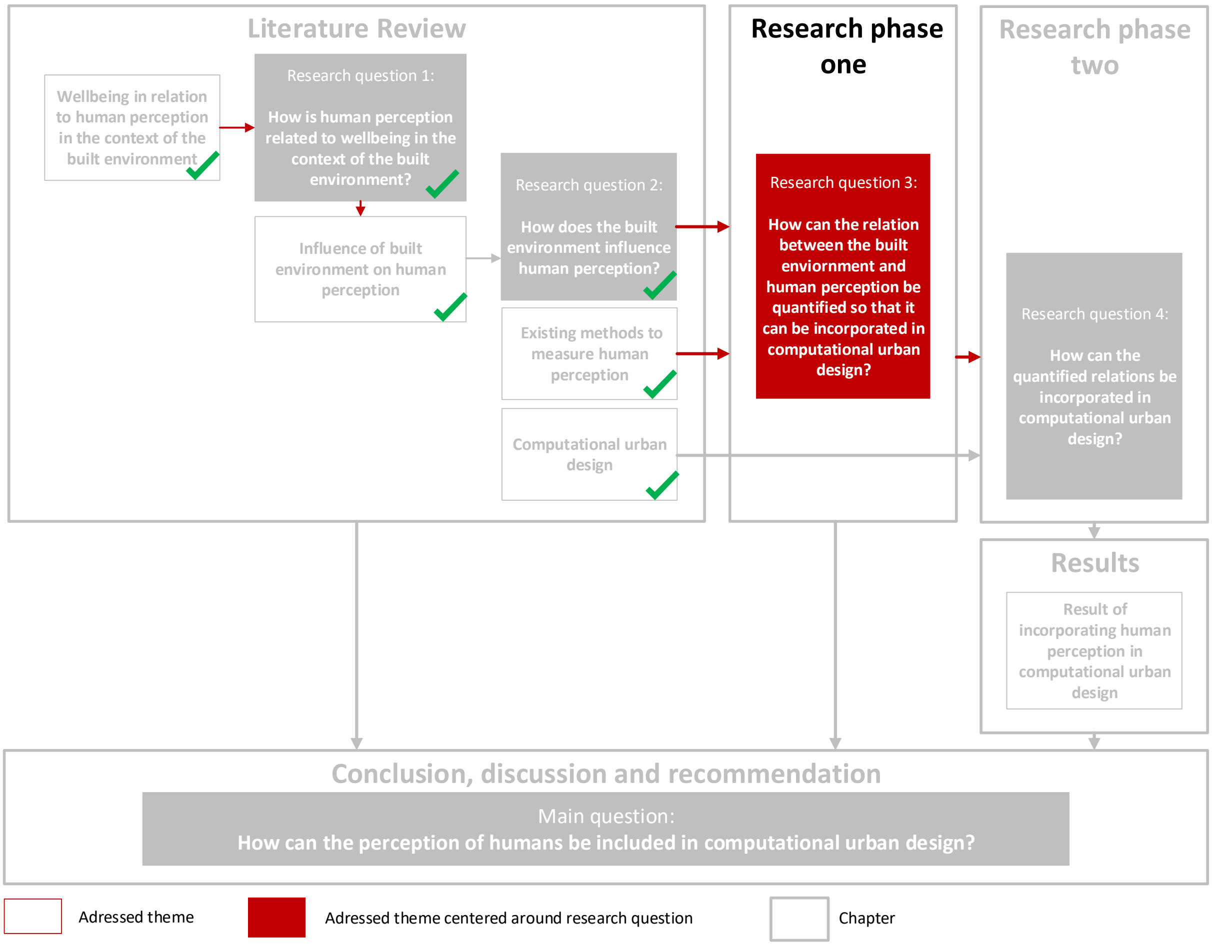



*Figure 10: Research phase one in relation to the overall research design*

## 3.1. Methodology

Literature review section 2.3. described multiple methods to measure human perception in the built environment. From this section, it was concluded that street view images are suitable means to gather data on the perception of humans in relation to the built environment. Besides measuring human perception of street view images, also the built environment characteristics of the street view images should be measured. The selection of the built environment elements that are included in this research is among others based on literature review section 2.2. However, the selected built environment elements should also be volumetric built environment elements and data should be available that allows these elements to be measured.

As a result of the above, the Place Pulse 2.0 dataset (Dubey et al., 2016) is used as base for this research. Place Pulse 2.0 contains over 110.00 street view images along with over one million made choices of humans on their perception of these street view images. These street view images contain pixels making up these images and for every image the location on which the image is taken is known. This means that in addition to the pixel data of the image, built environment elements can be expressed and measured using data from the built environment around the location of the image. However, this requires the relevant data describing the built environment context in terms of specific built environment elements to be openly available.

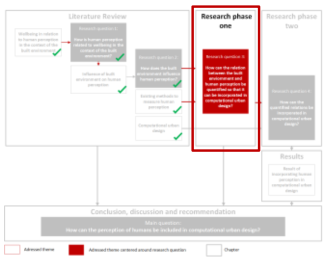
As a result of the above, the in Table 3 presented built environment elements and the belonging attributes describing the built environment elements have been selected to be included in the analysis in this research:

*Table 3: Attributes included in research phase one in relation to the built environment element they describe*

| Building environment element/ data category | Attribute |
|---|---|
| Image data | Tree share |
| | Sky share |
| | Building share |
| | Road share |
| Building Height | Height mean |
| | Height median |
| | Height standard deviation |
| | Height standard deviation relative |
| | Height minimum |
| | Height maximum |
| | Absolute height difference |
| | Average perceived building height |
| Building footprint | Façade length index |
| | Footprint area index |
| | Area mean |
| | Area median |
| | Area standard deviation |
| | Area standard deviation relative |
| Building volume | Volume index |
| Street perspective | Number of street segments |
| | Two or more street segments |
| | Offset distance median |
| | Offset distance standard deviation relative |
| | Offset height ratio |
| Other | Urban complexity factor |

With the use of data on the in Table 2 presented built environment attributes and the human perception choices on images, the choices have been analysed in relation to the attribute values. This analysis can be done in multiple ways. The overall dataset of Place Pulse 2.0 contains enough images and choices between images to analyse the relation between the images and human perception choices. However, since the built environment attribute values have to be retrieved from open data on the location of the street view images, not all street view images and therefore not all choices in the Place Pulse 2.0 dataset could be used. This makes the dataset that can be used too thin for deep learning analysis techniques. However, as the Place Pulse 2.0 dataset contains choices, the dataset is very well suitable for discrete choice modelling techniques. As will be presented in subsection **Fout! Verwijzingsbron niet gevonden.**, discrete choice modelling techniques have the advantage that the found relations are well quantified and understandable.

Altogether, Figure 11 visualizes the methodology that has been used to quantify the relationship between human perception and the built environment so that it can be incorporated in computational urban design.



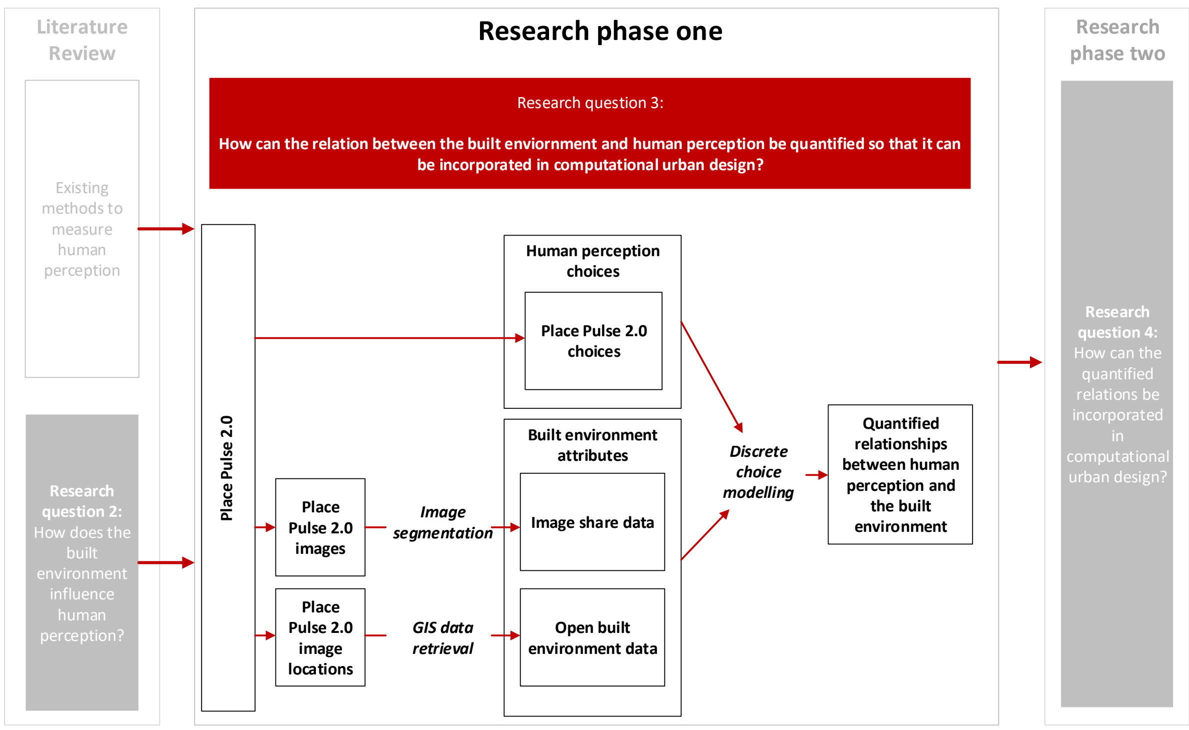



*Figure 11: Detailed visual of the method applied in research phase one*

## 3.2. Data gathering

This section describes the data gathering process in detail, from used input data to an exploration of the output data. The main aim of the data gathering process is to create a dataset that can be used for analysis. Within this section, first the input datasets used in this research are described. Next, the data preparation and data processing is described. Finally, the exploration of the prepared and processed data is described. Figure 12 visualizes a simplified overview of the data gathering and exploration process.

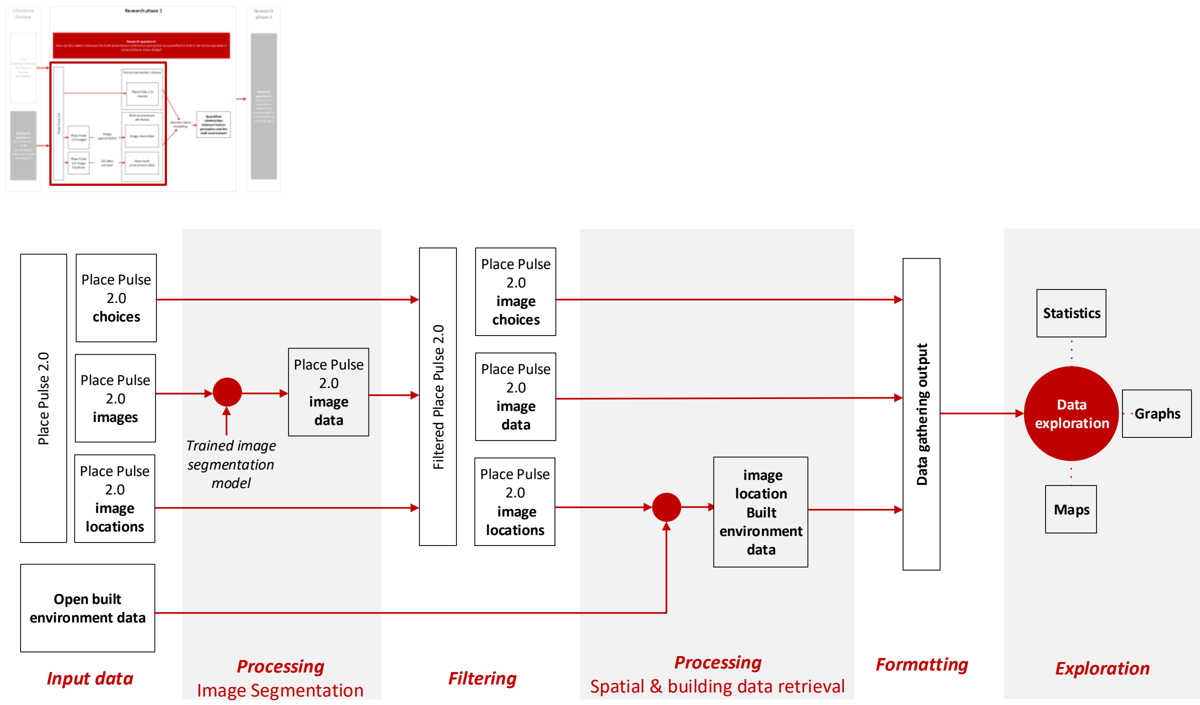



*Figure 12: Data gathering process in relation to the overall research phase one methodology*

### 3.2.1. Input data

The input data and sources can be classified in two categories. The first category consist of data containing choices between alternatives, in which an alternative is a street view image, on human perception and metadata on the choice alternatives. This data is retrieved from the Place Pulse 2.0 dataset (Dubey et al., 2016). The other category of datasets can be referred to by open built environment data. Datasets in this category contain data that is used to retrieve or calculate the attribute values per image, describing the built environment elements visible in the images. Figure 13 highlights the focus of this subsection within the overall data gathering process.

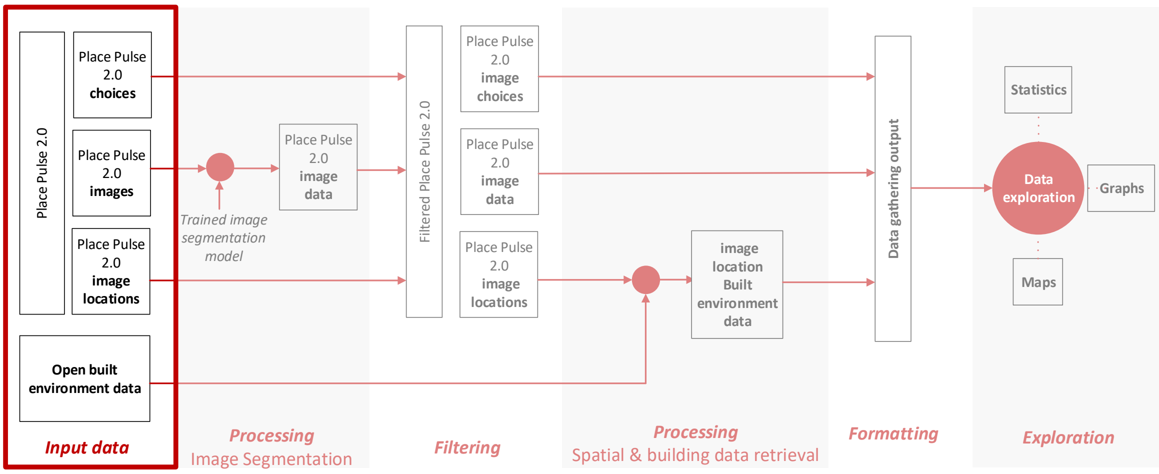



*Figure 13: Focus of the subsection within the overall data gathering process*

## Choice and alternatives datasets

The data containing the choices and alternatives metadata are retrieved from the MIT Place Pulse 2.0 dataset (Dubey et al., 2016). The MIT Place Pulse 2.0 dataset contains two main datasets, one image dataset containing over 110,988 Google Street view images and one metadata dataset containing 1,223,649 choices of people between two images on their preference in relation to six human perception categories. The images are taken at locations in different cities, laying in 6 different continents. The majority of the images are taken in Europe and North America. Table 4 provides an overview of the images included in the dataset and its location. From Figure 13, it can be seen how the different data in the Place Pulse 2.0 dataset is used for image segmentation process and the spatial and building data retrieval and processing process, described later in this chapter.

*Table 4: Overview of the image locations in the dataset*

| Continent | Images per continent | Number of cities | Cities |
|---|---|---|---|
| **Europe** | **38,636** | 22 | Amsterdam, Barcelona, Berlin, Bratislava, Bucharest, Copenhagen, Dublin, Glasgow, Helsinki, Kiev, Lisbon, London, Madrid, Milan, Moscow, Munich, Paris, Prague, Rome, Stockholm, Warsaw, Zagreb |
| **North America** | **33,961** | 16 | Atlanta, Boson, Chicago, Denver, Guadalajara, Houston, Los Angeles, Mexico City, Minneapolis, Montreal, New York, Philadelphia, Portland, San Fransisco, Seattle, Washington D.C. |
| **South America** | **16,168** | 5 | Belo Horizonte, Rio de Janairo, Santiago, Sao Paulo, Vina del Mar |
| **Asia** | **11,342** | 7 | Bankok, Hong Kong, Osaka, Singapore, Taipei, Tel Aviv, Tokyo |
| **Africa** | **5,069** | 3 | Capetown, Gaborne, Johannesburg/ Pretoria |
| **Oceania** | **6,082** | 2 | Melbourne, Sydney |

### *Gathering of the MIT Place Pulse 2.0 dataset*

The choice data of the MIT Place Pulse 2.0 dataset is gathered in 2016, using crowdsourcing, via a website where pairwise comparison of street photos are presented to respondents. In total, 81,630 different respondents have been included. Every respondent had to choose an image that he or she perceived as most beautiful, lively, safe, depressing, boring, or wealthy. Figure 14 shows an example of a choice that the respondents had to make. The dataset does not contain any respondent data, so the subjective influence on the choice of a respondent cannot be related to personal characteristics or experiences of a respondent and therefore captured in this research.


*Figure 14: Example of a choice that a respondent had to make* (Dubey et al., 2016)

The Place Pulse 2.0 dataset was originally set up with the main goal of training a set of deep learning algorithms that could predict the human perception rating of an image that was not originally included in the dataset (Dubey et al., 2016). However, since the dataset contains pairwise comparisons, it can be considered a choice dataset.

### Attribute data

To be able to analyse the relation between human perception and the built environment, we need to enrich the above dataset with attribute data describing the built environment on the photo location. For this, multiple datasets have been used. These datasets can be categorized as datasets containing building data and datasets containing street network data. The building data datasets are generally used to compute data on the building height and footprint and the street network data is generally used for data describing the street pattern. The exact attributes retrieved from the datasets will be described and explained later in this thesis. Table 5 provides an overview of the datasets used per city. From all the cities included in the dataset, only for fourteen cities building height data was available and retrieved. This results in a major reduction in suitable images from the Place Pulse 2.0 dataset, therefore the data availability is one of the filter criteria described in section 3.2.3 of this chapter.

*Table 5: Overview of the building data and road network data used per city*

| Building dataset | Building Height data reference | City | Source reference |
|---|---|---|---|
| Boston open building height data | Maximum height | Boston | (Boston Planning and Development Agency, 2021) |
| Chicago open building data | Stories | Chicago | (City of Chicago, 2021) |
| OSM | Maximum height | Boston, Denver, Houston, Los Angeles, Minneapolis, New York, Portland | (BuildZero, 2021) |
| LA County LARIAC4 | Unknown | Los Angeles | (BuildZero, 2021) |
| Toronto 3D massing | Mean height | Toronto | (City of Toronto, 2021) |
| Canada open building data | Maximum height | Montreal | (Statistics Canada, 2021) |
| 3D BAG | Maximum height | Amsterdam | (TU Delft 3D geoinformation group, 2021) |
| Stockholm open building data | Median height roof | Stockholm | (Stockholms Stad, 2021) |
| Helsinki 3D city model | Unkown | Helsinki | (Helsingin kaupunginkanslia, 2021) |
| **Street network dataset** | | **City** | **Source reference** |
| U.S. Street Network Analytic Measures | | Bostion, Chicago, Denver, Houston, Los Angeles, Minneapolis, New York, Portland | (Boeing, 2017) |
| OpenStreetMap | | Amsterdam, Helsinki, Montreal, Stockholm, Toronto | (OpenStreetMap contributors, 2021) |

*Building data*

In total eight different building height datasets have been used. The largest dataset, Opencitymodel, is used for retrieval of building height data for all nine US cities included in the Place Pulse 2.0 dataset. Additional datasets containing building footprints and heights are used for Chicago, Boston, Toronto, Montreal, Amsterdam, Stockholm and Helsinki. Although more than these fourteen cities in the Place Pulse 2.0 dataset have a 3D model publicly available or have published open building height data, not all of these cities are included in this research. This is mainly because of time limitations, as including an additional dataset requires additional understanding of this dataset. For example, the Tokyo and Osaka dataset are openly available, but the documentation is not available in English which makes retrieving it a difficult process. In order to make a useful selection, European and North American cities have been included as these continents are mostly represented in the overall dataset and as the cities in these continents have the highest coverage of accessible building (height) data. A brief description of all the data sources used for the building data can be found in appendix A.

As can be seen from Table , not all data refers to the same level of building height. Some building height data refers to the mean, some building height data refers to the maximum building height and for some cities the building height is an approximation. This is a consequence of the scarce availability of uniform building height data throughout the world. When a choice could be made, the maximum height is used. Otherwise the only height data available has been used. This results in less accurate data regarding the attributes related to the building height.

*Street network data*

The dataset used for the street network in the United States is the 'U.S. Street Network Analytic Measures' (Boeing, 2017), consisting of the street network of every United States city or town. Here, every object represents a street segment. Every street segment is a non-intersecting line which could be a segment of a longer street or the complete street itself. Furthermore, every street segment has, for this research, relevant attributes such as an id, street type and the street name. The dataset is created from OpenStreetMap data (Boeing, 2017). For the non-United States cities, the street network data is directly retrieved from OpenStreetMap. In accordance with the data from the US Street Network Analytic Measures, this data also consists of street-segments with an id, type and street name.

### 3.2.2. Processing: Image segmentation

The first processing applied to the data is done using image segmentation. The image segmentation process contributes to the output data by including the attributes concerning the built environment shares in the images. Additionally, the image segmentation process contributes to the filtering of the input data, in terms of relevant images. Figure 15 visualizes this process and shows its relation to the larger context of the data gathering and processing process. This section describes the application of image segmentation to the images present in the input data.

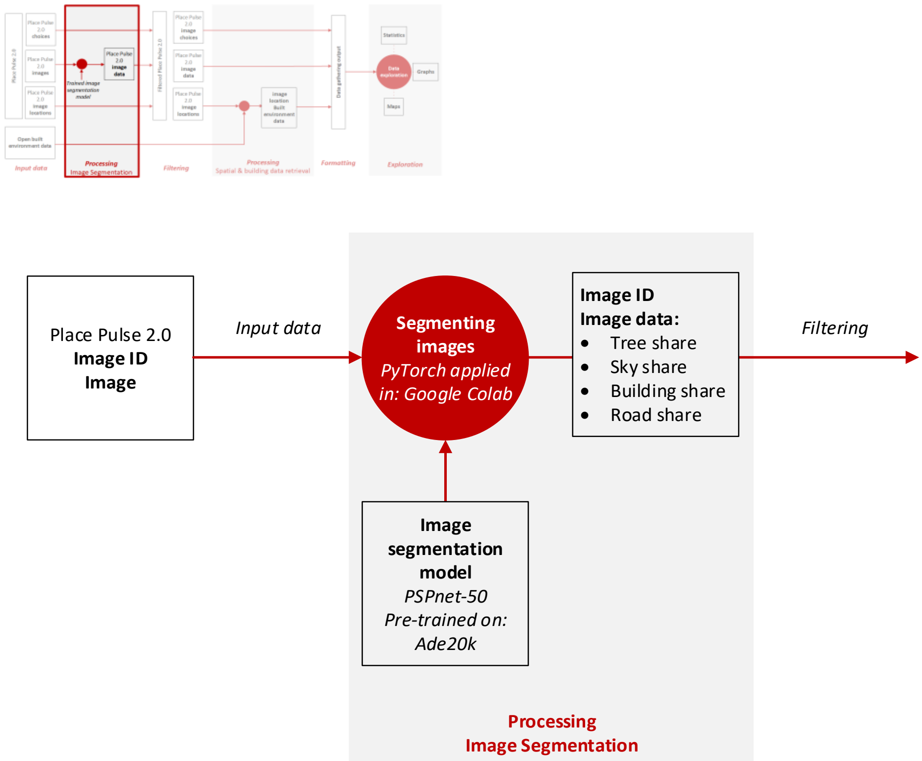



*Figure 15: Image Segmentation process as described in this section in relation to the overall data gathering process*

In order to calculate the built environment element shares in the images, image segmentation has been used. More specifically the PSPnet-50 model pre-trained on the Ade20k dataset (Zhao et al., 2017) has been applied to every image in the Place Pulse 2.0 dataset. This pre-trained model has been selected based on the following criteria: First of all, the model should be able to find the for this research relevant built environment elements in the image, namely: building, road, tree and sky, as accurate as possible. Furthermore, the application of the model should be well documented and open source. Using PyTorch and Google Colab, the pre-trained PSPnet50-Ade20k model has been applied to all 110,998 images. Using the segmented image data, the share of the relevant built environment elements has been calculated for every image. These shares are used as attributes in the analysis. Figure 16 shows several examples of segmented images.

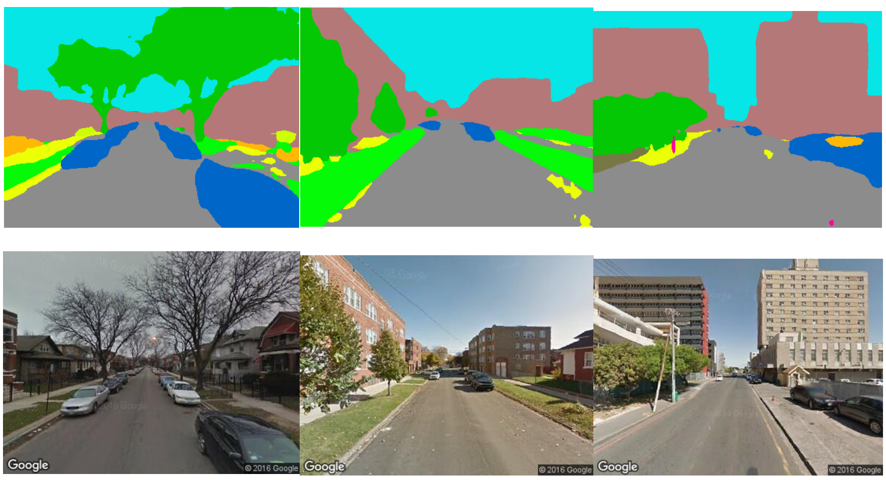


*Figure 16: Three sets of segmented images with its original images from Place Pulse 2.0* (Dubey et al., 2016).

Several remarks can be made based on the segmented images. First of all, it can be seen that seasonal differences are partly reflected in the image segmentation results. As trees in winter are somewhat smaller in size after segmentation due to the lack of leaves. Furthermore, some inaccuracies can be seen. For example, sometimes the sidewalk is segmented as sidewalk and sometimes as part of the road. Thirdly, the segmented images are not able to tell a lot about the building typology. The depth of the images disappears in the segmented images, stressing the importance of the need for additional data on the buildings. For this research, irrelevant objects that are located in front or on top of built environment elements could influence the output. For example, cars located on roads and in front of buildings are segmented as cars resulting in a lower share of road and buildings in the images. This is not a problem in itself, since this is how the image is represented, however a road filled with cars can be large in size whereas the road share can be relatively low due to the fact that a large part of the road is segmented as car. Again, this stresses that image segmentation alone would not be sufficient to draw conclusions on in relation to human perception.

### 3.2.3. Filtering

Not all the data in the input data is relevant in relation to this research. Based on the metadata of the input data and the retrieved image segmentation data, it is possible to filter out the non-relevant data. First of all, concerning the made choices of respondents on human perception and in relation to this research, we are only interested in choices between images regarding perceived safety, perceived beauty, and perceived liveliness. Also, we are only interested in choices between two images of urban, livable, streets. These images will be referred to in the remainder of this section using the term urban streetscapes. Furthermore, we are only interested in images for which the relevant attribute values can be calculated, which means that only images can be included that are taken on locations which are surrounded by buildings for which building (height) data is available. The subsections below will explain how and why we have filtered certain images and choices. Figure 17 schematically visualizes the filtering process described in this subsection and how it relates to the overall data gathering process.

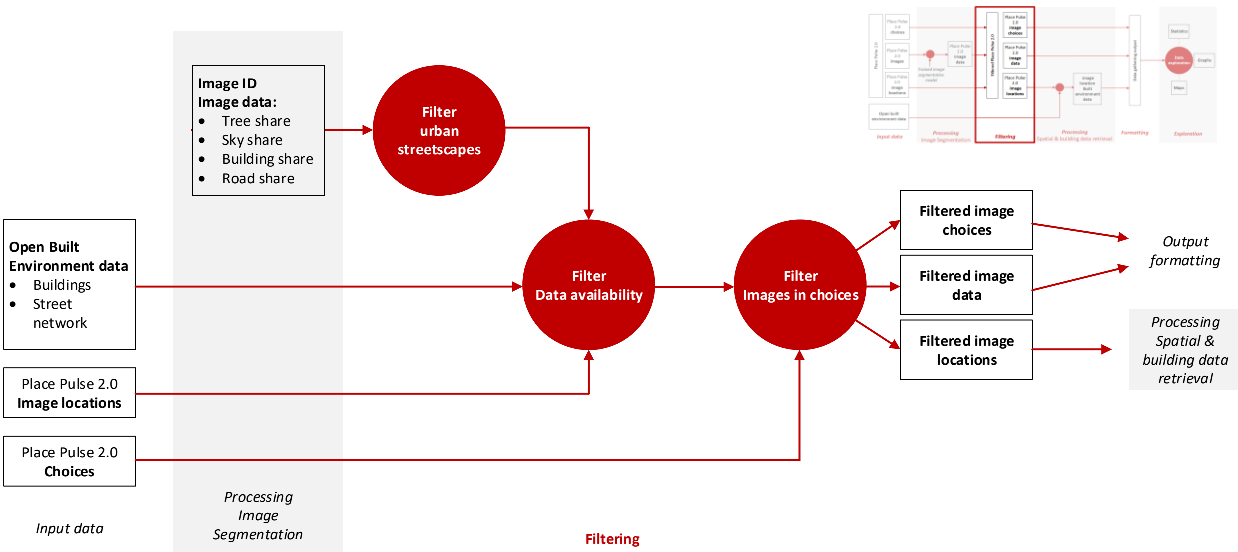



*Figure 17: Filtering process as described in this section in relation to the overall data gathering process*

### Urban Streetscapes

The Place Pulse 2.0 dataset contains images taken in urban areas. However, there are images in the dataset that have been taken in a non-urban environment or from a highway. Furthermore, the Place Pulse 2.0 dataset also contains images that are fully focused on one building or one row of buildings. These images concern a different street view then most images that have been taken with an orientation into the street. As a result, the information that is communicated in these images is different from the images with a perspective into the street. This potentially influences someone's choice on selecting an image that he or she perceives as more safe, beautiful, or lively. The images taken on highways and fully oriented towards a building or a row of buildings have been classified as non-urban streetscapes.

Using the calculated shares of built environment attributes in the images of the Place Pulse 2.0 dataset, as described in subsection 3.2.2., the non-urban-streetscape images can be filtered out. For example, images that are taken in a non-built-up area do not contain a large share of buildings in the image. In order to filter out the non-urban-streetscape images multiple filter conditions have been applied to the segmented images. For example, building share > 0.005. The complete set of conditions are provided in appendix B. The combination and parameters of the conditions have been determined based on manual assessment of the results after applying the conditions on a sample of images. This sample consisted of all the images taken in New York City, San Francisco and Amsterdam. Figure 18 shows a row of images that are filtered out, Figure 19 shows a row of images that are not filtered out.

*Figure 18: Typical images that are filtered out* (Google Maps, 2021) .

*Figure 19: Typical images that remain in the dataset* (Google Maps, 2021).

### Open building height data availability

Another filter condition that the images in the Place Pulse 2.0 dataset should meet is the availability of open data on the building height of the buildings in the images. The building height data and its availability and source per city has been presented in subsection 3.2.1. As a result of this requirement, a large share of the images from the Place Pulse 2.0 dataset are filtered out. Furthermore, buildings in the input data are filtered out if they contain an inaccurate building height. Because these buildings are not included in this research, situations could occur that some buildings in the surrounding of an image are not included in this research. In order to make sure that a representative sample of buildings are always related to one image, we removed images for which more than 20% of the selected relevant buildings contain predicted building heights.

### Filter results

As a result of the above described filter conditions, 7,158 images from the Place Pulse 2.0 dataset are relevant for this research. Since we filter the number of relevant images, also the number of choices is reduced significantly as we want both images included in the choice to be one of the relevant images. This results in a total number of 6,522 choices that are included in this research. Table 6 provides an overview of the number of images and number of choices included.

*Table 6: Overview of the images per city after filtering*

| | City | Amount of relevant images | | Involved in amount of choices per city | | |
|---|---|---|---|---|---|---|
| | | Per city | Per continent | Beautiful | Lively | Safety |
| 1 | Boston | 257 | 6522 | 103 | 146 | 220 |
| 2 | Chicago | 1151 | | 409 | 707 | 902 |
| 3 | Los Angeles | 597 | | 209 | 304 | 500 |
| 4 | New York | 1518 | | 587 | 953 | 1225 |
| 5 | Portland | 377 | | 141 | 225 | 285 |
| 6 | San Fransisco | 440 | | 152 | 268 | 335 |
| 7 | Montreal | 886 | | 336 | 575 | 698 |
| 8 | Toronto | 1296 | | 570 | 818 | 1052 |
| 9 | Amsterdam | 196 | 636 | 84 | 112 | 145 |
| 10 | Stockholm | 295 | | 106 | 169 | 255 |
| 11 | Helsinki | 145 | | 68 | 96 | 107 |

### 3.2.4. Processing: Spatial & Building data attributes

In this section the process of retrieving built environment data on the location of the filtered images is described. The input datasets used for this process is are the building and street datasets, described in the input data section as the Open built environment data class. This section will first describe the selection of relevant buildings and streets per image. Second, the calculation method per individual-built environment attribute will be described. Figure 20 shows the processing of the spatial and building data attributes within the overall data gathering process.

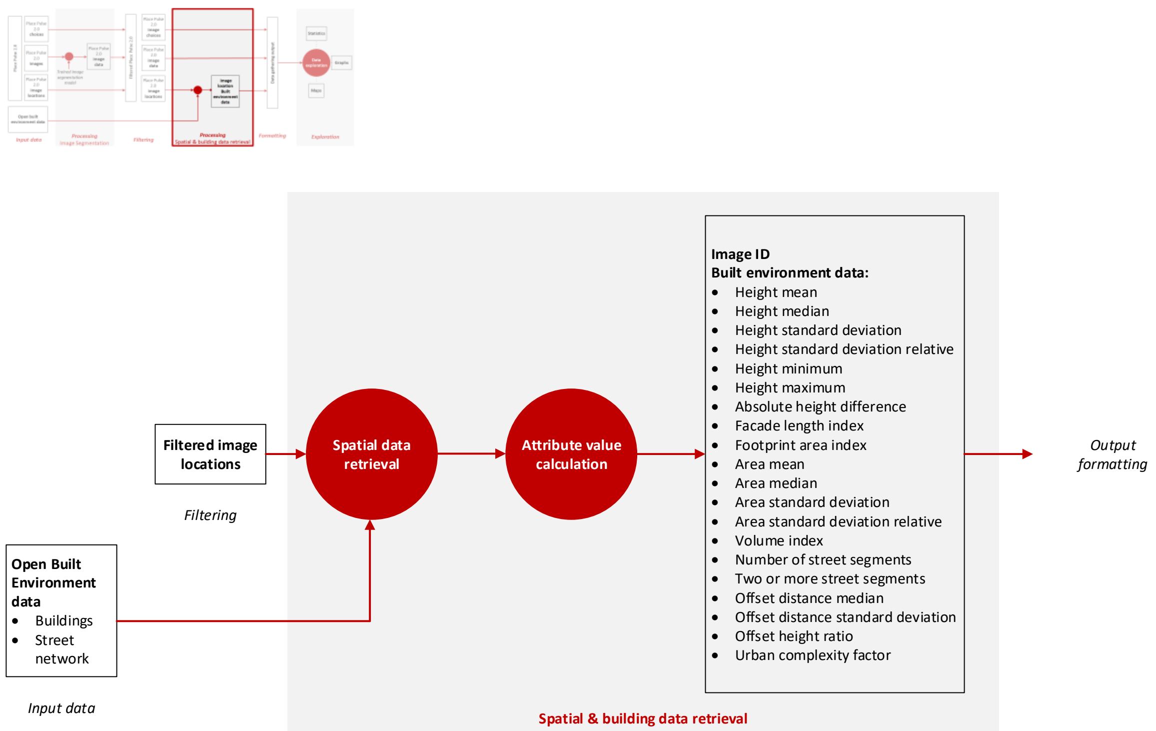



*Figure 20: Image Segmentation process as described in this section in relation to the overall data gathering process*

### Building selection

Knowing the location, footprint and height of every building that is in the proximity of an image that is included in the Place Pulse 2.0 dataset, the main building statistics of the buildings on the images can be calculated. These statistics are either one of the attributes or are used to compute an attribute. However, as the orientation of the images in the Place Pulse 2.0 dataset is not known, calculating these statistics solely for the buildings on the image is not possible. Therefore, a general selection approach for all images has been created to select the buildings that are relevant per image.

#### *Assumptions and points of consideration*

A building is considered relevant for an image if it has a reasonable chance to be visible in the image. For the setup of a general selection approach, the following points of consideration should be taken into account:

- The building statistics should be calculated for different types of images at locations with a varying urban typology and function. Resulting in:
    - Different visible street depths of the images
    - Different orientation of the buildings towards the street
    - Different building densities
    - Different dominant building types
    - Not all buildings visible in the images are completely visible in the image
    - Variety in the building heights of the buildings visible in the images
    - Variety in functions of the buildings
    - Variety in functions of the streets

- The building statistics should be calculated for images for which the orientation is not known but for which the orientation is most likely equal to the direction of the street, resulting in:
    - Not knowing in which direction of the street the orientation of the image is
    - At crossings, to which street the image is orientated

Figure 21 visualizes the different types of images that are present in the Place Pulse 2.0 dataset in the top row and a different orientation of that image at the same location in the bottom row. From Figure 21, it can be seen that another view direction at the same location can result in different building typologies but also in comparable building typologies.


*Figure 21: Three images in Place Pulse 2.0 (top)(Dubey et al., 2016) and images of the same location taken into another direction (bottom)*(Google Maps, 2021)

As these points of consideration result in a lot of uncertainties, an attempt should be made to find a building selection method that is general but as accurate as possible for all the relevant images in the Place Pulse 2.0 dataset. Therefore, the following assumptions and rules were set:

- An image is dominated by buildings that are located along the street on which the image is taken, thus only buildings along the street on which the image is located are relevant
- After a certain distance, the buildings along a street are not visible anymore. This distance varies per attribute and is presented in Table 6.
- At crossings, the street towards the image is orientated is unknown and therefore all streets that are intersecting at the crossing on which the image is taken are included as relevant streets

These assumptions are based on visual inspection of the dataset. Even though we have tried to set the assumptions as accurate as possible, there are many situations in which the assumptions do not completely apply to an image. For example, a selection process based on the above made assumptions would exclude the high-rise buildings visible in the skyline of the top right image in Figure 21. However, as these images are relatively unique in the dataset and due to time limitations within this research, it has been ought that these set of assumptions will result in the best possible selection of buildings that have to be included in the calculation of the building statistics per image.

*Selection of relevant buildings per image*

The locations of the images are known, as well as the location, footprint and height of the buildings. In order to make a selection of relevant buildings based on its location along the street on which the image has been taken, street network data is used.

Using FME, every street segment has been checked on intersection with an image by creating a small buffer around the image and checking for intersection between the buffer and the street segment. Since a street segment can be relatively short (<50 meters long) and can be part of a series of street segments making up the complete street, relevant street segments can also be street segments that are adjacent to the intersecting street segment and which are part of the same street.

Therefore, using the street name as common attribute value, the street segments that touch with a street segment that intersects an image are dissolved with the intersecting street segment. This process has been done two times, which can result in new street segments that consists of five loose original street segments (one original street segment intersecting with an image, two first order adjacent street segments and two second order adjacent street segments). All part of the same street and all adjacent to each other. At crossings, this process has been done for every street that intersects with an image. So, if an image is crossed by two streets, the maximum number of potentially relevant street segments is 10 (two original street segments, four first order street segments and four second order street segments). Figure 22 visualizes the street selection and joining process. In Figure 22, the image intersects through a small buffer with Kings Street. The two adjacent Kings Street segments, segment one and two, are joined with intersecting segment, segment four. Segment three is a different street so is excluded. If the image buffer would intersect segment three as well, also all relevant street segments of University Avenue would be included.

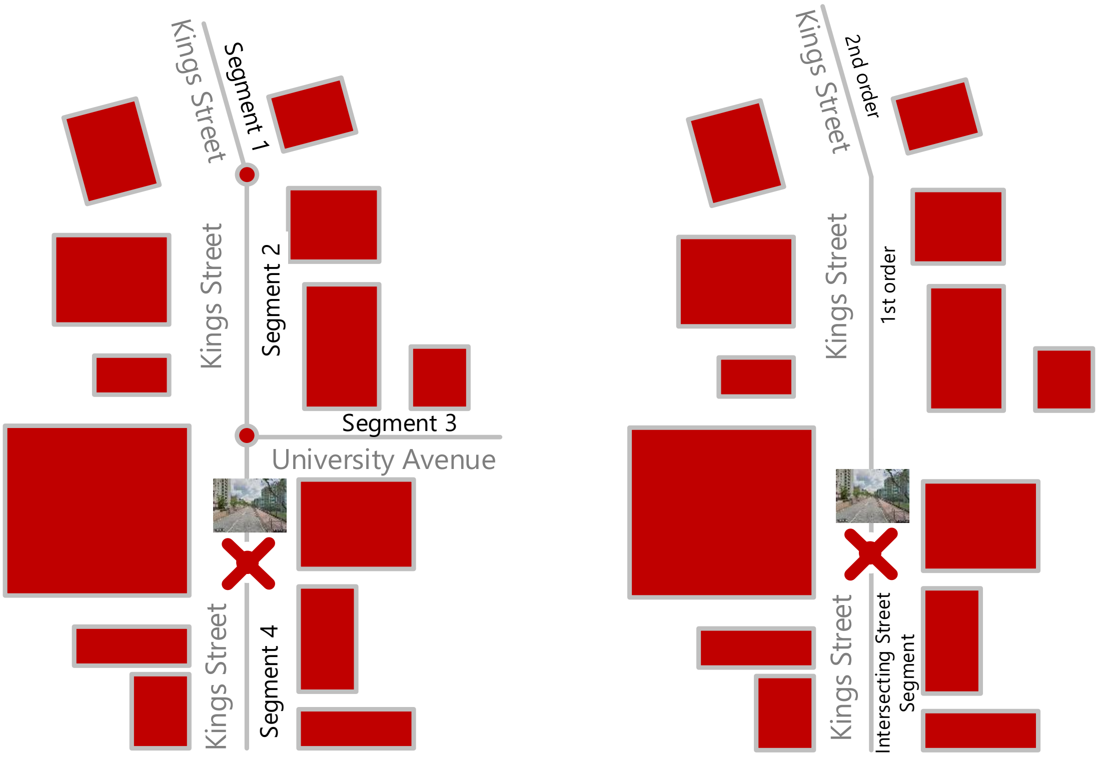



*Figure 22: Selecting and joining relevant street segments*

Eventually, the selection of the relevant buildings for every image has been done using the following process:

First every street segment is buffered. The size of the buffer is dependent on the street type. Since residential streets are generally less wide than primary roads, the buffer of residential streets is smaller than the buffer of primary roads. By making the buffer size street type dependent, the buffers around wider roads are able to include the buildings that are adjacent to that road, whereas it is prevented that a too large buffer size results in the inclusion of non-adjacent buildings along narrow roads. After the buffering of every street segment, the buffers of the street segments belonging to the same image are dissolved. In the remainder of this section the term 'buffered images' will be used to refer to these buffers. This process has been done in FME.

Secondly, the attributes of the buffered images are joined with every building based on its location. If a building lays in a certain buffered image, the buffered image attributes and its values are attached to the building attributes. This has been done using the 'join attributes by location' algorithm in QGIS. This results in building objects that contain building data as well as an image id. If a building lays within the buffer of more than one image, additional building objects are generated so that every building object is a unique building-image combination. Now an initial selection has been made on relevant buildings per image.

Thirdly, the distances of the buildings to the location of every relevant image is computed. This is the distance between the centroid of the building polygon and the image location to which the specific building is related. Based on this distance, two selections of buildings are made for every image. One selection of buildings that are within 300 meter of an image and one selection of buildings that are within 100 meter of an image. The 300 meter selection will be used for calculating the building height statistics, mean building height, median building height, standard deviation of building height, maximum building height, minimum building height and perceived average building height. The 100 meter selection will be used for calculating the building footprint and building volume statistics. The building height statistics have a larger distance as filter criterion as there is chance that high buildings at larger distances are visible in the image. The building footprint and volume statistics have a shorter distance as filter criterion as these statistics describe the density of the buildings around the image. It is assumed that buildings at distances larger than 100 meters do not have a significant impact on the felt density by looking at street view images. Figure 23 visualizes the selection process.

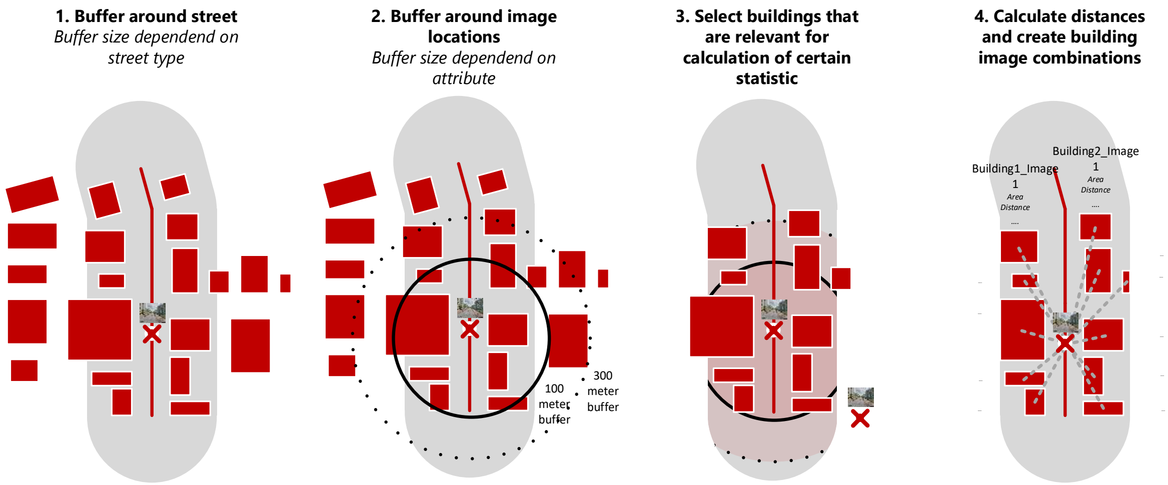



*Figure 23: Selection of relevant buildings per image*

## Attribute calculations & retrieval

Now that a selection has been made on buildings that are relevant for every image and for every attribute, the attribute values per image can be calculated. The attributes are classified in different groups based on the built environment characteristic that it describes. Per built environment characteristic it is briefly described how the related attribute values are retrieved or calculated. A complete overview of the built environment characteristics can be found in appendix C.

### *Building Height*

#### *Height statistics*

The height mean, height median, height standard deviation, height standard deviation relative, height minimum, height maximum, and absolute height difference are all computed based on the building height of all buildings along the relevant street(s) per image and within a distance of 300 meters. For the standard deviation a sample standard deviation has been used. The height standard deviation relative is calculated by dividing the height standard deviation by the height mean.

### *Building footprint*

#### *Façade Length Index*

The façade length index is computed using FME. By creating offset lines from the relevant streets for a certain image, the intersecting length between the offset lines and buildings is calculated. The intersecting length is divided by the overall length of the offset lines resulting in a value between zero and one, in which one indicates that the sides of the streets are completely filled with building facades and in which zero indicates that the sides of the streets are not filled with building facades.

Since the offset of buildings to the street may vary per urban typology and road type, seven offset distances have been used. These distances are set based on a visual inspection of the input data in which an attempt has been made to cover the façade length index for every street and urban typology as accurate as possible. These distances are 10, 15, 20, 25, 35, 50 and 70 meters. For every image the façade length index is calculated for all seven offset line distances. Then, the highest façade length index is selected per image. Figure 24 visualizes the computation process for calculating the façade length index.

The applied approach means that the situation could occur that the façade index that is set for a certain image location, does not represent the façade index of the building line standing closest to the street. However, if the façade index that is calculated based on one or more buildings that stand behind other buildings and is found to be the largest, the view to the sides of the streets is still blocked by these buildings located behind the first row of buildings. Yet, this situation is not preferred as the impression received by an individual standing on the street is different when the building row directly adjacent to the street is relatively open whereas the side view eventually is blocked by buildings behind it. Especially when these buildings are orientated towards a different street or if there is a different street in between. Therefore, a visual inspection of the results in QGIS has been conducted in different urban areas and cities to gain an impression on how often it was the case that the façade length index represented the façade length index of another row of buildings behind the row of buildings standing directly along the respective street. The visual inspection showed that this was rarely the case and that in almost all cases, the façade length index represented the façade length index of the buildings standing directly adjacent to the respective row. Furthermore, although the buildings on one side of the street could be standing closer to the street than the buildings on the other side of the street, the façade length index is always calculated based on the same offset distance on both sides of the street. Although, a more customized approach could have been selected here, this was not done to reduce the complexity of the approach. If the façade index shows to be an important attribute, a more customized approach could be applied in future studies.

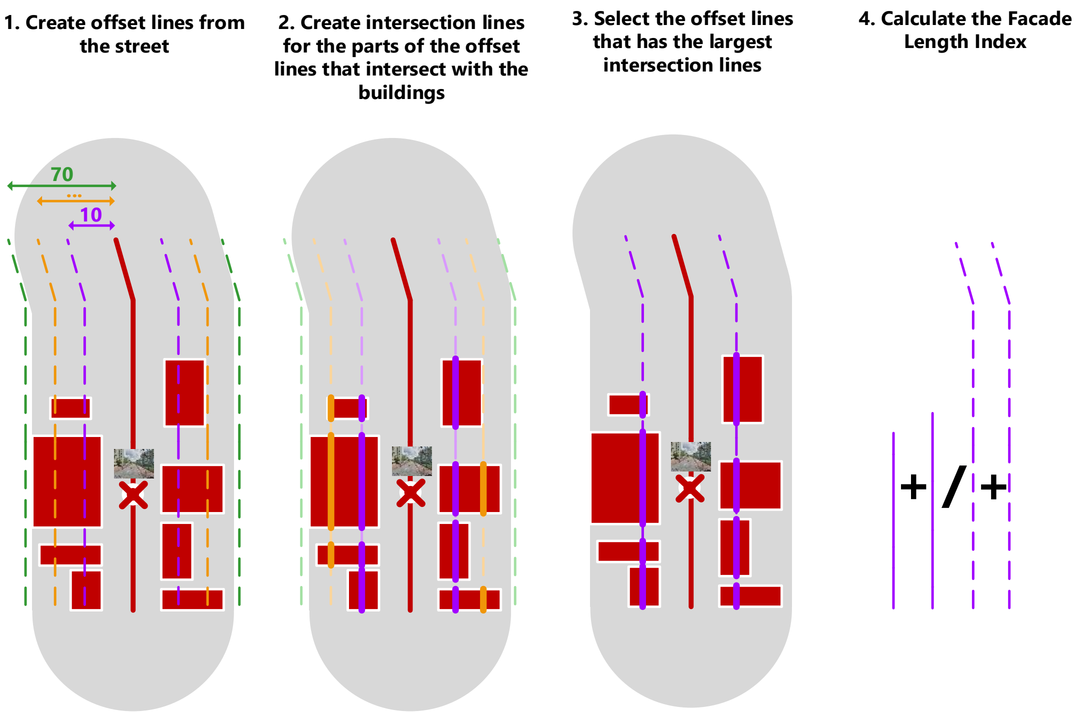



*Figure 24: Computation process of the Façade Length Index*

*Footprint Area Index*

The footprint area index is also computed in FME. For every image location, the image buffer is shrunk to a maximum of 100 meters. However, still the same street buffer is used. As a result, an area is left that covers a strip along the street of which the furthest point in that area is maximally 100 meters away from the location of the image. For this area, the relevant image location area, the area is calculated in square meters.

Additionally, the sum of the area of the footprints of all the buildings laying within the image location area is calculated. This results in the total building footprint area per image. Then for every image the total building footprint is divided by the overall area, resulting in the footprint area index. A value of 1 would mean that the area is completely covered by buildings, whereas a value of 0 would mean that the area does not contain any buildings. Figure 25 visualizes the computation process. Here, it can be noted that there is a zone in which a building can lay within the circular buffer distance of 100 meters but cannot lay with the relevant image location area. This is a result of the buffer size used for the initial selection of buildings along a street. As the buffer size of relevant buildings along a street varies per street type between 50 and 90 meters, the buildings that lay within 100 meter of the image location but not within the buffer along the street are not included.

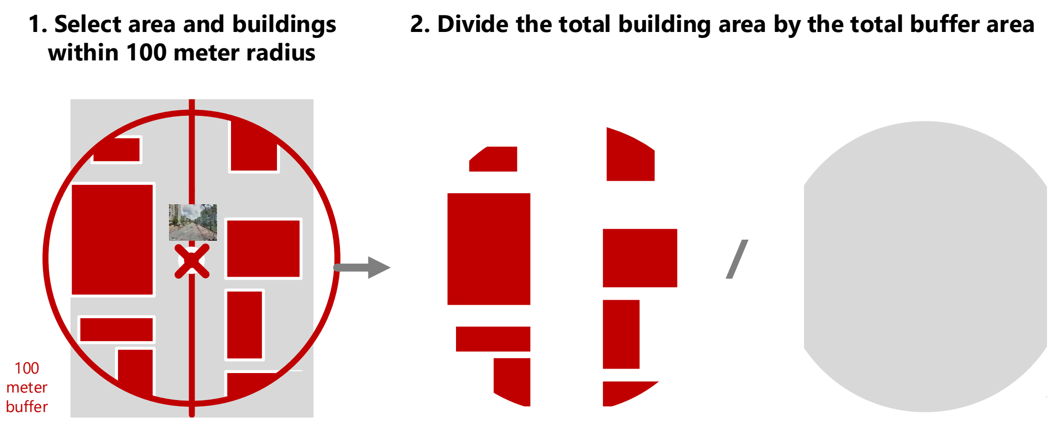



*Figure 25: Computation process of the footprint area index*

*Area statistics*

The area mean, area median, area standard deviation and area standard deviation relative have all been computed by selecting buildings that are located along the street on which the image is taken and within 100 meters from the location of the image. The smaller maximum distance, 100 meters and not 300 meters, has been chosen because from a certain distance on it is likely to be impossible for a building to have a major impact on the image based on the façade that is visible due to its area. The area standard deviation relative is computed by dividing the area standard deviation by the area mean.

*Building volume*

*Volume area index*

The only statistic in relation to the building volume is the volume area index. The volume area index is computed with the same approach as the footprint area index. However, in contradiction to the area footprint index, this statistic is calculated in volumetric terms. So instead of the total building footprint area, the total building volume is calculated. Also, instead of the total area size in square meters, the total area volume in cubic meters is calculated. Since, theoretically, the sky is the limit in terms of building size, a reference height will be taken for the calculation of the total area volume. This reference has been set to 40 meters. The total building volume then is divided by the total area volume, resulting in a positive value. This value can exceed the value of one if the total building volume is higher than the taken area volume based on the reference height.

### *Street perspective*

#### *Number of street segments & One or more street segments*

The attribute 'number of street segments' has been computed by counting the number of street segments in the input street data within a 50 meter radius of every image location. In Figure 26, a case has been provided in which the number of street segments is equal to five. In addition to the total number of street segments, the attribute "more than one segment" has been computed. The value of the attribute is zero if there is only one street segment in a 50 meter radius and the value is one if there are more than one street segments within a 50 meter radius. The, smaller, 50 meter radius has been selected because this attribute is specifically included with the purpose of representing refuges in the urban streetscape. After a longer distance, a side road might not be felt as a refuge anymore and might not be well visible.

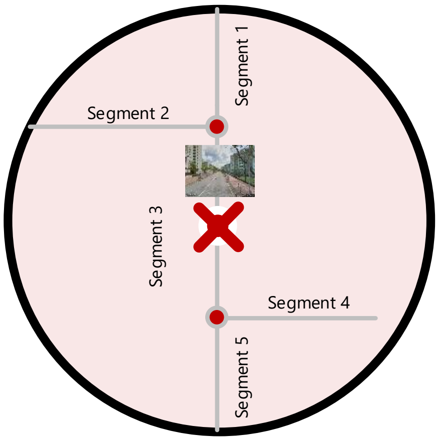



*Figure 26: Computation process of street segment attributes*

#### *Building offset statistical attributes*

In relation to the building offset, two attributes are included. The offset distance median and the offset distance standard deviation relative. The mean was not included here as crossings and other areas with open spaces in multiple directions can cause offset lines to be extremely long whereas these offset lines are not representative for the image and the aim of the attribute. The attribute should namely describe the distance of buildings from the road along which it is standing. Since many images have several of these cases, the mean would not be very representative whereas the median excludes these cases. The offset distance standard deviation relative is calculated by dividing the offset distance standard deviation by the offset distance mean since the standard deviation also includes the cases described above. This should be taken in consideration in the analysis on the relationship with one of the human perception attributes. Furthermore, the building offset height ratio is calculated by dividing the offset distance median by the height median.

#### *Urban complexity factor*

The urban complexity factor is computed by multiplying the height standard deviation relative by the area standard deviation relative and the offset distance standard deviation relative. A higher value would thus mean that, in general, there is more relative variation in building volumes expressed by its area, height and offset.

### 3.2.5. Formatting

Now that the computation of all attributes has been described, this section describes how the retrieved data and choices from the different datasets have been constructed in a format that is suitable for analysis. This has been done by combining the choice data with the image attribute data. The resulting Table consists of rows in which every row is one image and every set of two rows is one choice set. Whether an image is chosen or not is marked using binary notation, where one represents a 'winner' and zero a 'loser'. Table 7 is a snip of the complete dataset in the right format.

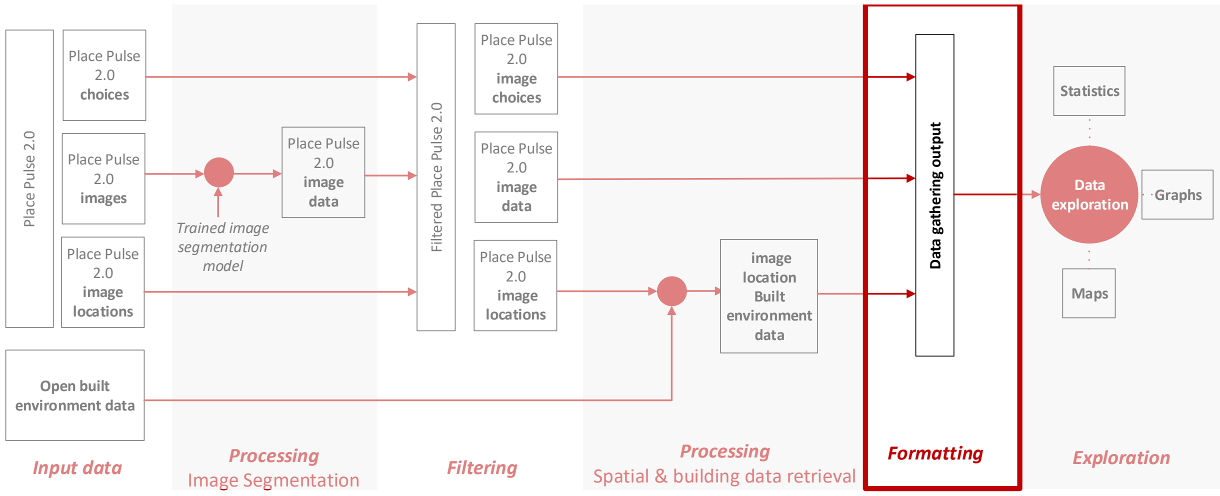



*Figure 27: Focus of the formatting subsection within the overall data gathering process*

*Table 7: Snip of the complete dataset*

| | id | city | category | winner | Tree share | .... | Urban complexity factor |
|---|---|---|---|---|---|---|---|
| **0** | 1 | Chicago | safety | 1 | 0.17 | ... | 0.004 |
| **1** | 1 | New York | safety | 0 | 0.06 | ... | 0.020 |
| ... | | | | | | | |
| **12861** | X | Boston | Beautiful | 0 | 0.12 | ... | 0.054 |
| **12862** | x | Portland | beautiful | 1 | 0.23 | ... | 0.044 |

After formatting the overall composed dataset containing the choice data as well as the built environment attribute values per image, the complete dataset has been split in two additional datasets. Allowing a distinction to be made in the analysis on the relation between human perception and the built environment in relative high density and relative low density areas. This is done as human perception can be influenced by different attributes in low density areas then in high density areas. The dataset has been split using the attribute "volume index". The high density dataset is created by selecting all data, choices and image data, related to the 50% largest volume index images. The low density dataset is created by selecting all data, choices and image data, related to the 50% lowest volume index images. As a result there are three datasets: the complete dataset, the low density dataset and the high density dataset. Although splitting the dataset significantly reduces the amount of choices, it is still considered large enough. Table 8 provides an overview of the datasets used for analysis. In the remainder of this thesis, the term 'split datasets' will sometimes be used to refer to the low and high density datasets.

*Table 8: Providing overview of the datasets*

| Human perception category | Dataset | Number of rows | Number of choices |
|---|---|---|---|
| Perceived beauty | Complete | 2766 | 1383 |
| | Low density | 588 | 294 |
| | High density | 690 | 345 |
| Perceived liveliness | Complete | 4374 | 2187 |
| | Low density | 930 | 465 |
| | High density | 1048 | 524 |
| Perceived safety | Complete | 5724 | 2862 |
| | Low density | 1410 | 705 |
| | High density | 1346 | 673 |

### 3.2.6. Data exploration

This subsection describes the exploration of the complete datasets, thus not on the split datasets for low and high densities. The complete datasets have been explored on a potential relation between cities and choices, the location of the images and choices, the urban typologies of the buildings around the image locations and choices, correlations between the attributes and finally on the potential relations between the attributes and choices. Figure 28 visualizes how this subsection relates to the overall data gathering process.

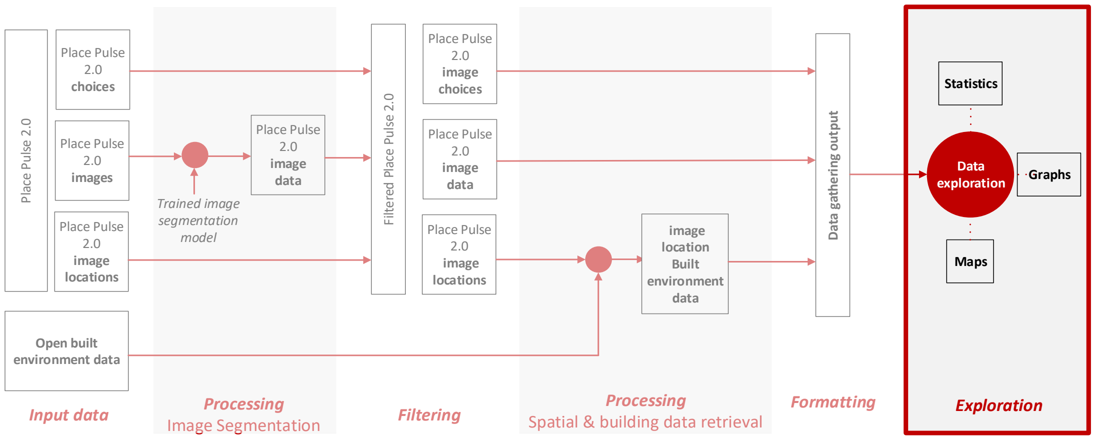



*Figure 28: Data exploration in relation to the overall data gathering process*

#### City – choice exploration

To better understand the input data, the differences between the winner-loser ratio for the individual cities in the dataset have been visualized in Figure 29. Although it is not very relevant for this research which city exactly has the highest or lowest winner-loser ratio, the fact is that there are significant differences between them is relevant. This could be a result of one of the attributes included in this research, Boston which is perceived as most beautiful and lively could have many trees for example. However, this could also be the consequence of uncaptured built environment characteristics. For example, the architectural style of a city, the wealth of a city, the maintenance level in general of a city or the general urban typology of a city are not included as attribute s in this research. In addition, other factors could explain the differences such as the composition of the dataset, including the orientation of the images, the randomly chosen locations, the lighting of the images, etc. However, altogether, the significant variation in winner-loser ratio per city does indicate that it is possible that city wide characteristics have an influence on human pe rception.

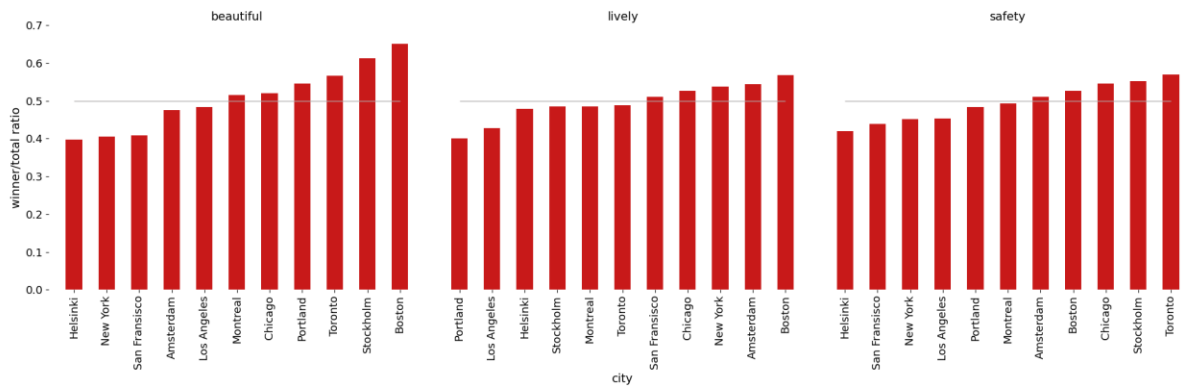



*Figure 29: Bar charts city – winner-loser ratio*

### Spatial human perception choice exploration

The potential influence of a location of an image on human perception could indicate uncaptured geo-spatial related attributes such as the average neighborhood or city income, the average building age of a neighborhood or city, the function of an area etc. However, it can also indicate potential relationships that can be captured such as building density. The spatial exploration can contribute to identifying the scale (e.g., city or neighborhood) on which there might be a potential relationship between human perception and the location of an image.

Before exploring the datasets spatially, it is relevant to mention that existing literature mentions that the visual quality of streets assessed using street view imagery has been found to vary per district (Ye et al., 2019). Although the visual quality of streets cannot be considered the same as the perception of streets, it might indicate that similarities in human perception rating can be expected within districts whereas differences might be expected between different districts. Furthermore, Middel et al. (2019) mention the following on the likely presence of potential relevant attributes in street view images based on the location of the image: Street views taken in suburbs generally contain a higher percentage of tree share compared to street view images taken in the city center. Street view images taken in low-income neighborhoods generally contain the least tree share in relation to street view images taken in the city center or suburban locations. Sky share on the other hand is generally more present in street view images taken in low-income neighborhoods in relation to street view images taken in suburban and city center locations. Street view images in city center locations generally contain most building share (Middel et al., 2019). Relating these indications from the literature to the findings from the spatial exploration and eventually to the results of the analysis could contribute to explaining the findings from the spatial exploration.

The choices and location of the images have been spatially visualized in order to retrieve insight on the spatial distribution of perceived safety, liveliness and beauty of the images. For all relevant images, an image is marked as loser if it has lost more than that it has won. Whereas the image is marked as winner if it has won more than that it has lost. This approach provides a relative easy method to receive an indication on the preference of an image concerning how people perceive it. However, it must be noted that the situation could occur that an image that is generally perceived as safe is only related to an image that is perceived as even more safe in the data retrieval process. As a result the image might be marked as loser whereas it would be perceived as relatively safe. Also, some images might have won relatively more than other images, for example one image could have won three out of five times whereas another image would have won five out of five times. In order to maintain simplicity in the overview, only a distinction between winners and losers has been made for individual images. Additionally, the images have been marked if they are clustered with other images that have been marked as loser or winner as well. This has been done using a DBSCAN cluster algorithm in QGIS. DBSCAN is preferred over other clustering algorithms, such as k-means and Fuzzy c-mean, as it is ought to be more suitable to find geospatial aggregation (Karayazi et al., 2021). It requires two input parameters, the areas of neighborhood and the minimum number of points (n), in this case image locations, within the areas of neighborhood. Here, neighborhood is defined as the area in which a cluster can be found. It is thus determined by a maximum distance from a certain point. The cluster input values vary per human perception rating as there are less images involved in the perceived beauty choices then in for example the perceived safety choices. This results in a relative lower image location density for perceived beauty then for perceived safety, different densities require different cluster requirements. The cluster algorithm finds and classifies a point to be in a cluster if it lies together with at least n-1 others within the specified area of neighborhood distance. This process of assigning a point to a cluster is iterated over all the points until all points are classified in a cluster or no points can be classified in a cluster anymore. Table 9 provides the cluster parameter values for the different human perception attributes.

*Table 9: DBSCAN cluster requirements per human perception category*

| Perceived | Minimum points within areas (n) | Areas of neighborhood maximum distance (m) |
|---|---|---|
| Beauty | 3 | 1000 |
| Liveliness | 4 | 1000 |
| Safety | 5 | 1000 |

A disadvantage of the DBSCAN clustering analysis is that if there is a specific area with a high density of image locations in a city, images in that area might be clustered in a winner or loser cluster whereas there is actually a diverse spread in winner and loser images in this area. In order to deal with this disadvantage, a hexagon distribution has been created in addition to the DBSCAN clustering analysis. Any spatial clustering visible in the DBSCAN clustering can therefore also be checked in the hexagon analysis and the other way around. Using hexagons being in total two kilometers in horizontal and vertical direction, the hexagons are marked based on the average winner-loser ratio of the images taken in the hexagon. Every hexagon is marked with a color representing one of the five different intervals. The intervals have steps of 0.2 and vary between zero and one. A value of one means that 100 percent of the images in the hexagon are marked as winners. Below, the spatial distribution of the winners and losers have been visualized in New York City per human perception attribute, clustered and individually on two zoom levels.

Figure 30 up and until Figure 32 visualize on the left the location of all images that have been marked as winner (green circle) or loser (red circle) regarding perceived safety, liveliness, or beauty. If the image is included in a cluster, the circle representing the image is filled with red (loser cluster) or green (winner cluster). On the right the hexagon grids are visualized, representing the winner-loser ratio in each hexagon in which a winner-loser ratio of one is green and of zero is red.

### *Perceived beauty*

Concerning beauty, looking at the cluster analysis, the location of images having a comparable winner-loser ratio does not seem to be clustered on a city level but does seem to be clustered on a local level. Furthermore, from the hexagon distribution, it can be seen that several hexagons seem to be bordering predominantly on hexagons with a comparable winner-loser ratio, although many hexagons do not border a hexagon with a comparable winner-loser ratio as well.

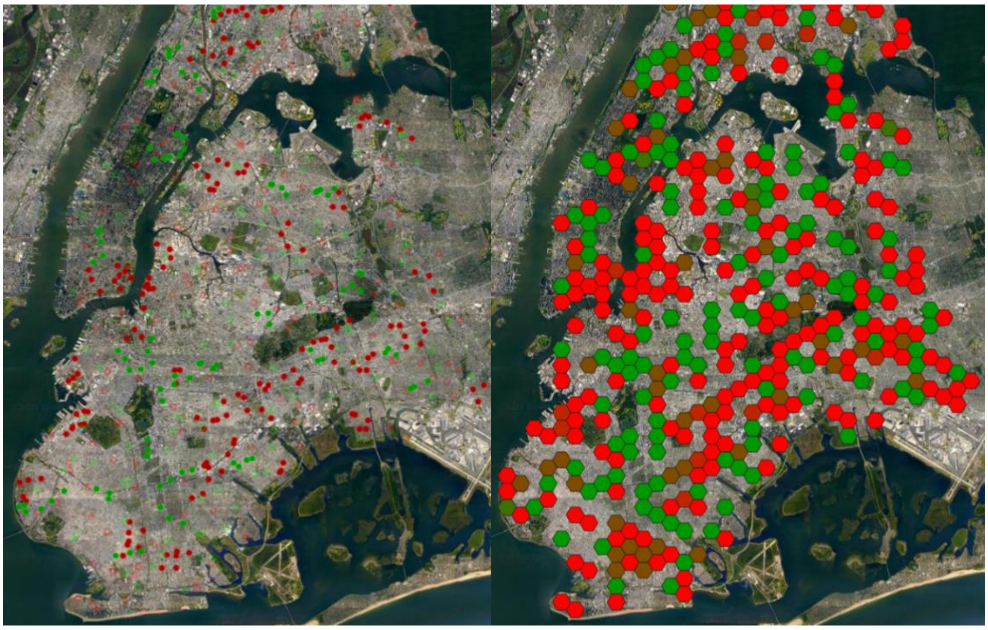


*Figure 30: Spatial exploration perceived beauty in New York*

### Perceived liveliness

Regarding perceived liveliness, more or less the same remarks can be made as for perceived beauty. However, the number of winners regarding perceived liveliness seem to be larger. Which could indicate that New York City is a more lively city than the average city included in this research. The clusters still are mainly visible on a local scale and less on a city scale.

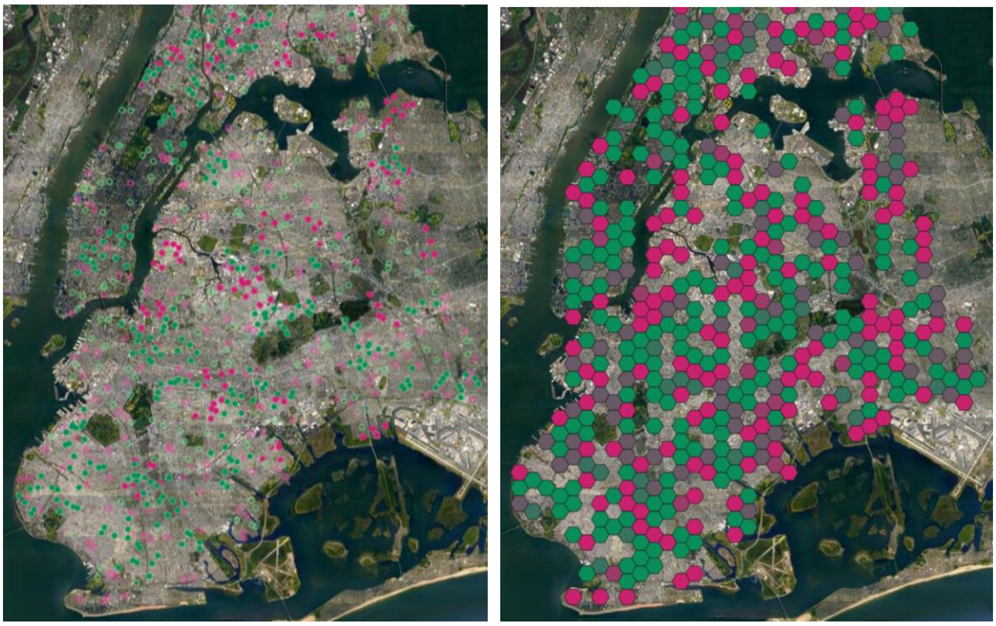


*Figure 31: Spatial exploration perceived liveliness in New York*

### Perceived safety

Regarding perceived safety, more or less the same trend can be seen as for the other two human perception categories. There does not seem to be a relation between the location of an image and the winner-loser ratio on a city scale. However, on a more local scale, there do seem to be clusters of winners and losers. Although, this does not always apply as there are also quite some areas where a mix is visible between winner and loser images.

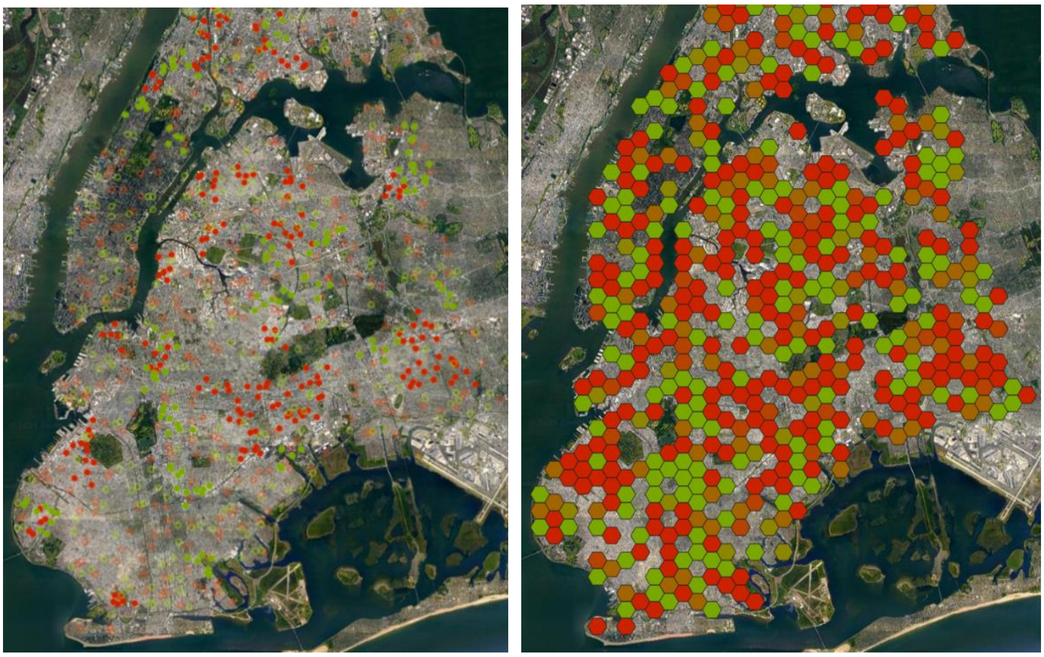


*Figure 32: Spatial exploration perceived safety in New York*

### *Conclusion spatial exploration*

In conclusion, the spatial exploration concerning the locations of the winners and losers, indicates that on a local scale within a city winners and losers seem to cluster, although this does not apply to all cases. This could mean that certain urban characteristics that vary on a local scale within a city have an influence on each of the three human perception categories whereas urban characteristics that vary within a city, on the scale of the complete city seem to have less influence on each of the three human perception categories. For example, it might be relevant in which neighborhood an image is taken but the location of this neighborhood within the city seems to be irrelevant.

### Urban Typology – choice exploration

Insights retrieved from the winner-loser ratio per urban typology could contribute to an understanding if there might exist relations between certain urban typologies and human perception. If these relations exist, the differences in the data distribution could indicate which urban typologies contribute most or least to a positive perception of a street. Additionally, it indicates if a combination of the individual attributes included in this research influences human perception. In this exploration, nine different urban typology groups have been formulated: 'Highrise', 'High density', 'Medium density closed', 'Medium density open', 'Low medium mix', 'Row house', 'Free standing dense', 'Free standing' and 'Other'. These typologies have been formulated based on a set of conditions. The complete set of conditions can be found in appendix D.

As an example, the following condition is used to classify an area around an image locations as 'Highrise' or not: Façade length index > 0.5 AND Area median < 300 AND Volume index > 0.03 AND Offset distance median < 20. The conditions and condition values have been set by a process of formulating conditions and manually inspecting the correctness of classification of an image location in multiple cities. In Figure 33, the average winner-loser ratio is visualized per urban typology class.

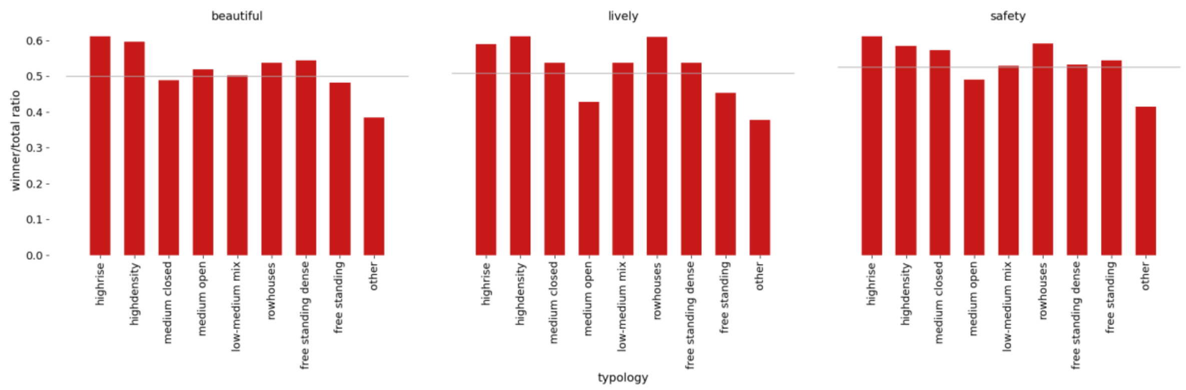



*Figure 33: Winner-loser ratio per urban typology class*

From Figure 33 it can be seen that the urban typologies show remarkable differences in their winner-loser ratio. Specifically, the following remarks can be made: First of all, the urban typology 'other' has the lowest winner-loser ratio for all three human perception attributes. These images are mainly located in open low density areas such as industrial sites and traffic areas. Thus, apparently, industrial sites are generally not perceived as beautiful, safe or, lively.

Secondly, the higher density typologies, 'Highrise' and 'High density', both have a relative high winner-loser ratio for all three human perception categories. Although the spatial exploration did not indicate any relation between the human perception choice and the location within a city, higher density areas seem to be perceived as somewhat more beautiful, lively, and safe. Thirdly, the bars of perceived liveliness and safety show more or less the same pattern. Although, based on this exploration it cannot be stated what the cause of this is, it could be that certain urban typologies are also related to certain other characteristics such as average income and land value that generally define an attractive neighborhood or are in general more attractive as perceived by humans. Furthermore, it is specifically interesting to note here that the urban typologies which generally have more closed building blocks, medium closed versus medium open and row house versus free standing, have a higher winner-loser ratio.

These differences between winner-loser ratios and urban typologies could also partially explain the differences between the cities, as certain cities can have higher shares of certain building types then other cities. Additionally, this could partially explain the clustering of winner and loser images on a local scale within a city as seen in the spatial exploration. Finally, the differences in winner-loser ratio between many urban typologies indicates that the volumetric built environment is likely to have an influence on human perception as the individual attributes defining the volumetric built environment are used to classify areas as a recognizable urban typology.

### Correlations

The Pearson correlation coefficient has been calculated for every combination of the attributes that will be included in the statistical analysis. This has been done, so that during the analysis, certain combinations of attributes can be avoided as the selected analysis method, multinomial logit models, do not allow highly correlated attributes to be included in one model. In line to this, the attributes having a correlation coefficient that exceeds or is equal to the value of 0.6 will be briefly highlighted in this subsection. Below, the correlation coefficients will be discussed per building characteristic class. A correlation matrix including all research attributes can be found in appendix E.

*Image share data*

First of all, the attributes 'sky share' and 'tree share' have quite a high correlation coefficient of -0.62. The other correlation coefficients of the 'share' attributes do not exceed 0.6.

*Building height data*

Since many different attributes are used to describe the height of the buildings in an image, it is not surprising that many correlation coefficients exceed the value 0.6. Although this might not be a surprise, several interesting remarks can still be made here. First of all, the median height shows less correlation coefficients exceeding the value of 0.6 than the mean height and the average perceived building height, whereas the median height correlates very strong with the mean height (r=0.96). As a result, the median height might be preferred over the mean height in the analysis since it describes more or less the same building characteristic but is less correlated to other attributes. Furthermore, the absolute height difference tends to describe approximately the same as the maximum building height, as these two are strong correlated (r=0.96). The absolute building height difference is retrieved by subtracting the minimum building height from the maximum building height, making this not very surprising. However, the minimum building height on the other hand is not strong correlated with the absolute height difference (r=0.10). Additionally, the absolute height difference correlates less strong with the median building height (r=0.48) compared to the minimum building height (r=0.72) and the maximum building height (r=0.65). Finally, the relative standard deviation correlates less strong with the other building height attributes than the regular standard deviation.

*Building footprint*

Although, façade length index and footprint area index do describe the footprints and their location of the buildings they do not correlate strong with the footprint area attributes. However, they do correlate strong with each other (r=0.79). This could be explained by the way the data was gathered, which has attempted to only include the buildings directly adjacent to the road. A higher façade length index represents a higher share of building footprints along a street, a larger area of building footprints in a row is thus also likely to result in a higher footprint area index. The width of the road and shape of the buildings still explain the difference between the two attributes. Furthermore, the mean area and median area correlate strong (r=0.89) and the standard deviation and the mean area correlate strong (r=0.86).

*Building volume and street perspective*

The volume index correlates strong with many building height attributes and not with any of the footprint attributes. This indicates that the building volumes around an image location are mainly influenced by the height of the buildings.

The only attributes that correlate strong with each other regarding the street perspective attributes are offset distance median and offset height ratio (r=0.72). This is not a surprising correlation as the offset height ratio is retrieved by dividing the offset distance median by the height media

### Attribute – choice exploration

The winner-loser ratio has been computed for every attribute and are represented in bar charts, the bar chart of tree share in relation to the winner-loser ratio based on the complete beauty dataset is shown in Figure 34. Through visual inspection, the distributions in the bar charts can give an indication for potential relationships between an attribute and all three human perception attributes. All bar charts potentially indicating a relationship are presented in appendix F.

The bar charts specifically visualize the winner-loser ratio for 20 equal sized bins per attribute for the complete datasets and for 10 equal sized bins per attribute for the split datasets. For a certain attribute, the first group will thus be the images with the 5% or 10%, depending on the dataset, smallest values of that attribute.

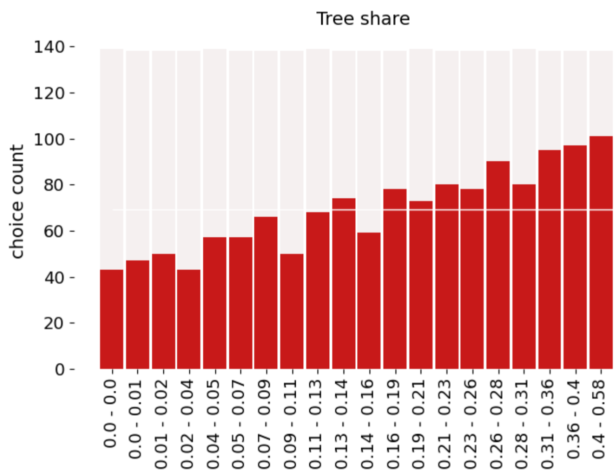



*Figure 34: Bar chart of tree share in relation to number of time an image was chosen (red) or not (light red)*

The potential relationship identified in these bar charts are summarized in Table 10. In this table, indications for potential positive relationships are marked with a '+' sign in green and indications for potential negative relationships are marked with a '-' sign in red. A darker color and double sign indicates a stronger potential relationship. There are multiple insightful indications that can be seen in Table 10. However, the following are most interesting to highlight: First of all tree share seems to influence all human perception categories the strongest, specifically perceived beauty. Building share seems to positively influence liveliness but negatively influence perceived beauty and safety. Furthermore, building height variation generally seems to contribute to perceived liveliness but seems to have a negative influence on perceived beauty. Finally, only perceived safety seems to be positively related to the width of the streets. In line with this, in relation to the building height and specifically concerning perceived beauty in relative high density areas, perceived safety seems to be positively related to the offset height ratio (defined by the street offset divided by the building height). Perceived beauty and liveliness, on the other hand, seem to be negatively related to the offset height ratio.

*Table 10: Overview of relationship indications of bar charts and correlated attributes*

| | Attribute | Beauty | | | Liveliness | | | Safety | | | Correlation > 0.6 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Complete | Low density | High density | Complete | Low density | High density | Complete | Low density | High density | |
| Image share | Tree share (TS) | ++ | ++ | ++ | + | + | + | ++ | + | + | SS |
| | Sky share (SS) | -- | -- | -- | - | - | - | - | - | - | TS |
| | Building share (BS) | - | -- | - | + | + | + | - | - | - | |
| | Road share (RS) | - | - | - | - | - | - | - | - | | |
| Building Height | Height mean (Hmean) | + | | + | + | | | | | + | Hmedian, Hstdev Hmax, Hmin, AbHdif, AvPerH |
| | Height median (Hmedian) | + | | + | + | | + | | | + | Hmean, Hmax, Hmin, AvPerH |
| | Height standard deviation (Hstdev) | | | | + | | | | | - | Hmean, Hstdevrel, Hmax, AbHdif, AvPerH |
| | Height standard deviation relative (Hstdevrel) | | | - | | + | | - | | - | Hstdev, AbHdif |
| | Height minimum (Hmin) | | | | | | - | | | + | Hmean, Hmedian, AvPerH |
| | Height maximum (Hmax) | | | | | | | | | | Hmean, Hmedian, Hstdev, AbHdif, AvPerH |
| | Absolute height difference (AbHdif) | | | - | + | | + | | | | Hmean, Hstdev, Hstdevrel, Hmax, AvPerH |
| | Average perceived building height (AvPerH) | + | | + | + | | | | | | Hmean, Hmedian, Hstdev, Hmax, Hmin, AbHdif |
| Building footprint & volume | Façade length index (FLI) | + | | + | + | + | + | + | + | | FAI |
| | Footprint area index (FAI) | | | | + | + | + | +,- | + | | FLI |
| | Area mean (Amean) | - | - | - | - | - | - | - | - | | Amedian, Astdev |
| | Area median (Amedian) | +,- | - | | - | - | - | - | - | | Amean |
| | Area standard deviation (Astdev) | - | - | - | - | - | - | - | - | - | Amean |
| | Area standard deviation relative (Astdevrel) | - | - | - | | - | | - | - | - | |
| | Volume index (VI) | + | | + | + | + | + | + | + | | Hmean, Hmedian, Hstdev, Hmax, AbHdif, AvPerH |
| Street perspective & other | Number of street segments (NSS) | | | | | | | | - | | |
| | Two or more street segments (TMSS) | | | | | | | | | | - |
| | Offset distance median (ODmedian) | + | | | - | | - | + | | + | OHR |
| | Offset distance standard deviation relative (ODstdevrel) | - | | | | | | | | | |
| | Offset height ratio (OHR) | | | - | - | - | - | | + | | ODmedian |
| | Urban complexity factor (UCF) | - | - | - | | | | - | - | - | |

## 3.3. Analysis

In the analysis we aim to retrieve three models that describe the relationship between perceived beauty, liveliness, and safety and the built environment attributes. Since the choices of people make up the input data, discrete choice models are suitable for describing these relationships. Based on a discrete choice model, the relationships can be estimated. Also a model fit is calculated, describing the extent to which these estimated relations fit the choices that are made by the respondents. This section starts with a brief introduction to discrete choice models, including an explanation on how they are used for the analysis in this research. After this, the analysis results are presented and the most important findings from the results are described. Finally, the findings are reflected upon the indications from the bar charts and the findings from the literature.

### 3.3.1. Discrete choice models

Choice analysis is about studying the behavior of individuals. To do so, individuals should be presented with a set of alternatives from which they can choose (Henscher et al., 2015b). Discrete choice models are models designed to model choice behavior using disaggregate level data (Henscher et al., 2015a). In other words, they model choice behavior using attributes that describe a certain alternative. In this research, the Place Pulse 2.0 dataset is used as choice dataset. In the Place Pulse 2.0 dataset, a respondent got to choose between two alternatives.

For every alternative in the choice set, a probability that the alternative is chosen is calculated. The probability of an alternative is based on the utility of an alternative and on the utility of the other alternatives in the choice set. The total utility of an alternative is the sum of the observed and the unobserved utility components. The observed component is the sum of the weighted attribute values. The coefficients (weights) are estimated such that the predicted probabilities match the observed choices as closely as possible.

For the implementation phase of this research, the estimated coefficients for the attributes are the most interesting and relevant values to be found in the statistical analysis. The coefficients determine the influence of built environment attributes on human perception. These attribute effects will be implemented in the computational urban design tool.

In order to keep the observed utility function, and therefore the to be implemented relationship, as simple as possible, the attribute values are not transformed to include non-linear relationships in the observed utility function. Also, no interaction variables are included in the observed utility function as several attributes are already a composition of other attributes. There is no indication in the literature and from the data exploration that further interactions should be included. The overall utility of an alternative consists of a structural and random part, as can be seen in equation 1. The structural utility component of an alternative is calculated based on the estimated weight of the attributes multiplied by the respective attribute values of an alternative (equation 2).

$$U_{iq} = V_{iq} + e_i \qquad (1)$$

$V_{iq} =$ structural utility of alternative i for individual q

$e_i =$ random utility component for alternative $i$

$$V_{iq} = \sum_n \beta_n * X_{inq} \quad (2)$$

$\beta_n$ = Weight of attribute $n$

$X_{inq}$ = Score of alternative $i$ on attribute $n$ *according to individual* $q$

If the random components are assumed to be independently and identically (IDD) Gumble distributed, the multinomial logit model is derived (Henscher et al., 2015b).

The multinomial logit model is the simplest random utility model and is defined as follows (Equation 3):

$$P_{iq} = \frac{exp(V_{iq})}{\sum_{j=1}^{J} exp(V_{jq})} \quad (3)$$

$P_{iq}$ = Probability that individual $q$ will choose alternative $i$

$V_{iq}$ = Structural utility of alternative $i$ for individual $q$

To retrieve the values for the parameters (the $\beta$'s in eq. X), maximum likelihood estimation is used. The likelihood measures how well the parameters represent the observed data; a higher value means a better fit between predicted probabilities and observed choices. The optimal parameters are found by maximizing the likelihood value. The likelihood value is a relative cumbersome calculation, instead the log likelihood (equation4) is commonly used instead.

$$LL(\beta) = \sum_q \sum_i y_{iq} \ln(P_{iq}) \quad (4)$$

$P_{iq}$ = Probability that individual $q$ will choose alternative $i$
$y_{iq}$ = 1: alternative $i$ was chosen by $q$, 0: otherwise

Using, formulas 1 up and until 4, the parameters of the structural utility function can be estimated by optimizing the log likelihood function. However, the structural utility function is not the only thing we are interested in. In order to retrieve insight in the predictive power of the included attributes, also the model goodness of fit has to be determined. The model goodness of fit can be expressed by McFadden's Rho-Square (Henscher et al., 2015c). Which is calculated by equation5.

$$\rho^2 = 1.0 - [\frac{LL(\beta)}{LL(0)}] \quad (5)$$

$LL(\beta)$ = Log likelihood using estimated parameters

$LL(0)$ = Loglikelihood using the null model (with equal choice probabilities)

The McFaddan's Rho-square value varies between 0 and 1. In which 1 would mean that the model is able to predict exactly how the respondents made their choices. Since, in practice, this is impossible and there will always be unknowns, getting a value of 1 is not the objective. In ideal circumstances, a rho square value of 0.3 is considered well acceptable (Henscher et al., 2015c). In this case, since the respondent characteristics are unknown and since the data exploration and literature review already indicated that there are many influential factors that have not been included in this research, a well acceptable rho square value would be a value approaching 0.2.

#### Likelihood Ratio Statistic test

Within this research, a multinomial logit model is estimated on nine different datasets. Being, the complete, relative low and high density dataset for each of the three human perception categories. Since the relative high and low datasets are quite thin in relation to the complete dataset, found relationships in the complete dataset can be considered as more reliable. Thus, only when the estimated models for the relative low and high datasets show better model fits and the difference in performance is significant, the estimated models for the relative low and high density datasets are considered to be more suiable for implementation than the estimated model on the complete dataset.

$$LRS = -2\big(LL(\beta complete) - LL(\beta low \beta high)\big) \qquad (6)$$

$LL(\beta complete) = Log\ likelihood\ parameters\ from\ complete\ model\ on\ split\ datasets$

$LL(\beta low \beta high) = Sum\ log\ likelihood\ estimated\ models\ low\ and\ high\ dataset$

In order to check this, a Likelihood Ratio Statistic (LRS) test is done. With the LRS test, the difference in performance of two models can be tested. Equation 6 is the equation for the Log Likelihood Ratio Statistic. In order to test the difference in performance of the model estimated on the complete dataset and the models estimated on the low and high density datasets, new models are estimated on the low and high density datasets with the parameters found to be significant by the multinomial logit model estimated model on the complete dataset ($\beta complete$). The performance of these models are then related to the performance of the estimated model on the low and high datasets, including the attributes found to be significant on the low and high datasets ($\beta low \beta high$).

In order to test if the, by the LRS, calculated difference in model performance is significant, the Chi-Square test has been applied to LRS. In which the number of degrees of freedom is equal to the difference in number of parameters between the split datasets and the complete dataset (= $Npar_{\,low} + Npar_{\,high} - Npar_{complete}$). If the Chi-Square probability is below 0.05, the difference can be considered significant. If the difference is significant, the model with the highest model performance is the best.

In the result section below, the estimated multinomial logit model is presented and described per human perception category. Also the LRS on the difference between the model performance of the model estimated on the complete dataset and the models estimated on the split datasets is calculated and tested on significance.

### 3.3.2. Multinomial logit model results

In order to retrieve the multinomial logit model results, including the rho square model fit and the utility coefficients, several steps have been taken. First the complete set of built environment attributes have been included in the model. This generally resulted in the highest model fit including multiple relevant attributes. However, the eventual model should only include significant attributes as the significance of an attribute indicates whether the addition of an attribute effectively increases the predictive power of the model and if the contributions of that attribute to the predictive power of the model is not caused by chance. In this research, a significance level of 10%, ($p \leq 0.10$) is accepted, meaning that the probability that the estimated parameter value is equal to zero is not higher than 10%. In addition, no strong correlations between attributes should exist. Correlated attributes may result in biased parameter values or even values with a wrong sign or unreliable significance values.

Using the significance values, the attributes with the highest p value have been removed from the model first. This process has been repeated until the most significant attributes, which all have a p value lower then 0.1, are left. Based on the data exploration results, all attributes have been added and removed to and from the model that showed a potential relationship. Finally, the set of significant attributes that do not correlate strongly with each other, have the highest model fit expressed in rho square and include a maximum variation in attributes has been included in the eventual model.

The included attributes, their coefficients ('Estimate') and significance p values ('Pr') are presented in Tables 11 - 21 per human perception category and per dataset. Furthermore, the rho square of the estimated model is included for every model.

### Perceived beauty

*Table 11: Beauty complete*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 4.351 | 2.200e-16 |
| **Height mean** | 0.663 | 1.558e-4 |
| **Façade length index** | 0.018 | 3.394e-3 |
| **Area standard deviation relative** | -0.197 | 0.020 |
| Log likelihood | -820.38 | |
| Log likelihood null model | -921.19 | |
| **Rho square** | 0.11 | |

*Table 12: Beauty low density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Sky share** | -5.147 | 3.849e-5 |
| **Building share** | -5.208 | 6.789e-8 |
| Log likelihood | -179.36 | |
| Log likelihood null model | -204.00 | |
| **Rho square** | 0.12 | |

*Table 13: Beauty high density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 4.393 | 1.712e-9 |
| **Height standard deviation relative** | -0.846 | 0.019 |
| **Offset distance height ratio** | -0.130 | 0.065 |
| Log likelihood | -211.38 | |
| Log likelihood null model | -239.14 | |
| **Rho square** | 0.12 | |

Starting with the relationship between the included volumetric built environment attributes and perceived beauty, the multinomial logit models indicate that this relationship is not very strong with a model fit expressed in rho square of 0.12 for the split datasets. The model fit for the complete dataset is 0.01 lower, being 0.11.

For the high density dataset, the height standard deviation relative and offset height ratio have a significant influence on perceived beauty in addition to the tree share. Whereas for the low density dataset, only sky and building image share attributes seem to be relevant.

Concerning the model predicted on the low density dataset, the following remark can be made. Including tree share, sky share and building share in one model leads to insignificant attributes in the model. Either only tree share or only sky share and building share can be included in a model with solely significant attributes. Although tree share is of large influence on the perceived beauty in low density environments, the combination of sky share and building share resulted in a better model fit then when only tree share was included. This, probably, since sky share (r=-0.62) and building share (r=-0.49) both correlate negatively with tree share and the included street view images are generally dominated by trees, buildings, and sky. As a result, the combination of sky share and building share would generally indicate a higher tree share but also make a distinction between sky share and building share. Tree share alone on the other hand would not be able to indicate anything on whether the non-tree elements in the image are buildings, a sky or something else.

### LRS

*Table 14: LRS variables and values perceived beauty*

| Variable | Value |
|---|---|
| LL(βlowβhigh) | -390.74 |
| LL(βcomplete) | -396.29 |
| LRS | 11.10 |
| Difference number of parameters | 1 |
| Chi-square p-value | 0.001 |

The LRS on the log likelihood values of the models estimated on the split datasets and the model estimated on the complete dataset is 11.1. Resulting in a Chi-Square p-value of 0.001, being smaller than 0.050 and thus considering the performance of the models estimated on the split datasets as significantly better than the performance of the model estimated on the complete dataset. In other words, there is a significant difference between the relationship between perceived beauty and the volumetric built environment in higher density environment and in lower density environments.

### Perceived Liveliness

*Table 15: Liveliness complete*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 1.9370 | 2.479e-10 |
| **Building share** | 1.5810 | 7.270e-6 |
| **Façade length index** | 1.1440 | 6.201e-10 |
| **Area mean** | -0.0003 | 4.868e-3 |
| **Absolute height difference** | 0.0060 | 5.101e-4 |
| Log likelihood | -1371.80 | |
| Log likelihood null model | -1446.00 | |
| **Rho square** | 0.051 | |

*Table 16: Liveliness low density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 2.677 | 1.766e-5 |
| **Building share** | 3.458 | 1.051e-3 |
| **Area standard deviation relative** | -0.436 | 3.313e-3 |
| Log likelihood | -305.10 | |
| Log likelihood null model | -322.00 | |
| **Rho square** | 0.054 | |

*Table 17: Liveliness high density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 1.101 | 0.032 |
| **Absolute height difference** | 0.005 | 0.062 |
| **Façade length index** | 1.470 | 2.682e-4 |
| **Offset distance height ratio** | -0.119 | 0.048 |
| Log likelihood | -350.91 | |
| Log likelihood null model | -363.21 | |
| **Rho square** | 0.034 | |

The multinomial logit models estimated on the three datasets regarding perceived liveliness have a low model fit, varying between 0.034 and 0.054 depending on the dataset. The attributes that have been found to have a significant influence on perceived liveliness vary per dataset as well. For the complete dataset, the tree share (+), building share (+), façade length index (+), area mean (-) and absolute height difference (+) influence perceived liveliness. This set of attributes indicates that a more built up environment with green is perceived as more lively. Having a look at the model estimated for the relative high density dataset, this model indicates that environment's tree share (+), absolute height difference (+), façade length index (+) and offset distance height ratio (-) have a significance influence on perceived liveliness. Although, the very low model fit also indicates that other attributes that have not been captured in this research may have a more significant influence.

The multinomial logit model estimated on the relative low density dataset also indicates that tree share (+) has an influence on perceived liveliness. It also indicates that building share (+) and area standard deviation relative (-) have a significant influence on perceived liveliness. This model has the highest model fit of all three models regarding perceived liveliness but still has a relative low rho square of 0.054.

### *LRS*

*Table 18: LRS variables and values perceived liveliness*

| Variable | Value |
|---|---|
| LL(βlowβhigh) | -655.96 |
| LL(βcomplete) | -659.77 |
| LRS | 7.62 |
| Difference number of parameters | 2 |
| Chi-square p-value | 0.022 |

The LRS on the log likelihood values of the models estimated on the split datasets and the model estimated on the complete dataset is 7.62. Resulting in a Chi-Square p-value of 0.022, being smaller than 0.050 and thus considering the performance of the models estimated on the split datasets as significantly better than the performance of the model estimated on the complete dataset. In other words, there is a significant difference between the relationship between perceived liveliness and the volumetric built environment in higher density environment and in lower density environments.

## Perceived safety

*Table 19: Safety complete*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Tree share** | 2.0650 | 2.200e-16 |
| **Height median** | 0.0130 | 8.488e-5 |
| **Façade length index** | 0.9660 | 4.057e-10 |
| **Area mean** | -0.0003 | 3.264e-4 |
| **Area standard deviation relative** | -0.1140 | 0.043 |
| **Offset distance median** | 0.0040 | 0.033 |
| Log likelihood | -1808.60 | |
| Log likelihood null model | -1895.06 | |
| **Rho square** | 0.046 | |

*Table 20: Safety low density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Sky share** | -2.4630 | 1.036e-05 |
| **Building share** | -3.1460 | 2.830e-4 |
| **Façade length index** | 0.9880 | 3.236e-3 |
| **Area standard deviation** | -0.0004 | 0.052 |
| Log likelihood | -459.490 | |
| Log likelihood null model | -489.000 | |
| **Rho square** | 0.060 | |

*Table 21: Safety high density*

| | Estimate | Pr(>\|Z\|) |
|---|---|---|
| **Sky share** | -2.557 | 1.877e-05 |
| **Building share** | -1.073 | 0.030 |
| **Height median** | 0.014 | 0.013 |
| **Area standard deviation relative** | -0.259 | 0.032 |
| **Offset distance height ratio** | 0.132 | 6.740e-3 |
| Log likelihood | -445.80 | |
| Log likelihood null model | -466.49 | |
| **Rho square** | 0.044 | |

Finally, the multinomial logit analysis on the relation between the volumetric built environment attributes and perceived safety. Here the same behavior of the models as for perceived liveliness and perceived beauty can be seen as the models estimated for the different datasets include different attributes. The model fit of the model estimated on the complete dataset is low with a rho square value of 0.046. The significant attributes are tree share (+), height median (+), façade length index (+), area mean (-), area standard deviation relative (-) and offset distance median (+).

For the low density dataset, the model fit of the estimated model is slightly higher with a rho square of 0.060. The significant attributes are sky share (-), building share (-), façade length index (+) and area standard deviation (-). As for the model predicted on the low density dataset concerning perceived beauty, including sky share and building share rather than solely tree share in the model results in a higher predictive power.

For the high density dataset, the model fit of the estimated model is the lowest with a value of 0.044. The significant attributes in this model are sky share (-), building share (-), height median (+), area standard deviation relative (+) and offset distance ratio (+). Here, the same applies as for the estimated model on the low density dataset: sky share and building share together result in a higher model fit than solely tree share. In the model having tree share in it rather than sky share and building share, tree share is significant and has a high positive coefficient.

*LRS*

*Table 22: LRS variables and values perceived safety*

| Variable | Value |
|---|---|
| LL(βlowβhigh) | -905.29 |
| LL(βcomplete) | -913.24 |
| LRS | 15.90 |
| Difference in number of parameters | 3 |
| Chi-square p-value | 0.001 |

The LRS on the log likelihood values of the models estimated on the split datasets and the model estimated on the complete dataset is 15.9. Resulting in a Chi-Square p-value of 0.001, being smaller than 0.050 and thus considering the performance of the models estimated on the split datasets as significantly better than the performance of the model estimated on the complete dataset. In other words, there is a significant difference between the relationship between perceived safety and the volumetric built environment in higher density environment and in lower density environments.

### 3.3.3. Reflection on multinomial logit results, data exploration, and literature

Table 23 provides an overview of the found relevant built environment attributes along with the signs of the coefficients, related to the indications received from the bar charts presented in the data exploration section and the findings in the literature. It can be seen from Table 23 that not all built environment elements that have been found to significantly influence human perception have been mentioned in existing literature to influence human perception. However, concerning the attributes that have been found to be related to any of the three human perception categories in the multinomial logit analysis, literature generally mentions the same relation between the related built environment elements and the respective human perception category. Furthermore, as expected, the signs from the analysis are equal to the signs listed in Table 23 (based on the bar charts). The multinomial logit analysis added statistical significance to the explorative insights from the bar charts. Reflecting to the main conclusions from the literature, the findings from the multinomial logit analysis are more or less in line as well.

*Table 23: Reflection overview of multinomial logit results*

| Human perception category | Dataset | Built environment attribute | Result coefficient sign | Indication from bar charts sign | Indication from literature sign |
|---|---|---|---|---|---|
| Beauty | Complete | Tree share | + | + | + |
| | | Height mean | + | + | +/- |
| | | Façade length index | + | + | + |
| | | Area standard deviation relative | - | - | |
| | Low density | Sky share | - | - | - |
| | | Building share | - | - | - |
| | High density | Tree share | + | + | + |
| | | Height standard deviation relative | - | - | - |
| | | Offset distance height ratio | - | | - |
| Liveliness | Complete | Tree share | + | + | +/- |
| | | Building share | + | + | |
| | | Façade length index | + | + | |
| | | Area mean | - | - | - |
| | | Absolute height difference | + | + | |
| | Low density | Tree share | + | + | +/- |
| | | Building share | + | + | |
| | | Area standard deviation relative | - | - | |
| | High density | Tree share | + | + | +/ |
| | | Absolute height difference | + | + | |
| | | Façade length index | + | + | + |
| | | Offset distance height ratio | - | - | |
| Safety | Complete | Tree share | + | + | + |
| | | Height median | + | | |
| | | Façade length index | + | + | + |
| | | Area mean | - | - | - |
| | | Area standard deviation relative | - | - | |
| | | Offset distance median | + | + | +/- |
| | Low density | Sky share | - | - | - |
| | | Building share | - | - | - |
| | | Façade length index | + | + | + |
| | | Area standard deviation | - | - | |
| | High density | Sky share | - | - | - |
| | | Building share | - | - | - |
| | | Height median | + | + | |
| | | Area standard deviation relative | - | - | |
| | | Offset distance height ratio | + | | - |

## Perceived beauty

Starting with perceived beauty, the following remarks can be made: The positive influence of the attributes tree share and façade length index, together with the negative influence of sky share and offset distance height ratio are in line with the literature that mentions enclosure related elements as a positive contributor to perceived beauty (Joglekar et al., 2020; Karimi, 2012; Rossetti et al., 2019; Weber et al., 2008). Although, the exact combination of attributes varies per dataset. For the low density dataset, the negative influence of building share is a contradicting result considering the enclosure, however as found in the literature as well, people prefer a space to be bounded by vegetation (Weber et al., 2008). Also, no differentiations have been found in the literature between high and low density environments. The negative influence of building height variation could be explained by the literature in which uniformity (Karimi, 2012) is mentioned as a positive contributor to perceived beauty.

### Perceived liveliness

Concerning perceived liveliness, few findings from the multinomial logit analysis have been explicitly supported in the literature. However, the negative influence of mean building area can be related to the findings in the literature mentioning a finer division of building masses to positively influence liveliness (Simpson et al., 2022). Partly contradicting results can be found regarding tree share in relation to perceived liveliness. However, as mentioned in the literature review, the findings for a negative influence of vegetation on perceived liveliness are based on analysis on a dataset consisting of rural and urban areas in which no distinction has been made between the density of an urban area. In this research rural areas have been excluded and a distinction was made between high and low density areas.

### Perceived safety

Finally, regarding perceived safety, findings from the literature generally align with findings from this research. Tree share contributes strongly to perceived safety (Harvey et al., 2015; Jansson, 2019; Mouratidis, 2019a; Zhang et al., 2018), the positive influence of the median building offset can be related to the in the literature found positive influence of open space and sight (Loewen et al., 1993; Rahm et al., 2021) and the negative influence of the mean building footprint area can be related to the findings from the literature that many individual buildings rather than few large buildings positively contribute to perceived safety (Harvey et al., 2015; Jansson, 2019). The feeling of enclosure was also found to positively relate to perceived safety (Harvey et al., 2015; Stamps, 2005), which is in line with the result that the façade length index positively influences perceived safety. However, the found positive influence of offset distance height ratio contradicts with the findings from the literature as this does not contribute to the feeling of enclosure. Although, it does contribute to open space and sight.

### Relative low rho square

The relative weak rho square of the multinomial logit models for perceived beauty, liveliness, and safety highlight that the built environment elements that have been found to influence human perception in this research, have a limited influence on human perception. Also this could indicate that the gathered data is lacking on accuracy, that the selected method of using discrete choice models does not align very well to the complexity of the relations or a combination of the above. This subsection contains a brief reflection on how choices and limitations in the data gathering and analysis process might have influenced the low rho square of the models.

Considering the limited influence of the included attributes. This can be explained by the limited influence of volumetric built environment elements on human perception. this is supported by findings in the literature mentioning plenty non-volumetric built environment elements to influence human perception. Including built environment elements concerning the detailing of urban objects, the building facades and elements related to street life. Additionally, how humans perceive something varies per individual. Therefore, it can be considered as a subjective concept. However, there is generally a shared perception over a large group of people, in this the sis referred to as objective aspect of human perception. The limited influence of the included built environment elements could also indicate that the objective aspect of human perception is limited, at least concerning the respondents of the Place Pulse 2.0 dataset. Since the socio-demographic background of the respondents is not known from this dataset, it will remain unclear to which extent the perception of humans concerning the built environment from a street view perspective is influenced by someone's socio-demographic background. Literature on the other hand mentions that the socio-demographic and personal background of an individual does influence an individual's perception. Altogether, it is likely that the rho square of the estimated models is, among others, low because only volumetric built environment elements could and have been included and because only the human perception on objective characteristics of built environment is considered.

Additionally, inaccuracy of the data and limitations resulting from the available data could have negatively affected the rho square of the models. Regarding the inconsistency, building height data was not available in a consistent manner, the included height value sometimes referred to the median and sometimes to the maximum building height for example.

Furthermore, the dataset contained many different cities and urban settings. As a result, many non-measured built environmental elements are present in the images used to measure human perception and likely influencing people's choices. These non-measured elements do not only contain non-volumetric elements as referred to in the paragraph above but also non-measured volumetric data. Including for example the composition of volumes and sidewalk widths. This data was generally not available in a consistent manner for all cities that have been included. In addition, several well-known cities and different types of cities have been included, human perception could be affected by someone's general perception of a city. In relation to this, people seem to perceive different urban typologies differently on general, relating to the composition of the volumetric urban elements. As this composition is not included in the analysis, the perception of certain urban typologies has not been accounted for in the analysis.

Altogether, there are multiple potential explanations for the relative low rho square. Several are related to limitations as a result of the goal to incorporate human perception in computational urban design, some of them are related to the availability of data and some of them are related to choices made in the data gathering process. A further reflection on the overall method is provided at the end of this thesis in the conclusion, discussion and recommendation chapter.

## 3.4. Conclusion research phase one

The objective of research phase one, is to find an answer to the sub question: How can the relation between the built environment and human perception be quantified so that it can be incorporated in computational urban design?

In order to find an answer to this question, a methodology has been designed with the aim to find a quantified relationship between volumetric built environment elements and each of the three, in this research included, human perception categories. The selected methodology has been based on findings in existing literature on measuring human perception in relation to the built environment, available resources and the overall scope and objective of this research. As a result, a big data approach has been applied making use of street view images and human perception choices from the Place Pulse 2.0 dataset (Dubey et al., 2016). The images in this dataset have been segmented to retrieve built environment data of the built environment visible in the images and the location of these images have been used to retrieve built environment data of the built environmental context of the image locations. Using the choice data from Place Pulse 2.0 dataset and the retrieved built environment data, the relation between the volumetric built environment and human perception has been quantified using multinomial logit analysis. This approach has been selected for analysis since it results in easy interpretable and accurate quantified formula's describing the relations. Since this research is a first attempt to incorporate human perception in computational urban design, it was considered that easy interpretable and implementable relationships are of high importance when they are used to be implemented in computational urban design.

Formulating an answer to the raised sub question: the overall methodology of using a big data approach, using many different available open data sources to gather the data and using multinomial logit analysis to analyses the data can be considered as a suitable approach within the scope of this research.

However, it must be noted that there is still room for improvement concerning the accuracy of the quantified relations between the volumetric built environment and human perception. Relating mainly to a lack of accuracy in the available data and the subjective aspect of human perception. Whereas using street view images in a big data approach provided advantages such as the availability of data and the realistic choice alternatives, street view images are real environments visualized in an image taken from a human perspective, it is difficult to control the data. Resulting in many potential influential built environment and non-built environment elements that have not been captured in this research affecting the respondents' choices. Also, the availability of the built environment data was limited resulting in assumptions that had to be made and inconsistency in the built environment input data. Furthermore, the choice data did not contain any socio-demographical data on the respondents. A methodology that is able to limit the influence of non-captured elements influencing human perception, enables the inclusion of more consistent and accurate data and is able to include the influence of socio-demographic characteristics of respondents while still using discrete choice modelling to quantify the relationship between the volumetric built environment elements and human perception would likely be able to increase the accuracy of the analysis results while maintaining easy interpretable and implementable relationships.

# 4. Implementation Research Phase two

In this chapter, the process of incorporating the found relationships between the human perception categories and the built environment attributes in computational urban design is described. Within this chapter, first the applied methodology for incorporation of the quantified relationships between the built environment and human perception in computational urban design is described. Followed by the description of the existing methodology and finally the implementation of the relationships between the volumetric built environment and the three human perception categories in computational urban design is described. Figure 35 provides an overview of how research phase two relates to the overall research design.

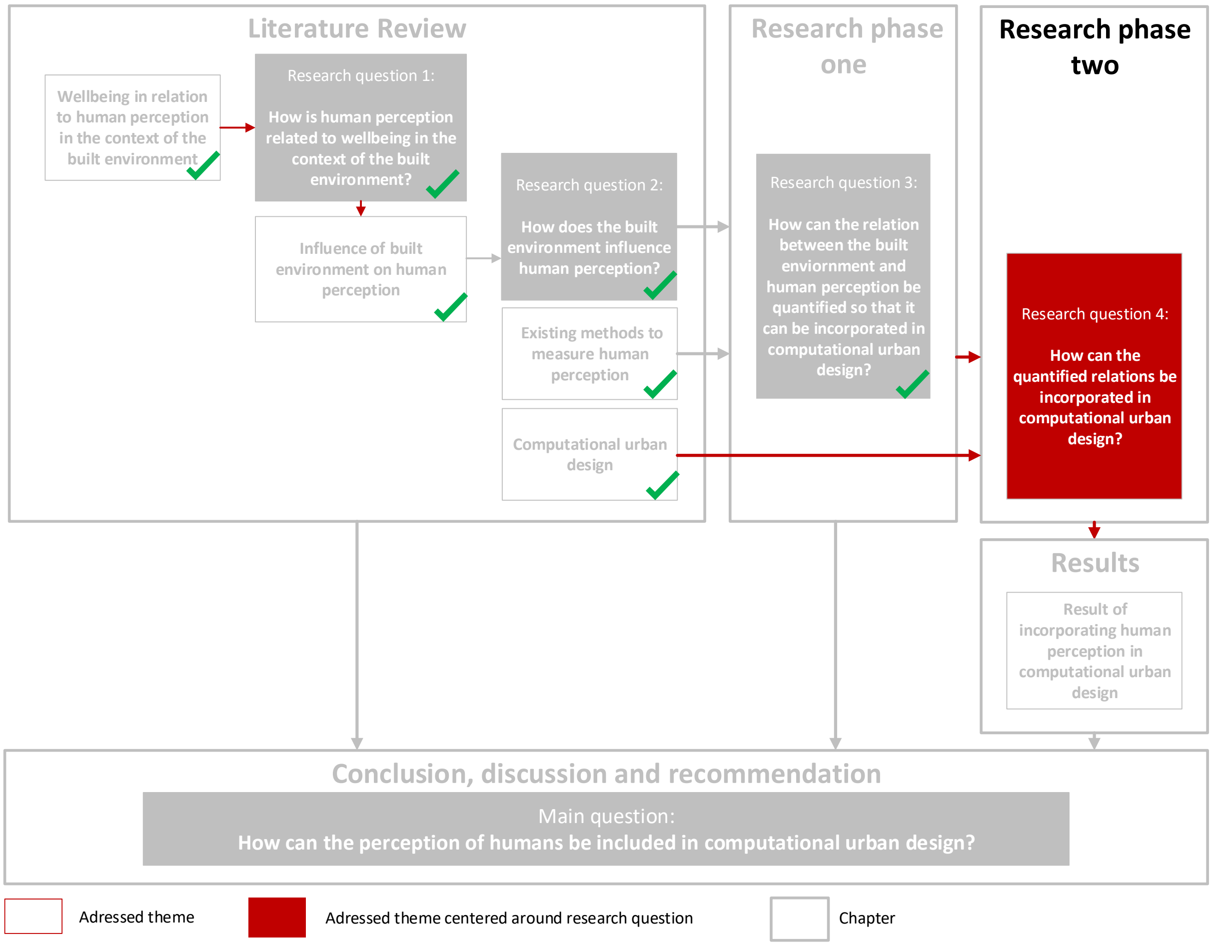



*Figure 35: Research phase two highlighted in the overall research design*

## 4.1. Methodology

In the literature review on computational urban design, the definition of computational urban design and the difference between parametric and generative urban design is described. Applying human perception in parametric design would limit the parametric urban design tool to the provision of information on the perception of humans of a design, while maximally maintaining the design freedom and tasks of the user. Applying human perception in generative design would limit the design freedom and tasks of the user but maximize the level of automatization in the design process and therefore limit the required design generation time. In order to make use of the strengths of both parametric and computational urban design, a combination of the two is selected in the in this research applied methodology for incorporating human perception in computational urban design.

Furthermore, as mentioned in the literature review, many applications of computational urban design have developed over time. In addition, the strength of computational urban design is to be comprehensive. As a result, within this research, human perception is incorporated in computational urban design by incorporating it on top of an existing computational urban design methodology. This existing computational urban design methodology complies a parametric urban design tool, so within this research the generative aspect has been developed on top of the existing parametric urban design tool. The overall result is a computational urban design methodology, including multiple design aspects as well as parametric and generative urban design components. Figure 36, visualizes the methodology applied in research phase two, within the context of the overall research methodology.

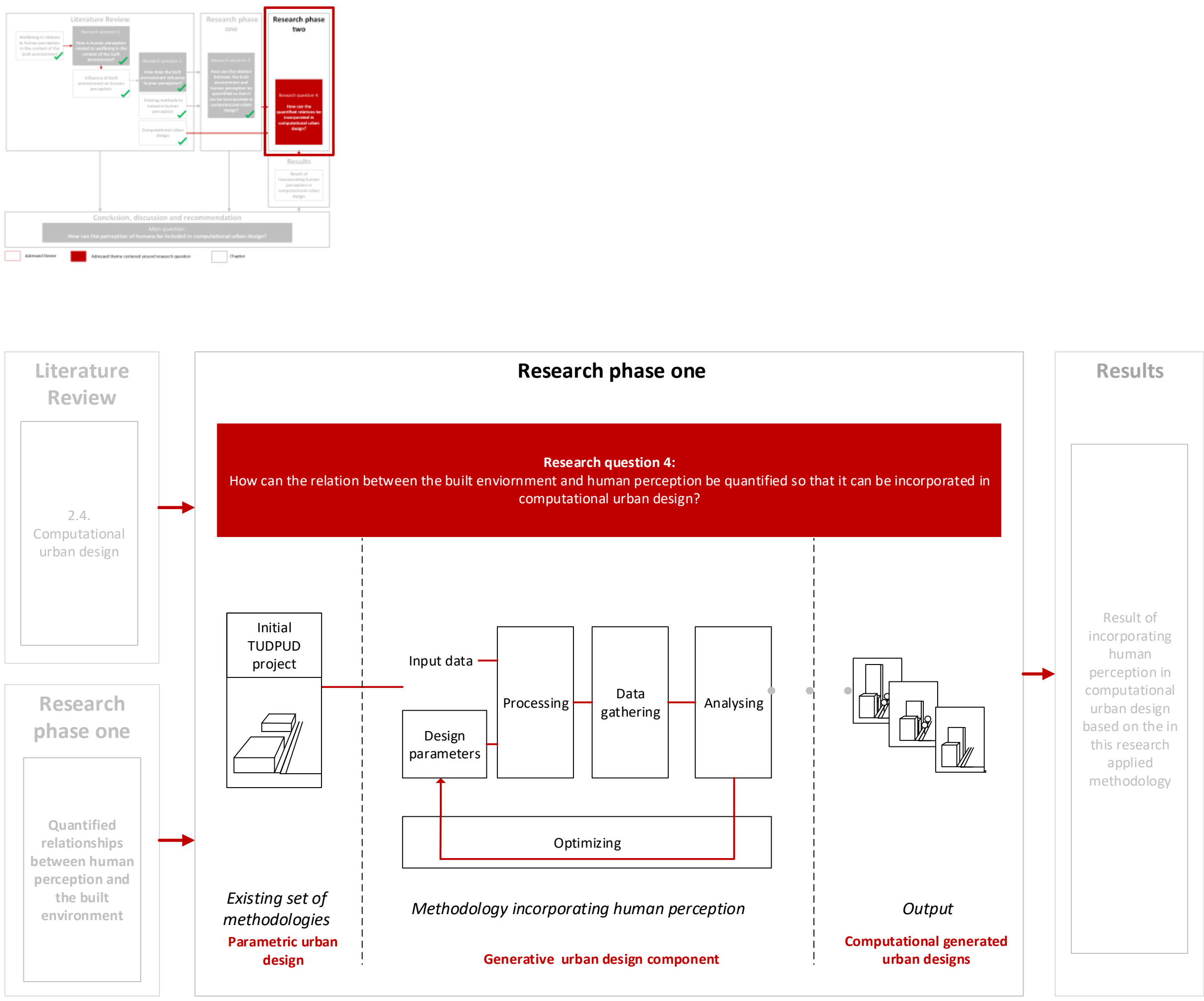



*Figure 36: Methodology applied in research phase two in relation to the overall applied methodology*

## 4.2. Existing set of methods

The existing set of methods have been developed as part of two graduation theses (Doan, 2021; García González, 2019). In this document this set of methods is referred to by the name TUDPUD (TU Delft Parametric Urban Design Project). Since the implementation within this research is executed on top of the created design output of the TUDPUD project, the objective, execution and output of the TUDPUD project will be described briefly in this section.

### 4.2.1. TUDPUD objective

The objective of the TUDPUD project is to enable interaction and knowledge sharing among all disciplines and stakeholders (Agugiaro et al., 2020). Furthermore, the tool is mainly designed for small-scale urban development projects. More specifically for a redevelopment project in Amsterdam Sloterdijk and in potential for other locations in other Dutch cities (Doan, 2021). The tool has the aim to be supportive in the urban design process and requires the interaction with an urban design expert. The main intended user of the TUDPUD project therefore is an urban designer. However, if the methodologies making up the TUDPUD project would be integrated in a user friendly manner, in principle every actor in the discipline urban development would be a potential user. The idea of the TUDPUD project is that the strengths of the computer are maximally combined with the strengths of the human design expert. The aim of the project therefore aligns with the conclusions from Perez-Martinez et al. (2020) on the potential of computational urban design, advocating a hybrid work process between the computer and humans in the design process.

This objective of creating a hybrid workflow between the design expert and the computer is translated in several input variables, for selecting these input variables the TUDPUD project has several objectives as well. The setting of the input variables is centered around the idea of setting the design variables based on the existing urban environment. Retrieving the values of the variables from existing, selected, reference neighborhoods (Agugiaro et al., 2020) and retrieving data from the direct context of the new to-be-designed area (Doan, 2021).

### 4.2.2. TUDPUD execution

Within the TUDPUD project, the user first has to select existing reference neighborhoods. Based on multiple datasets describing these existing neighborhoods in terms of buildings, land use, and quality of life (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, n.d.), parameters such as the dwelling size, building function, building density, and road typology are set for the to-be-designed area (Agugiaro et al., 2020). Additionally, Doan (2021) included the direct urban context by retrieving supportive decision data of the project site and its surrounding supporting the user to set the values of the additional design variables. Figure 37 provides an overview of the data retrieved from a specific neighborhood and how this is translated in the TUDPUD project to a building and street typology.

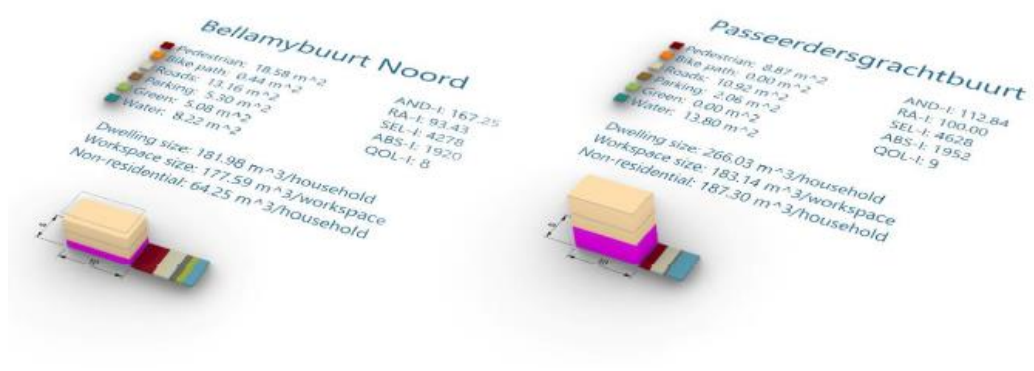



*Figure 37: Overview of retrieved data and created typology in TUDPUD project from existing urban environments* (Agugiaro et al., 2020)

In addition to these design variables, describing among others the division of building functions and the number of square meters per household, the user has to set the spatial design variables. This comes down to providing the computer with input on: the buildings that have to be kept, the to be developed plots, the geometric building type (solid buildings or courtyard buildings) and the spatial configuration of the road infrastructure. The design process is specifically developed to be suitable for a specific site, being Sloterdijk I in Amsterdam. This currently is an industry/ business park but is planned to be transformed into an urban living and working district. The existing buildings, parcel sizes and street network, have to be selected or defined by the user.

Furthermore, the user is also able to include requirements and limitations as input. The requirements and limitations vary from the required number of households to the maximum building height per building function type. The required input and the resulting output of the TUDPUD project is schematically visualized in Figure 38.

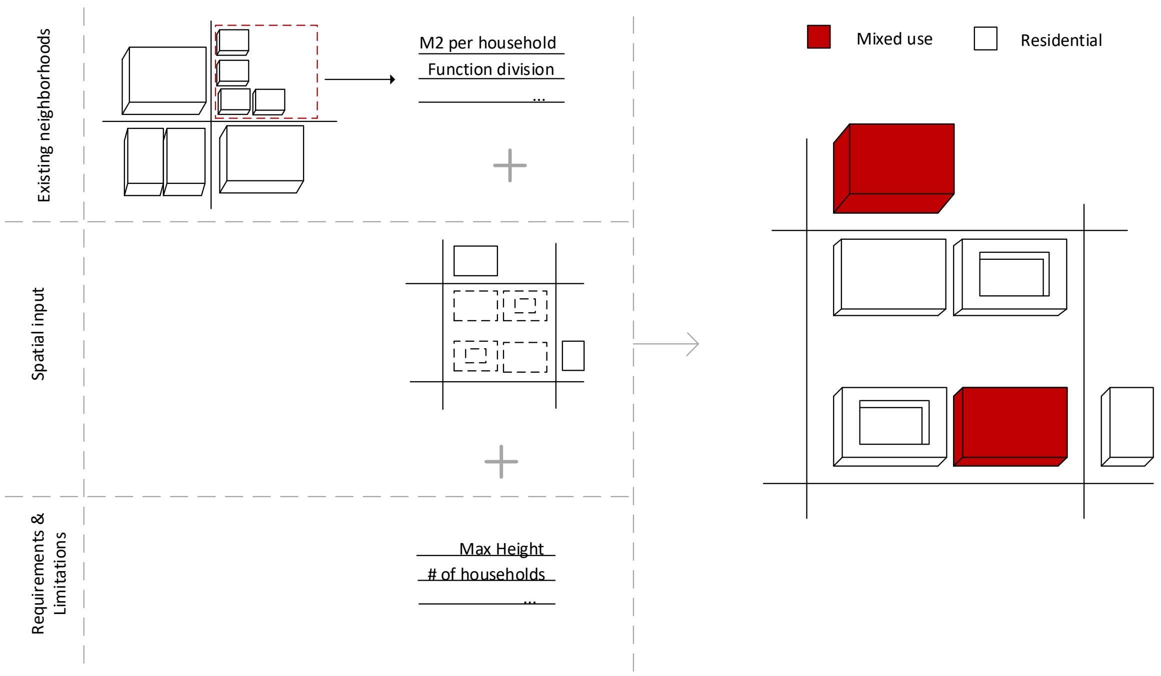



*Figure 38: The input (left) and the resulting output (right) in the TUDPUD project*

### 4.2.3. TUDPUD output

Due to the design parameters and process in the TUDPUD project, the output results in specific designs. Meaning that the output of the TUDPUD project results in a certain urban form and structure that is likely to be different from many existing urban environments or outputs from other urban design methodologies. An example is the option between a courtyard building and a solid building that is used in the design input and directly affecting the design output by restricting the building typologies to these two, as is visible in Figure 38.

Overall, the output can be categorized in two categories: the building output and the street output. Both the buildings and the streets have a specific typology. The output can be stored as a scenario in a 3D City Database, based on PostGIS. From database, for this research specifically, the output has been exported to a shapefile. This shapefile contains 2D footprints of the street segments and the buildings along with semantic data on the function(s) of the building and street segment. Here the street is built up out of strips in which every strip has a function, varying between a pedestrian path, bike path, street parking strip, car road, vegetation, and canal. The buildings contain semantic data on the function, multifunctional or residential, the building height and if it is an existing building or not. The shape of the newly designed buildings is generally rectangular, although exceptions exist, and new buildings always have a flat roof. The shape of the existing buildings is approximately the actual shape of the building with a flat roof. Figure 39 provides an overview of two different design scenarios created within the TUDPUD project. In Figure 39, visible are among others the options to vary in street typology, building function (residential in yellow vs mixed use in blue) and building type (courtyard or closed).

*Figure 39: Overview of two different output scenario's (Agugiaro et al., 2020)*

## 4.3. Implementation Method

Within this subsection, the used implementation method is described. Starting with a complete overview of the used implementation method, followed by in depth descriptions of the different components of the overall method. Figure 40, provides an overview of the overall method used to build the computational urban design tool.

### 4.3.1. Overview of the overall implementation method

The parametric design aspect of the TUDPUD project has been created in Grasshopper. The in this research created extension is also created in Grasshopper. The aim of the created extension is to be able to analyze a generated output, a scenario, of the TUDPUD project on perceived beauty, liveliness, and safety but also to optimize a scenario on each of these three human perception categories. As a result, the implementation lays a link to the TUDPUD project by importing a scenario generated in the TUDPUD project. However, the main element of the implementation method is to retrieve the relevant data from the design, analyze the design and optionally to optimize the design by changing design variables.

Important to note is that although the eventual aim of the created tool is to enable an optimization so that the designs maximally align to human perception, the tool also enables solely an analysis of the imported scenario on human perception. Therefore, in Grasshopper, the user can select the analysis mode or the optimization mode. The analysis mode analyzes the loaded output design of the TUDPUD project on human perception whereas the optimization mode allows the user to optimize the loaded TUDPUD project design.

From a technical perspective, the tool consists of five technical components. In this subsection, a brief introduction to these components is given in which the reference number to the component in Figure 40 is provided in between the brackets (). The first component concerns the loading of the data retrieved from the initial TUDPUD project (1) which is then processed into a 3D environment (2). These two components only run once and are not part of an iterative process. When the initial urban design is processed, data is gathered from the initial design (3). This data is then analyzed on each human perception category (4). After that the initial design is analyzed, the user can start with adjusting and optimizing the design. When the user wants to do this, he or she switches to the optimizing mode, triggering the initial design to be decomposed and re-composed based on values of the design variables. These design variables can be set by the optimization algorithms. Based on the new set values of the design variables, a new 3D environment is generated (5), data is gathered again from the new design (3) and the new design is analyzed (4). Within the optimization process, components 3, 4 and 5 are iterated.

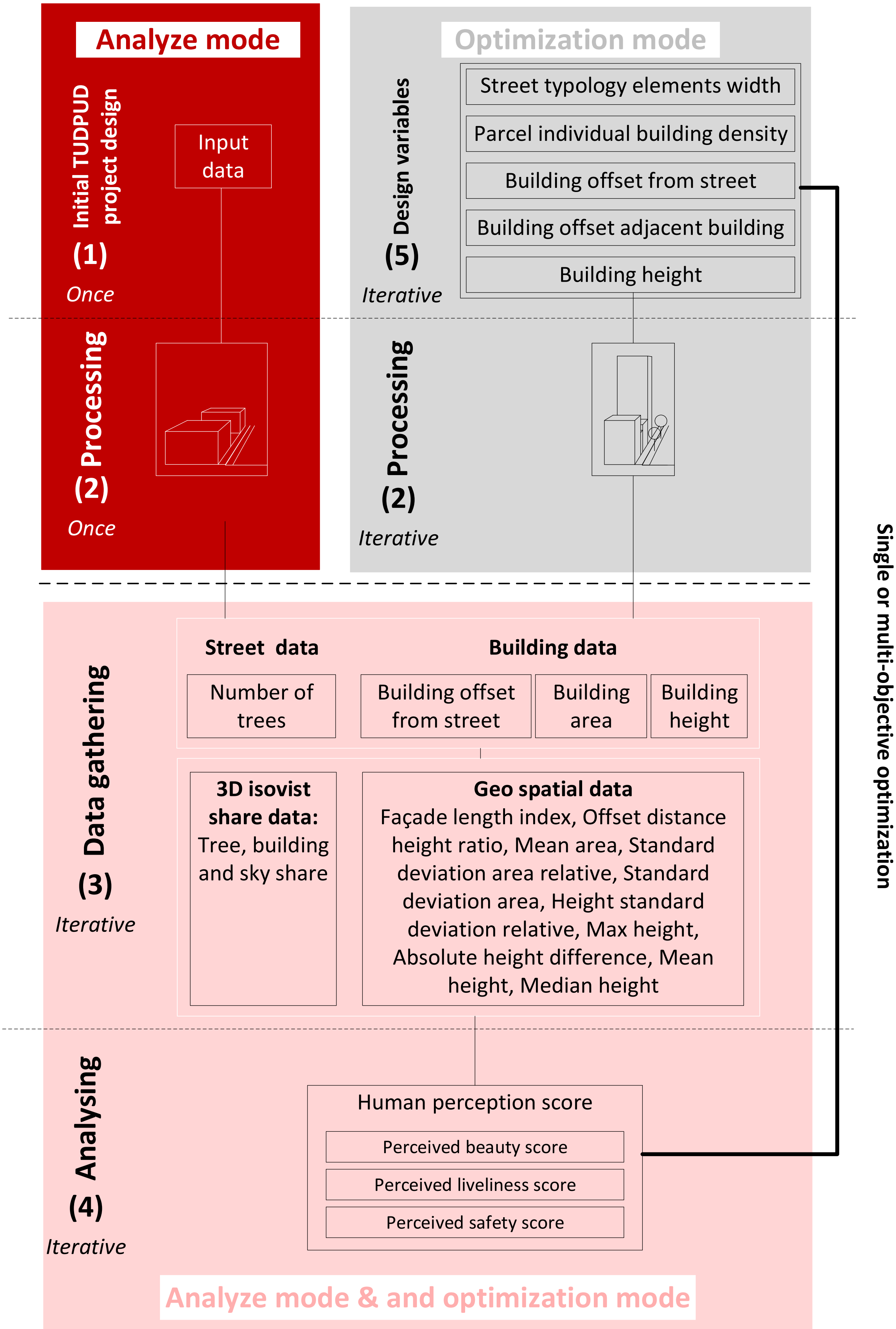



*Figure 40: Complete overview of the implementation method*

### 4.3.2. Data import & processing

The first step is loading the input data. The input data is loaded into Grasshopper using the Urbano plugin (Dogan et al., 2020) and the data format of the input data is a shapefile. The input data consists of geometric data in the form of points and semantic data. Using the point data, the street strips and the building footprints can be regenerated in Rhino into polylines and surface boundary representations. Since Grasshopper makes use of data trees to link semantic data with geometric data, the street strip function and building height is stored in a nested tree in the same order as the geometric data. There are likely to be more and possibly more straightforward methods for regeneration of 2D geo files, such as shapefiles, into 3D in Grasshopper however this method was selected as the process was well documented and resulted in the desired outcome.

Following the data import from a shapefile into geometric and semantic data trees, the 2D building footprints are extruded into 3D volumes. Additionally, the vegetation strips in the street layout are filled with trees. Every street segment can have two vegetation strips in the initial loaded design (analyze mode). In the optimization phase (optimization mode), the computer can add two additional vegetation strips resulting in a total of maximal four vegetation strips per street segment. This has been done to provide the computer with more design freedom in terms of tree placement during the optimization phase. The number of trees per vegetation strip are based on both the length of the vegetation strip and the total area of the vegetation strip. The required number of square meter vegetation strip and required length of vegetation per tree can be set by the user. In the demonstration process used in this thesis, the numbers have been set to one tree per 200 square meter strip area and one tree per 30 meters strip length. Grasshopper then places the calculated number of points of origin of the trees randomly in the vegetation strips. Since this can result in trees located that close to each other that they intersect after 3D generation, Grasshopper removes a point of origin of a tree in the same strip if it is within a distance to the tree smaller than the radius of the sphere making up the branches of the tree. Then, from every point of origin the tree is generated in 3D. Every tree consists of a cylinder tree trunk and a sphere making up the tree branches. The user is able to set the parameters for the cylinder and sphere and every tree has exactly the same shape. Making the vegetation strip layout the determinant factor in the number of trees visible from a certain point. Table 24 presents the tree design variables which are inflexible during the optimization phase.

*Table 24, Inflexible tree design parameters*

| Design parameter type | Design parameter |
|---|---|
| Tree shape | Stem length |
| | Stem radius |
| | Sphere radius |
| Tree density | Number square meter required per tree |
| | Strip length required per tree |

Besides the buildings and the trees, a ground surface and sky is generated. The ground surface is a flat planar surface generated at the height of the lowest points of the buildings and street strips. The sky surface is an enlarged duplicate of the ground surface at several meters above the highest building.

Finally, the boundary representations of the trees, buildings and street strips are transformed into meshes, as a mesh is a more useful geometrical data format in the analysis. The meshes are then visualized in Rhino. Figure 41 visualizes the process of importing the TUDPUD output into the for this research created Grasshopper script.

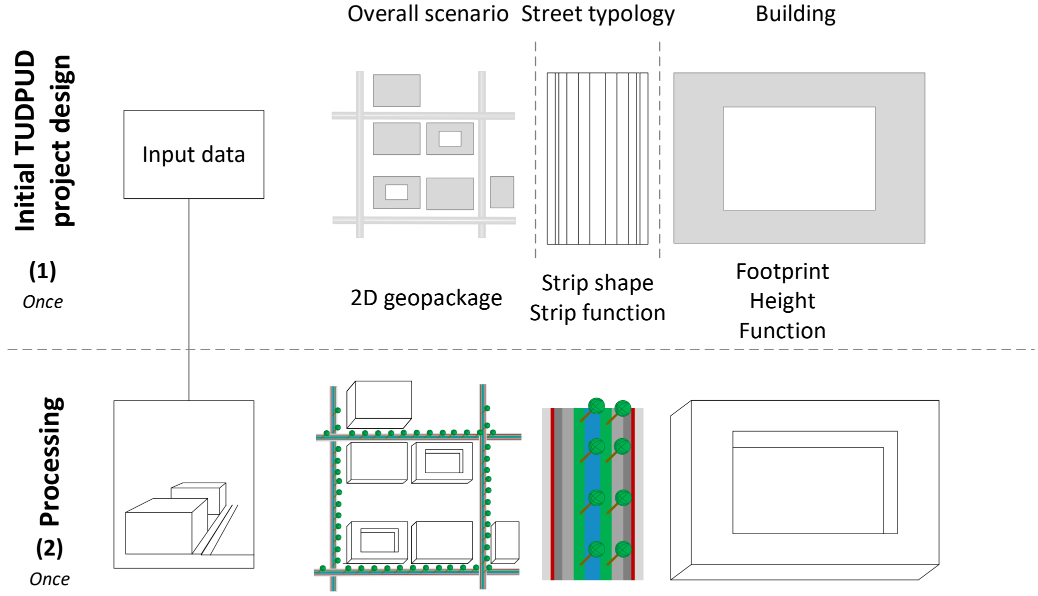


*Figure 41: Importing the TUDPUD output into the for this research created Grasshopper script*

### 4.3.3. Data retrieval

After the processing of the loaded design generated as a result of the TUDPUD design process, data is retrieved from the design that is used as input for the analysis. This data retrieval process is following as much as possible the same procedure used in the data retrieval process used in phase one of this research, in which the relation between the volumetric built environment and human perception has been analyzed.

The first step in the data retrieval process is the generation of points of analysis, the points of analysis are comparable with the image locations in research phase one. The user has to provide the distance between two points of analysis, hereby influencing the accuracy and speed of the analysis. As smaller distances result in more points of analysis and therefore a more accurate analysis result but also a longer computation time.

For most attributes, the points of analysis have been used to gather data for that location. However, for some attributes that data has been gathered for the complete street segment. Mainly since gathering data on the street segment for these attributes is significantly less complex to program in the data gathering script. Table 25 provides an overview per attribute on the aggregation level of the data gathering process used for that attribute.

For every point of analysis both buffers and a 3D isovist is generated in order to retrieve the attribute data. The buffer is generated in the same manner as in research phase one whereas the 3D isovist is used to compute the image share data, whereas the image share data was calculated in research phase one based on image segmentation. Figure 42 visualizes the data retrieval process.

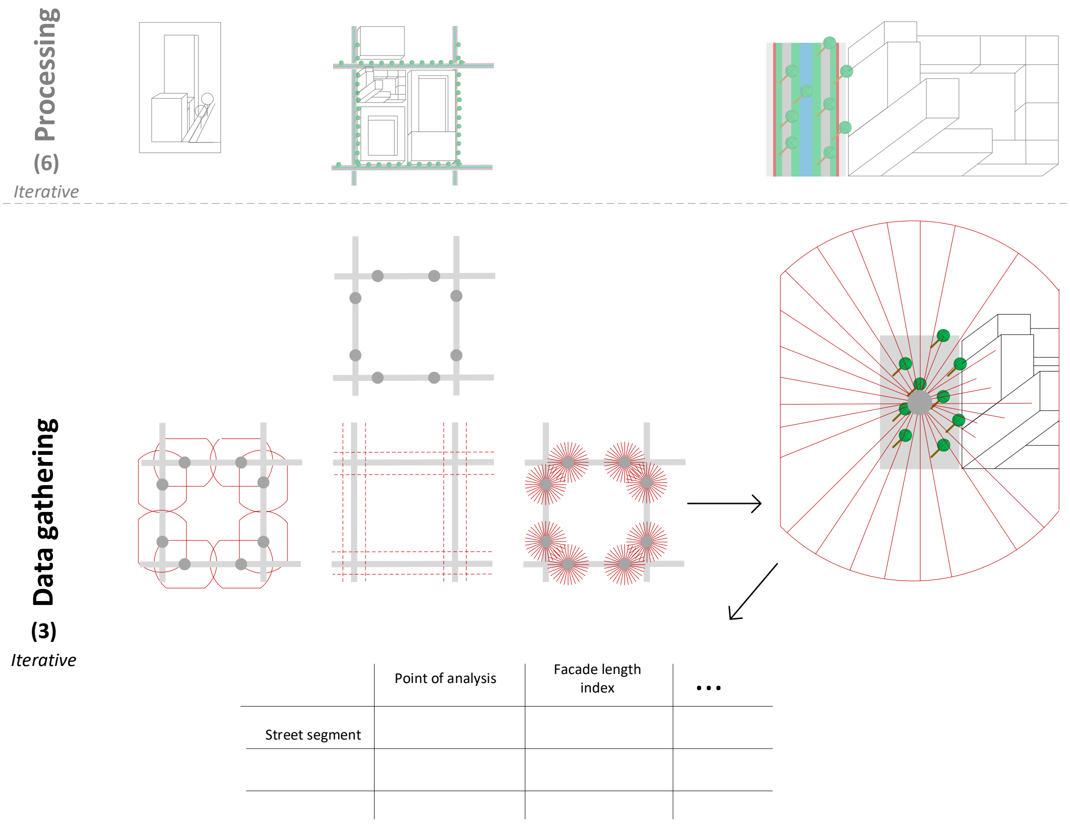



*Figure 42: Visualisation of the data retrieval process*

## 3D Isovist

The 3D isovist approach used in this research is of a comparable approach used in the research of Michailidou on the influence of visible views on cyclists' route choices (Michailidou, 2019). A sphere is generated with the point of analysis as center point, the point of analysis is set at an altitude of 1.65 meters to approach the average height of a human eye. The sphere is then subdivided in equal surface partitions. Then, rays are computed from the middle of the sphere to the corner points of the partitioned surfaces. The number of partitioned surfaces and therefore the number of rays from one point of analysis are provided by the user, again influencing the accuracy and speed of the analysis. After the computation of the rays, the rays having an angle that lays outside the potential view of a person looking straight forward are excluded. However, for every point of analysis it is assumed that a person can turn around 360 degrees around the z-axis. Thus, only the rays pointing sharp up or down are excluded. Rays with an angle larger than 50 degrees for the upper field and 70 degrees for the lower field have been excluded, these angles have been set based on the 3D isovist approach of Michailidou (2019). Figure 43 illustrates the resulting rays.

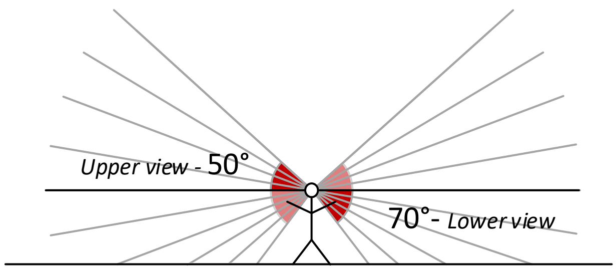



*Figure 43: 2D section view of the rays emerging from a point of analysis, representing the eyes of a human*

The resulting rays are then tested for intersection with buildings, trees, and the sky. Every ray is marked if it intersects with a building or not, if it intersects with a tree or not, and if it intersects with the sky or not. It could happen that one ray intersects with more than one of the three classes. In this case the ray is only marked to intersect with the class of which the intersection point is closest to the observer. Finally, the tree share, building share and sky share visible from a certain point of analysis are calculated by dividing the marked rays of each class by the total rays generated around that point of analysis.

*Table 25: Overview of attribute data gathered*

| Built environment element | Attribute | Attribute abbreviation | Measurement level | Retrieval technique | Max building distance (m) |
|---|---|---|---|---|---|
| Share data | Tree share | TS | Point of Analysis | 3D isovist | - |
| | Sky share | SS | Point of Analysis | 3D isovist | - |
| | Building share | BS | Point of Analysis | 3D isovist | - |
| Building Height | Height mean | Hmean | Point of Analysis | Buffer | 300 |
| | Height median | Hmedian | Point of Analysis | Buffer | 300 |
| | Height standard deviation relative | Hstdevrel | Point of Analysis | Buffer | 300 |
| | Height maximum | Hmax | Point of Analysis | Buffer | 300 |
| | Absolute height difference | AbHdif | Point of Analysis | Buffer | 300 |
| Building footprint | Façade length index | FLI | Street segment | Street offset | 100 |
| | Area mean | Amean | Point of Analysis | Buffer | 100 |
| | Area standard deviation | Astdev | Point of Analysis | Buffer | 100 |
| | Area standard deviation relative | Astdevrel | Point of Analysis | Buffer | 100 |
| Street perspective | Offset height ratio | OHR | Street segment | Buffer & street offset | 100, 300 |

### Area selection

Additionally, to the 3D isovist, buffers are generated around the points of analysis. Along the street, depending on the street type, a linear buffer is generated. Additionally, a circular buffer is generated having the point of analysis as center. The linear street buffer and the circular point of analysis buffer are then laid on top of each other and the intersecting area is selected as area of analysis for that specific point of analysis. Figure 44, visualizes the process.

These buffers then mark the buildings that have been included in the buffer zone of every point of analysis, resulting in a selection of relevant buildings per point of analysis. For each selection the building height and building area data is then retrieved.

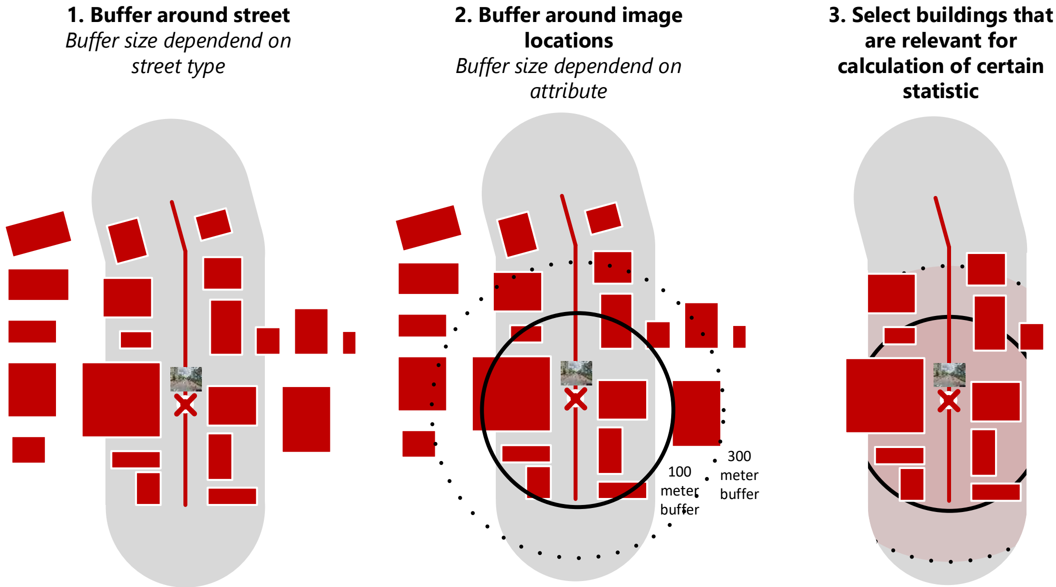



*Figure 44: Area selection from which data is retrieved*

#### Street segment data retrieval

Per street segment, the façade length index and the building offset of every building along a street is retrieved. The façade length index is calculated using the same procedure as in research phase one, by setting multiple offset lines from a certain street and dividing, for every offset line, the calculated length that is intersected by a building by the overall length of the offset line. The offset line with the highest façade length index is used to set the façade length index of that street segment. The median building offset is retrieved by taking the median of all smallest distances from an adjacent building to the street outer line.

The output of the data gathering process in Grasshopper are tables containing the attribute values for every point of analysis.

### 4.3.4. Data analysis

In the data analysis part, the relationships found in research phase one are incorporated in Grasshopper. For every relationship, for relative low and high density environments and for every human perception category a relationship was identified, the found coefficients have been inserted in Grasshopper. Using the incorporated relationships and the attribute values retrieved as result of the data gathering process in Grasshopper, every point of analysis can be analysed on human perception by multiplying the attribute values with the attribute coefficients. The sum of all relevant attributes per point of analysis is the perceived beauty, liveliness, or safety score.

The overall human perception score per category has been calculated for the design by taking the mean value of all points of analysis present in the design area. The overall score per human perception category is visualized relative to the overall score of the original design. The overall scores for the different human perception categories are then used in the optimization algorithm.

### 4.3.5. From original design to flexible design based on design parameters

In the first run, the original design being an output scenario of the TUDPUD project is analyzed on each of the three human perception categories. However, in order to allow the designs to be improved concerning each of the three human perception categories, the possibility to adjust them is incorporated. The process of adjusting the original design concerns of mainly two phases, the importing of the original design and the decomposition phase which only run once and the re-composition phase which runs every time in the iteration process. The re-composition phase is based on the design parameters and user requirements. Figure 45 visualizes the process of generating a new design based on design variable values from the original TUDPUD design.

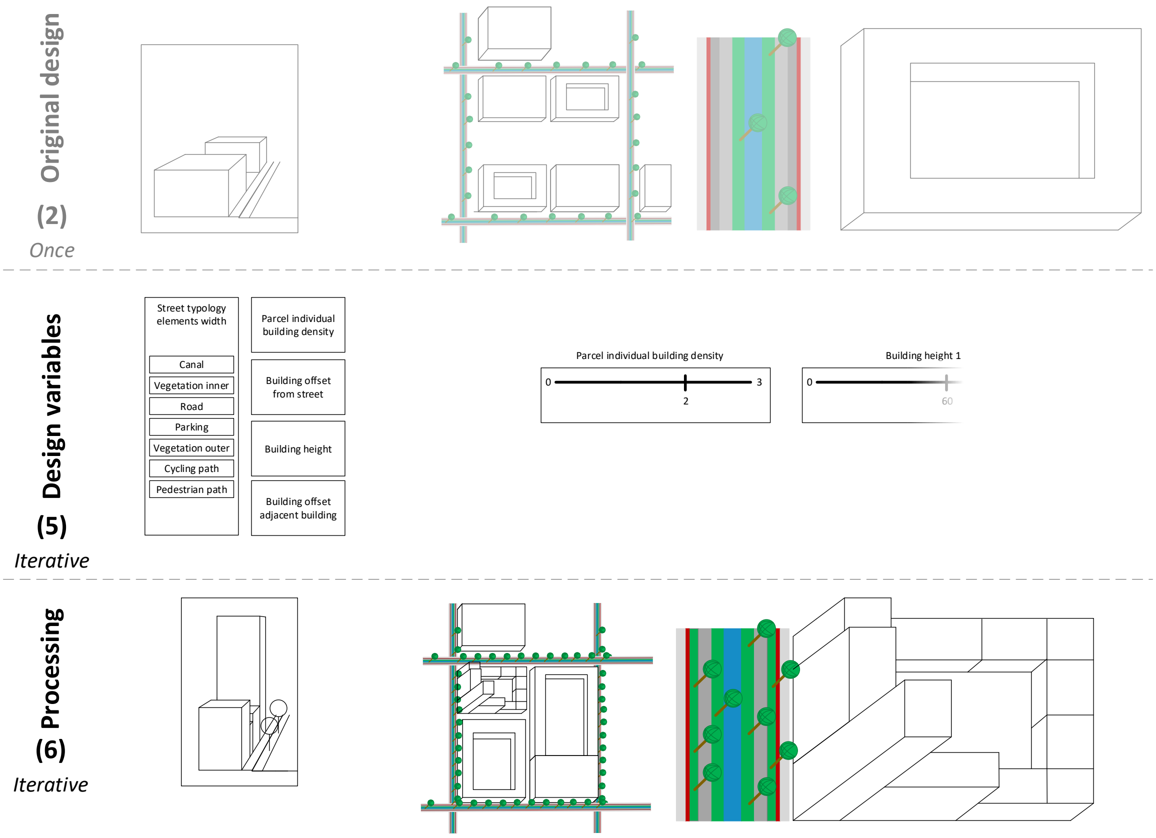



*Figure 45: Re-composition process original design to new design based on the design variable values*

### Decomposing the original design

The original design loaded into Grasshopper has been created as a result of the TUDPUD project. The TUDPUD project contains several design parameters of which multiple KPI's that have been set based on reference neighborhoods. These design parameters allow little variation in volumetric characteristics of the building and open space that influence human perception based on the found relationships in phase one of this research. Therefore, the original design has to be decomposed. The decomposed design then forms the basis of the design parameters that enable a new, flexible composition of the volumes again.

The decomposition process mainly comes down to finding the building plots and street centre lines. First the plot of the individual buildings is defined, this is done by finding the adjacent streets and setting them as plot borders. In addition, a line is created halfway between two adjacent buildings which becomes another plot border for the plots of both buildings. The plot lines are then merged into a polyline defining one plot.

The plot centre lines are found by computing the centreline of the canal, which is always the middle street strip in the output designs of the TUDPUD project.

### Re-composing based on the design variables (5)

In order to re-compose the original design into a flexible design based on the design variables as input, the user has to set several variables which are mainly the design variables and the user requirements. Below, first the design variables will be presented after which the user requirements will be presented. Finally, the process of re-composing the design based on the design variables and requirements will be described.

#### *Design variables*

The design variables used to re-compose the buildings and streets are presented in Table 26, they can also be subdivided in three categories: building height, building footprint and street typology. The design variables create the design freedom for the computer, these are the only values that can be adjusted in the optimization phase. The values of the design parameters can be adjusted automatically if they cause an interference with a requirement. For example, if the sum of the strip widths is larger than the maximum set street width.

*Table 26: Design parameters*

| Design parameter type | Design parameter | Variation level |
|---|---|---|
| **Building height** | Relative building height | Individual building |
| **Building footprint** | Plot division category | All plots |
| | Offset adjacent building | All building |
| | Offset street | All buildings |
| **Street typology** | Canal width | All streets |
| | Vegetation strip inner width | All streets |
| | Road width | All streets |
| | Street parking width | All streets |
| | Vegetation strip outer width | All streets |
| | Bike path width | All streets |
| | Pedestrian path width | All streets |

#### *User requirements*

The user requirements are different from the design variables as they cannot be touched by the computer but only by the user. Table 27 contains an overview of all included requirements.

*Table 27: Requirement overview*

| Requirement type | Options | Requirement | Remark |
|---|---|---|---|
| **Amount of square meters** | Original design | Every new design should contain an equal amount of total square meters as in the original design | |
| | New total | Every new design should contain a total of X square meters | |
| | New per dwelling type | Every new design should contain X dwellings of X square meters | Three types of dwellings can be inserted |
| **Building offset** | - | Minimum distance between adjacent buildings | |
| **Building height** | - | Maximum building height | |
| | - | Minimum building height | |
| **Street typology** | - | Maximum street width | |
| | - | Minimum strip width | |
| **Daylight** | - | Minimum daylight | The share of building faces allowing to drop below the minimum can also be set |

### *Re-composition process*

The re-composition process based on the design variables mainly takes place in three steps. First the street typology is re-composed, then the building footprints are re-composed and finally the building heights are set again. Below a description is provided per main step on how the Grasshopper script re-composes the design with the design variables.

### *Street typology*

The street centre lines form the basis of the re-composition process of the new streets together with the design parameters. Starting with the centre line, the canal is inserted in the 'new' street with the new canal width. Followed by the inner green strips on each side of the canal. If the inserted canal width is too small, the canal is removed and the inner green strips are merged into one green strip. Next to the inner green strips, the road strips are inserted followed by the street parking strips, the outer green strip, the bike path and the pedestrian path strips. The new width of the strips are the widths assigned to it by the design parameters. The strips furthermore have a minimum width except for the vegetation strips and the canal, to assure that a car, cyclist and pedestrian will always be able to move through the street. Finally, the user can set a maximum width for the street. If the newly composed street exceeds this width, the strips are shrunk based on their relative width. Figure 46 visualizes how the original street is re-composed based on the design variables, taking the centrelines as starting point.

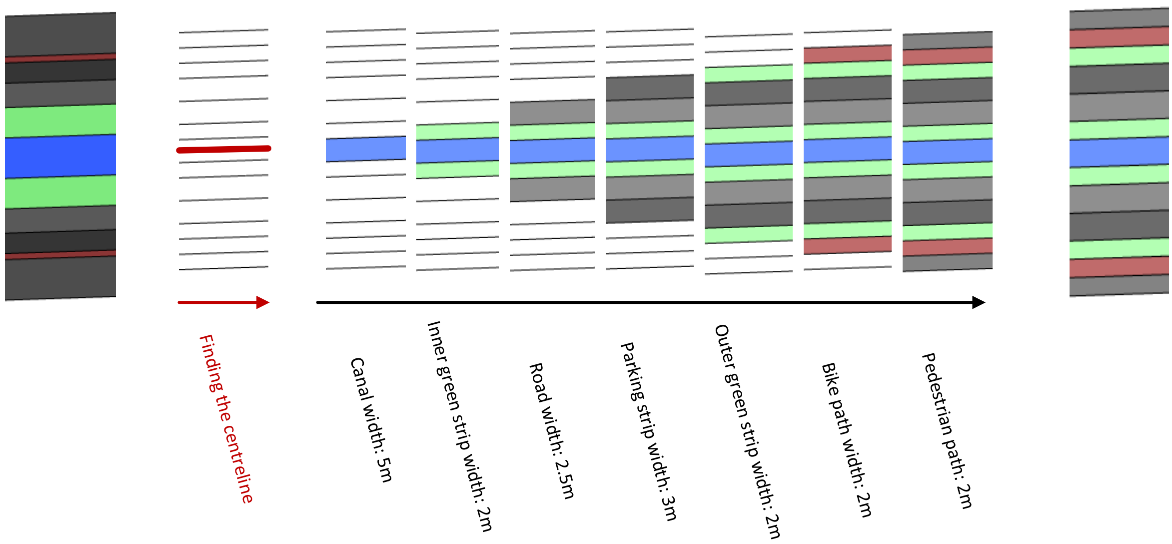



*Figure 46: Re-composition process of the street typology*

### *Building footprint*

In the composition process of the new building footprints, the following steps are taken: First the plot outline of each original building is defined. The plot border lines are defined on the following manner: The outer borders of the plot along the street take the street as border line, the plot border line between two original buildings is defined by a line laying exactly halfway the two buildings and if a side of the original building neither borders a street nor a building, the side of the original building is taken as plot border line. Second the new building outline is defined based on the values of the design variables. The new building outlines are thus, simply stated, a shrunk version of its plot or a copy of the plot if the offset distances are set to zero. Figure 47 shows how the original buildings are reshaped in the re-composition process, resulting in a defined plot per original building and eventually a new building footprint.

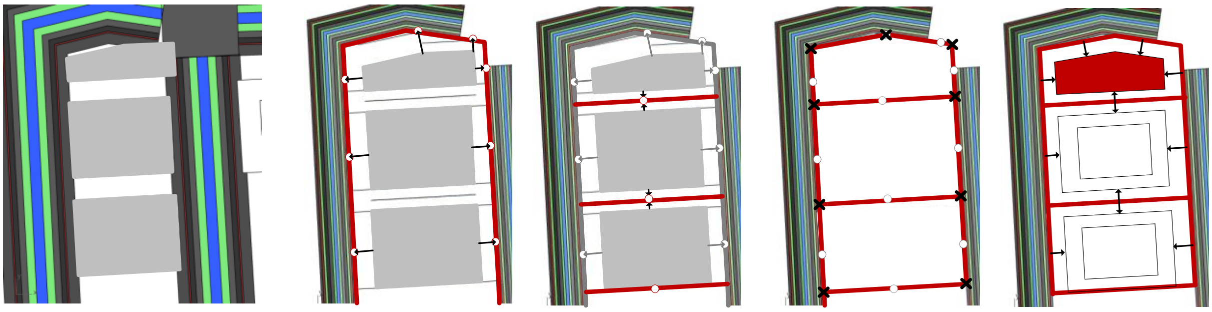


*Figure 47: Re-composition process of the buildings*

Here, two things are important to note. First of all, if a building is a courtyard building, the thickness of the building is kept the same as in the original design. Thus, if the building is shrunk, the courtyard is shrunk as well. If one side of the square courtyard becomes too small, the courtyard is deleted. Additionally, if one side of the building is pushed that far from the plot side that it crosses the other side of the building footprint causing the normal of the building footprint to flip or if a part of the building footprint crosses the building plot the building is deleted.

However, the process above does not describe the final output of the building footprints. Based on the parcellation category, the building footprints can be subdivided into finer footprints. There are four subdivision categories: zero up and until three. Category zero does not subdivide the buildings, category one cuts the courtyard buildings so that the corners and sides become separate buildings, category two additionally cuts the longest sides into two and category three additionally cuts the longest remaining building sides in two again. Simply stated, the larger the subdivision category, the finer the building footprints. Figure 48 visualizes the subdivision options of a building based on the parcellation categories.

When the buildings are subdivided into smaller buildings (category one up and until three), subdivided buildings can be automatically removed if they are too close to another building on another plot and if they are not corner buildings or adjacent to the street. The user can set the minimum required distance between two buildings on separate plots.

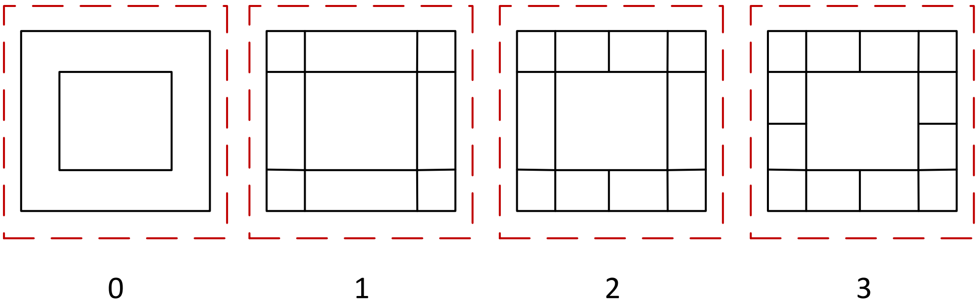



*Figure 48: Subdivision of parcels in parcellation category 0-3*

### Building height

Finally, the re-composition of the buildings is completed by setting the building heights of all buildings individually. Here, regardless of the buildings being subdivided or not, every single building can be set to an unique building height in the design parameters. For the setting of the building height, the following procedure is followed in the Grasshopper script:

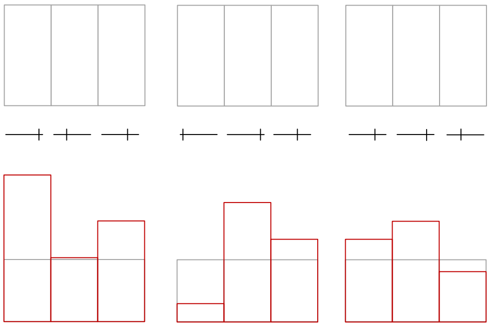


*Figure 49: generating new buildings based on the building height design variables*

First the Grasshopper script sets the individual buildings to the building heights provided by the design variables, visualized in Figure 49. Then, the volume of all buildings together in terms of total square meters is calculated by dividing the building heights of the individual buildings by a set floor height and multiplying these values with the footprint areas of the building. Then Grasshopper calculates the difference between the total required volume and the total generated volume with the set footprints and building heights. If the generated volume is more than the required volume, Grasshopper reduces the building heights of all buildings by removing floors, the amount of floors that are removed is set per building according to the contribution of that building to the total volume of all generated buildings together. If the generated volume is too little, Grasshopper adds additional floors to the buildings according to the contribution of that building to the total volume of all buildings together. Figure 50 illustrates this process if the total volume exceeds the required volume.

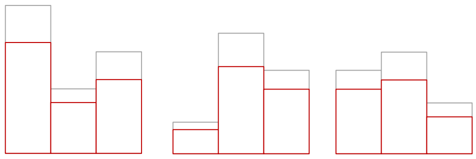


*Figure 50: Limiting the building heights to meet the required volume*

Besides the volume requirement, the user can also set a maximum height requirement. This requirement is important so that the computer cannot reduce the footprint area of a building almost limitlessly while still meeting the volume requirement by generating an extremely high building. The principle for limiting the heights of the buildings is the same principle used for maintaining the overall building volume. However, this process is somewhat more comprehensive including iterations over the buildings which is not well supported by Grasshopper. Therefore, a Python script is implemented in Grasshopper to limit the building heights. This script uses the following procedure:

The buildings are stored in a list and sorted from high to low. Iterating over the list of buildings, every building is checked on meeting the maximum height requirement. If the height of a building exceeds the maximum height, the building height is reduced to the maximum height. This means that a certain amount of square meters is removed from the building volume, this amount of square meters is then spread over the other buildings by adding additional floors to the other buildings according to the contribution of a building to the overall building volume. Thus, more square meters are added to a building already containing a lot of square meters than to a building containing relative little square meters. The addition of floors to the other buildings results in new building heights, the building heights are updated in the list of building heights and the script continues to the next building in the list. This process continues until all buildings in the building height list are checked on meeting the building height requirements. Figure 51 visualizes this process.

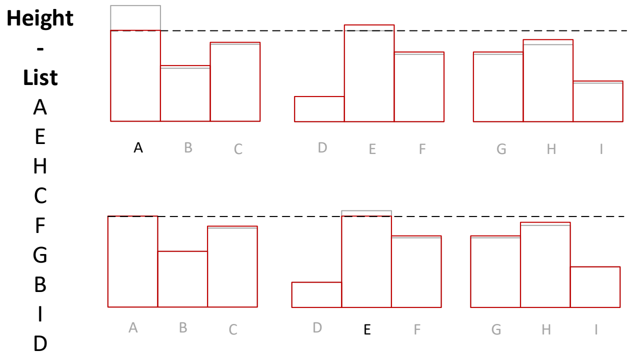



*Figure 51: Balancing of building heights to meet maximum height and volume requirement*

As a consequence, the initial absolute building heights inserted by the design variable values are transformed to relative building heights in order for the newly generated design to meet the volume and maximum height requirement. Also, if the volume requirement is relatively high while the maximum building height requirement is relatively low, the variation in building heights will decrease. Figure 52 visualizes the result of the height transformation process of the buildings so that it meets the maximum height and volume requirement.

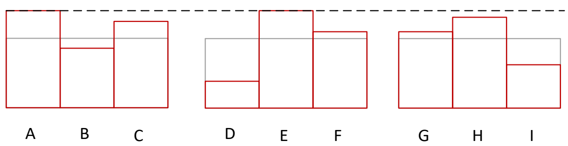



*Figure 52: Result of the building height setting process*

### Daylight requirement

The final requirement that the designs should meet is the daylight requirement. The daylight requirement is incorporated by calculating the daylight factor for every façade for all buildings in the generated design. The daylight factor is calculated using the ladybug plugin component "LB view percent" (Roudsari & Pak, 2013). This component calculates the percentage of view from certain points on a building to the sky and open outdoors. It is a fast component but providing accurate insight in the amount of daylight that a building receives on a certain façade. The view percent is expressed in percentages, a percentage of 100% would indicate that from a certain point on a façade, a sky can be seen from all view directions. As a consequence, this generally only occurs on the roofs of buildings. The general highest achievable percentage for a façade lays around 50% since also a significant part of the view is covered by the landscape even if there are no buildings present. For this research, a regular grid of points on every façade is created from which the view percentage is calculated. The average view percentage of all points on the façade is then calculated. The user is able to set a minimum required daylight factor for every building and a required average total daylight factor. If the daylight factor conditions are not met, all buildings are removed from the design in the analysis and the buildings are marked red in the visualisation of the design. This leads to relative low human perception scores and by marking the buildings red, it is communicated to the user that the design does not meet the requirements.

### 4.3.6. Design optimization

For the optimization of the design on human perception, perceived beauty, safety, or liveliness, the user can select if he or she would like to optimize for one human perception category or for two or three human perception categories, in other words the user can select a single optimization algorithm or a multi-objective optimization algorithm for finding the optimal design solution. Furthermore, the user can run an optimization algorithm for only the street typology, for only the building footprints, for only the relative building heights or for all design parameters together.

Every optimization algorithm in the Grasshopper script is connected to one or more objective value(s), one of the human perception categories or all depending on if it is a single - or multi-objective algorithm, and to multiple design parameters. Simply stated, the optimization algorithms try to maximize the connected objective value(s) by adjusting the connected design parameters.

The single objective optimization algorithms are accessible through the Galapagos plugin (Rutten, 2013). Galapagos enables the user to select from two different types of optimization algorithms, simulated annealing (SA) for finding a value that approaches the global optimum relative fast or a genetic algorithm (GA) for finding the global optimum relatively slow.

For the multi-objective optimization, the multi-objective optimization algorithm Octopus has been used (Vierlinger et al., 2018). Octopus is similar to the Galapagos optimization plug-in but includes the Pareto-principle for multiple goals in it, in contradiction to Galapagos.

#### The optimization algorithms

The optimization algorithms used in Galapagos are SA and GA.

*Simulated annealing*

SA is a heuristic algorithm that does not necessarily find the global optimum, however it does attempts to approach the global optimum. Specifically it does so based on the annealing process used in the domain of metallurgy (Kirkpatrick et al., 1983). In the optimization algorithm, this has the effect that the algorithm starts to explore neighboring values (design parameter values), in which the algorithm accepts a neighboring value if it results in a higher objective value or if results in a lower value laying within a certain maximum range. This range becomes smaller when the number of iterations increases. In other words, the algorithm always takes on the neighboring value if it results in a higher value allowing it to find the local optimum and it looks for potential optimums by exploring neighboring values having a lower value as well, enabling the jump from one local peak to another. In the beginning it takes on neighboring values even when it has a relative high decrease in the objective value whereas at the end it only accepts a neighboring value when it has a relative low decrease in the objective value.

*Genetic algorithm*

The genetic algorithm enables the finding of the global optimum. Genetic algorithms do so by initially generating many different design solutions. For every solution a fitness value is calculated, expressing the relative quality of the design solution. Based on the fitness value of a design solution, the best design solutions are selected for further calculation. In addition, new design solutions are added by reproducing the set of design solutions left in the selection. This process is then iterated until the stop condition is reached. The stop condition can be assigned by the user and can be based on a maximum number of generations, a time limit, unchanged design solutions, or a combination of the tree.

## 4.4. Conclusion Research Phase Two

In this chapter, research phase two, it has been described how the in research phase one found relationships have been implemented in a generative urban design component forming an extension of an existing parametric urban design methodology. Together, a computational urban design methodology is created. The designed and developed process demonstrates an answer to sub question 4: How can the quantified relations be incorporated in computational urban design?

The applied methodology to incorporate these relations has been based on the capabilities of parametric and generative urban design as well as earlier applications of computational urban design tools. This enables a user to initially generate many designs parametrically, supported by computer processes but maintain much design flexibility for the user. For every initially generated design, the user is able to optimize the design for any or a combination of the three human perception categories using the generative component created as part of this research. The quantified relationships can therefore be incorporated in computational urban design using a generative optimization approach. Altogether, enabling a user to generate an urban design based on desired input KPI's, set requirements and aligning maximally to human perception including the relation to the existing context in which the urban design is generated.

However, many improvements can still be made on the incorporation of these quantified relationships within the applied methodology. Concerning the used implementation, the following remarks can be made: The design freedom of the building shape, street layout and tree shape is, sometimes partially, limited. The building shape can only be adjusted with the building height, and footprint. Here, the footprint can only be changed by enlarging or shrinking it but the form of the footprint shape cannot be changed. The building height can only be adjusted for the complete building, even though the original buildings can be subdivided in smaller buildings. One of the potential solutions could be for example a voxel based building generation process, as this would increase the design freedom dramatically. This would mean that, instead of one building block that is customizable in shape through several design variables, buildings would be composed out of many smaller squared blocks. These blocks can then be stacked so that the blocks together can form any desired shape.

In addition, the incorporated quantified relationships between the built environment and human perception are not able to influence the street layout. The street layout is defined in the parametric urban design process, after which the optimization process is not able to adjust it anymore. Even though the street layout is expected to be able to significantly influence the human perception score.

Finally, the used implementation method does not allow trees to be flexible in their shape and in the tree density. As a result the spread is more or less equal over the different streets and the trees are all the same. Since trees have been found to have a significant influence on the overall human perception score, it would have been interesting to allow variation in tree density and dimensions based on a design variable.

The reason not to include the voxel based building shape generation process, the flexible street layout and the flexible tree density and shape in the optimization phase of the computational urban design tool, is that this would extent the design freedom significantly again, resulting in longer computation times and a more extensive computational urban design tool. Concerning the generation and analysis process, there is still room for improvement concerning its pace. A faster process would contribute to a significant faster optimization run, as an optimization run generally consists out of many iterations of this process.

# 5. Results

This chapter describes the results of incorporating human perception in computational urban design based on this research's applied methodology. The final results will be presented by describing the optimization outputs. However, first the results of the sensitivity analysis will be described. This sensitivity analysis focused on finding the individual effects of certain design variables on the human perception scores. Before the results are presented and described, section 5.1 first describes the test scenario that has been used to retrieve the results. Figure 53 highlights how this result chapter is related to the overall research design.

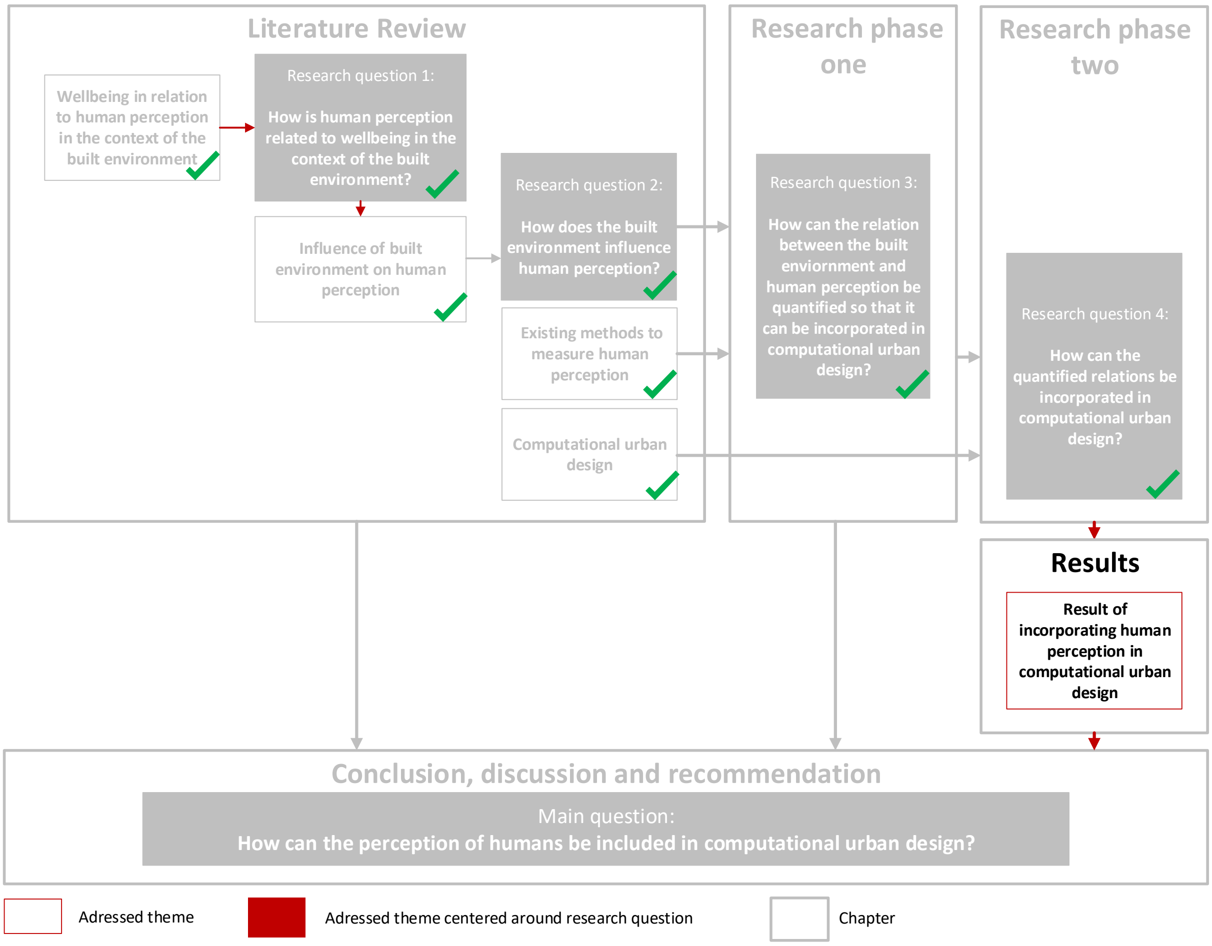



*Figure 53: Results in relation to the overall research design*

## 5.1. Test scenario

The results all have been retrieved by changing design variables or by applying optimizations to a set test scenario. This test scenario consists out of four plots and the adjacent streets snipped out of a larger design output of the TUDPUD project. The test scenario focusses on the high density relationships as high density environments are generally more complex. Since they are more complex, the application of supportive computational urban design tools would be able to contribute more to these environments. In order to generate a dynamic and high density environment, a fake context is generated around the test scenario. The actual context is yet namely predominantly infrastructure, industrial buildings and open space. Figure 54, below provides an overview of the general test scenario. In Figure 54 it is visible that the plots and centerlines are marked in red, the plots stay aligned to the and cannot be changed. The centerlines of the streets cannot be changed either. Figure 54 also indicates the original buildings on plot zero to three. The new buildings have taken over the shape of the plot. The fake context is made up of the grey buildings surrounding the plots. The scenario's used in the sensitivity analysis and the scenario's produced as a result of the optimization can vary through the design parameters but the in Figure 54 marked context remains the same. Finally, for the optimization runs on the test scenario, only the genetic optimization option has been used as, generally, the genetic optimization was found to be faster within the test scenario case.

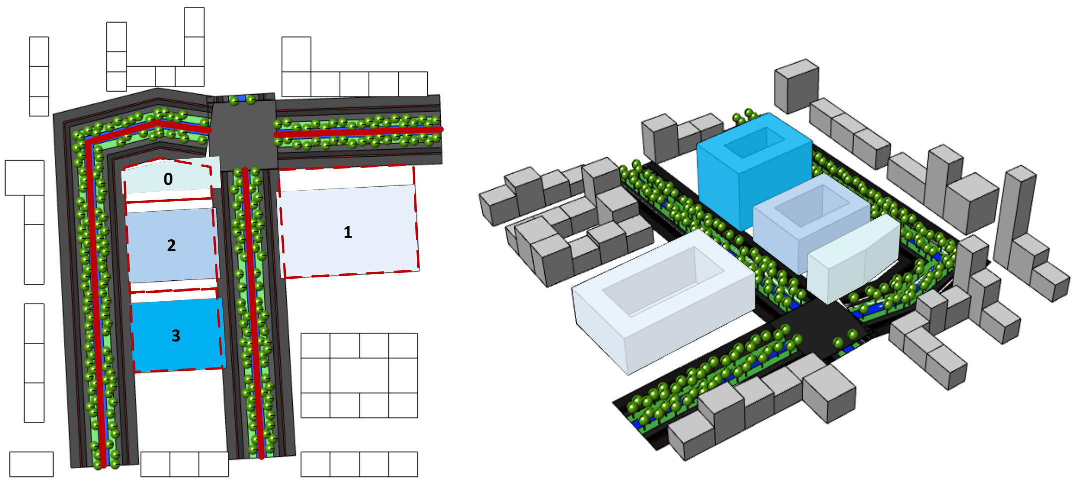



*Figure 54: Top and 3D view of original TUDPUD design*

## 5.2. Sensitivity analysis

A sensitivity analysis is "the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input" (Saltelli, 2002, p.1). The aim of the sensitivity analysis is to retrieve insight in the behavior of the computational urban design tool by analyzing the effect of the input of the tool, the design variables, on the output of the tool, the human perception scores. By reflecting the behavior of the tool on the found, and implemented, relations between the built environment and human perception, the sensitivity analysis can also function as a validation method for the created computational urban design tool. The created computational urban design tool is able to make a distinction between low and high density environments, for both environments different relations have been incorporated and thus a different behavior can be expected. For the aim of validating the created tool by understanding and reflecting upon its behavior, only the high density relations have been tested in the sensitivity analysis. This is considered to provide enough insight in the tool to draw conclusions on the validation of its behavior.

### 5.2.1. Sensitivity analysis method

It is possible to distinguish between two types of sensitivity analysis: one at a time analysis (OAT) and global analysis. OAT analysis varies an input variable stepwise while keeping the remainder input variables constant and relate this to changes in the output of the model. Whereas global analysis include interactions between variables when testing the influence of input parameters on the output of the model (Saltelli et al., 2019).

In an OAT analysis, insight on the influence of individual design variables on the overall behaviour of the model can be retrieved. However, the exact influence of a design variable can never be found when the other variables are kept at a constant level. If the context is kept the same or the variation of the context is limited, the chance is small that the exact combination is found that results in the worst or weakest design. A global sensitivity analysis does include all options or all potentially relevant options, however the computation time in case of the created computational urban design tool is too high to manage as part of this graduation research. An indication retrieved from an OAT analysis is considered to be insightful enough to better understand the dynamics of the created tool.

In order to retrieve insight on the effects of individual design variables on the human perception scores, every design variable has been analyzed using a one-at-a-time (OAT) analysis. This means that all but one variable are kept at a baseline value. The variable that is analyzed is then stepwise varied resulting in new outputs. These outputs, in this case human perception scores, are then saved along with the varied design variable value. This process is iterated for all variables that are tested. In order to conduct an OAT analysis, the baseline values need to be set. The overall set of baseline values of the non-tested variable are referred to in the remainder of this section as the context.

However, within the design generation process, the parcellation category can be considered as a fundamental design variable. The parcellation category only has four different design variable values in which parcellation category zero results in a different design generation process then parcellation categories one to three. Therefore, the decision has been made to extent the OAT analysis by not just varying every design variable stepwise in one context but in two different contexts. One context being parcellation category zero, the roughest parcellation category, and one context being parcellation category three, the finest parcellation category. As a result, the run sensitivity analysis cannot be considered as one pure OAT sensitivity analysis but as an OAT run on a base context with parcellation category zero and an OAT run on a base context with parcellation category three.

Furthermore, it is important to note that the daylight requirement has been switched off in the OAT analysis. This has been done since the daylight requirement has been incorporated in a manner that designs are deleted in case the design does not meet the daylight requirement which results in empty plots. Empty plots result in standard low human perception scores which disturbs the sensitivity analysis graphs and figures and empty plots are irrelevant as these do not concern an actual design option for the user. Therefore, the consideration has been made that it was more interesting to retrieve an insight in the pure effects of a design variable on the human perception scores by switching off the daylight requirement. The other requirements do not remove but adjust the generated design and have therefore been left intact as these are part of the geometry generation process rather than that they remove designs.

### 5.2.2. OAT setup

The OAT analysis has been conducted on all major design variables. The design variables have been subdivided in the categories ‘Offset’, ‘Building heights’ and ‘Green Strip’. Furthermore, several combinations of design variables have been made. Either the parcellation zero context or the parcellation three context has been applied; Figure 55 below is an image of these two contexts. For several design variables, the OAT analysis has only be conducted on the parcellation three context.

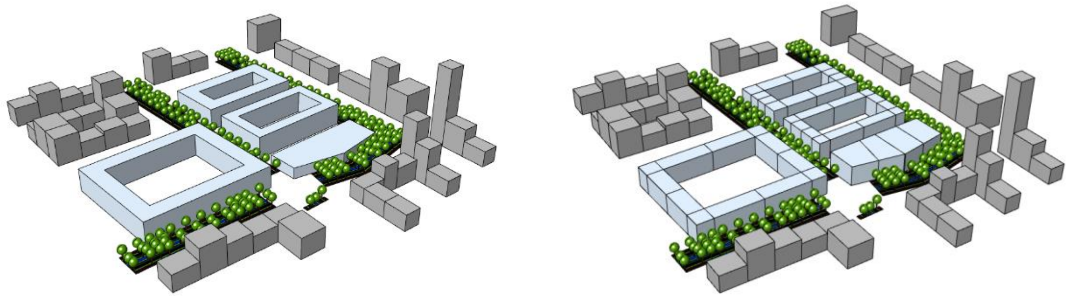


*Figure 55: The OAT context parcellation zero (left) and three (right)*

The OAT analysis results are expressed in the following values: the Pearson correlation coefficient between the design variable values and the human perception scores, the minimum and maximum found human perception values, the absolute difference between the maximum and minimum found human perception values and the relative found difference between the human perception values expressed as a percentage of the absolute difference divided by the found mean value.

### Offset

The offset related design variables are 'adjacent building offset distance' and 'street offset distance'. These distances apply to the buildings on all four plots. The distances have been set to vary between 0 and 30 meters in steps of two meters. Furthermore, the combination of the two design variables has been included separately in the sensitivity analysis. As a result, all potential footprint shapes of the buildings are tested and related to the resulting human perception scores.

### Building height

The building height is a somewhat more complicated design variable category to test. This, since every building in the design has its own design variable setting the height. In the case of the parcellation category resulting in the finest buildings, in total 40 design variables can be varied. In which every design variable composes six optional values. Testing every combination becomes too computational intensive. Therefore, for every plot and for both parcellation categories zero and three, one building varied on building height over all six optional values. As a result, insight can be retrieved on the potential influence the building height of one building has on each of the three human perception categories. By varying the building height of one building on each plot, in addition insights can be retrieved to which extent the location of an individual building might be able to influence its potential impact on each of the three human perception scores. Additionally, using the Galapagos optimization algorithm, the worst and the best findable design has been found by only varying the building height values. This way the steps cannot be traced but the overall influence for a specific context of building heights on the overall human perception score can be found. As a result, all the earlier mentioned output values of the OAT analysis can be computed except of the correlation coefficient.

### Green strip

Concerning the street typology, more design variables are included then just the green strip. These design variables together set the overall street width and the division of strips in the street. The overall street width influences the offset distance of a building from the centerline of the street. However, the influence of the offset distance on the human perception score is measured already using the offset design variables. Furthermore, the user can set a maximum road width so only when the total street width does not exceed this value, individual strip widths are able to influence the total offset distance. In addition to the limited influence of the street width, the strip widths of the street functions other than the green strip do not directly influence the generation of any geometry that influences the human perception scores. The green strip widths of the inner and outer green strip on the other hand does as the green strip total area is one of the values setting the number of generated trees. Therefore, only the green strip widths are included in the sensitivity analysis. The inner and outer green strip have been included individually and combined.

### 5.2.3. Reflection incorporated analysis

The human perception scores are the output of the computational urban design tool. These scores have been based on the incorporated relations found in research phase one. In order to judge if the influence of the design variables on the human perception scores make sense, as a recap, Table 27 contains the by the multinomial logit models estimated coefficients for the built environment attributes that have been found to be significant.

*Table 27: Recap of the multinomial logit model estimates for every human perception category estimated on the high volume datasets*

| Human perception category | Built environment attribute | Estimate |
|---|---|---|
| Beauty | Tree share | 4.393 |
| | Height standard deviation relative | -0.846 |
| | Offset distance height ratio | -0.130 |
| Liveliness | Tree share | 1.101 |
| | Absolute height difference | 0.005 |
| | Façade length index | 1.470 |
| | Offset distance height ratio | -0.119 |
| Safety | Sky share | -2.557 |
| | Building share | -1.073 |
| | Height median | 0.014 |
| | Area standard deviation relative | -0.259 |
| | Offset distance height ratio | 0.132 |

### 5.2.4. OAT results

Table 28 contains an overview of the sensitivity analysis results. The table has horizontally been subdivided in design variable categories and vertically in the three human perception categories per statistic. The correlation coefficient is expressed as Pearson correlation coefficient and is tested on significance. The grey marked cells do not contain a value as the correlation coefficient was found to be insignificant, if the cells contain a value it also means that the correlation is significant. For comparison between the design variables, it is important to take into account the base scenario, varying on parcellation category. Furthermore, Table 28 highlights the strength of the correlation coefficients per human perception category as well as the influence of an attribute per human perception category using a blue to red color scale. The bluer, the stronger the correlation coefficient and the bluer the larger the potential influence of a design variable on the respective human perception score as found from the sensitivity analysis. Since the absolute values for the three human perception scores on which the correlations and the percentages, indicating the influence of the design variable in terms of absolute difference as percentage of the mean score, are not standardized in relation to each other and vary in magnitude between the human perception categories, it is not possible to use the figures in Table 28 to compare between human perception categories.

*Table 28: Sensitivity analysis result overview*

| | Design variable | Base scenario - parcellation | building number (Plot – Building) | bea | live | saf | bea | live | saf | bea | live | saf | bea | live | saf | bea | live | saf |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | cor | | | min | | | max | | | dif | | | % of mean | | |
| offset | offset street | 0 | | -0.07 | -0.69 | -0.08 | 1.55 | 1.42 | -1.55 | 1.89 | 1.74 | -1.20 | 0.34 | 0.32 | 0.35 | 20% | 20% | 26% |
| | | 3 | | -0.95 | -0.99 | 0.97 | 1.27 | 1.18 | -1.13 | 1.71 | 1.66 | -0.50 | 0.44 | 0.47 | 0.64 | 29% | 33% | 78% |
| | offset adjacent building | 0 | | 0.64 | 0.20 | -0.66 | 1.46 | 1.56 | -1.70 | 2.02 | 1.90 | -1.09 | 0.56 | 0.34 | 0.61 | 32% | 20% | 43% |
| | | 3 | | -0.74 | -0.91 | 0.77 | 1.49 | 1.41 | -1.14 | 1.67 | 1.68 | -0.85 | 0.18 | 0.28 | 0.29 | 11% | 18% | 29% |
| | combined | 0 | | | | | 1.26 | 1.24 | -1.97 | 2.40 | 1.92 | -0.75 | 1.14 | 0.68 | 1.22 | 62% | 43% | 90% |
| | | 3 | | | | | 1.31 | 1.11 | -1.20 | 1.87 | 1.75 | -0.43 | 0.56 | 0.64 | 0.77 | 35% | 44% | 94% |
| building height | building height first building of each plot | 0 | 0 | -0.32 | -0.22 | 0.28 | 1.73 | 1.72 | -1.70 | 2.12 | 1.95 | -1.28 | 0.39 | 0.23 | 0.42 | 20% | 13% | 28% |
| | | | 1 | -0.63 | -0.60 | 0.55 | 1.76 | 1.73 | -1.76 | 2.24 | 2.06 | -1.30 | 0.48 | 0.33 | 0.46 | 24% | 17% | 30% |
| | | | 2 | -0.07 | 0.16 | 0.12 | 1.73 | 1.72 | -1.59 | 2.00 | 1.84 | -1.27 | 0.27 | 0.12 | 0.32 | 14% | 7% | 22% |
| | | | 3 | -0.29 | -0.28 | 0.21 | 1.73 | 1.72 | -1.72 | 2.15 | 2.00 | -1.27 | 0.42 | 0.28 | 0.45 | 22% | 15% | 30% |
| | | 3 | 0-0 | 0.86 | 0.78 | -0.89 | 1.65 | 1.59 | -1.18 | 1.79 | 1.71 | -0.98 | 0.14 | 0.12 | 0.20 | 8% | 7% | 19% |
| | | | 1-0 | 0.57 | 0.47 | -0.65 | 1.70 | 1.64 | -1.17 | 1.77 | 1.72 | -1.02 | 0.07 | 0.08 | 0.15 | 4% | 5% | 14% |
| | | | 2-0 | 0.13 | -0.39 | | 1.77 | 1.70 | -1.17 | 1.78 | 1.71 | -1.17 | 0.01 | 0.01 | 0.00 | 1% | 1% | 0% |
| | | | 3-0 | -0.64 | -0.39 | 0.83 | 1.76 | 1.70 | -1.18 | 1.78 | 1.72 | -1.17 | 0.02 | 0.02 | 0.01 | 1% | 1% | 1% |
| | building heights all building min max | 3 | | | | | 1.24 | 1.47 | -3.84 | 2.02 | 2.12 | -0.52 | 0.78 | 0.65 | 3.32 | 48% | 36% | 152% |
| green strip | green strip inner | 3 | | 0.34 | -0.84 | 0.90 | 1.77 | 1.60 | -1.22 | 1.97 | 1.77 | -0.88 | 0.20 | 0.17 | 0.34 | 11% | 10% | 32% |
| | green strip outer | 3 | | 0.66 | -0.77 | 0.89 | 1.75 | 1.61 | -1.23 | 2.04 | 1.75 | -0.88 | 0.28 | 0.14 | 0.36 | 15% | 8% | 34% |
| | Inner and outer green strip | 3 | | | | | 0.58 | 1.35 | -1.42 | 2.14 | 1.77 | -0.85 | 1.56 | 0.41 | 0.57 | 115% | 26% | 51% |

As can be seen from Table 28, the strongest correlations can be seen for offset design variables in parcellation category three. Furthermore, depending on the human perception category, all three design variable types can have a strong influence on a specific human perception score. The impact of individual buildings on the human perception scores is limited. A more detailed description of the findings is provided below.

### Offset

Regarding the impact of the offset variables on the overall human perception scores, it can be noted from the results of the sensitivity analysis that especially the two variables combined are able to influence the human perception scores relative strongly. This is especially the case for perceived liveliness, for which the offset distances are the most dominant design variable category based on the precentral ability to change the human perception score.

The correlation coefficients for the offset design variables for the parcellation category zero context is generally weak whereas the coefficients are generally strong for the parcellation category three context. Also, the signs swaps when the parcellation category changes concerning perceived safety in relation to the street offset and concerning all human perception categories in relation to the adjacent building distance. This behavior indicates a strong, specific, influence of the parcellation category. The change in direction of the correlation coefficient for the adjacent building offset distance can be explained by the behavior of the tool, as the tool removes buildings adjacent to each other if the offset between two buildings of different plots becomes too small only for parcellation categories one to three but not for parcellation category zero. Concerning the correlation coefficients in parcellation category three, it can be noted that in accordance with the MNL model, a larger street and adjacent building distance generally leads to lower perceived beauty and liveliness scores whereas it generally results in higher perceived safety scores.

Reflecting on Table 27, the relative high influence of offset distances on perceived liveliness can be explained by the relative large influence of the 'façade length index' attribute and the 'offset distance height ratio' attribute included in the relation between the built environment and perceived liveliness. For perceived beauty, the offset street distance directly influences the perceived beauty score through the attribute 'offset distance height ratio', which negatively influences the perceived beauty score as can be seen from Table 27. Explaining the negative influence of the design variable as well. Whereas the design variable 'offset adjacent building' does not seem to be directly related to perceived beauty through an influential built environment attribute, the influence and positive correlation for the parcellation zero base settings is likely to be the consequence of the attribute 'Offset distance height ratio' as well. As a result of larger distances between the building plots, the building footprints become smaller and the buildings become higher to meet the building volume requirements. Higher buildings that are not located further away from the street result in a lower offset distance height ratio and thus a higher perceived beauty score. Finally, concerning perceived safety, the offset distances result in different sky view shares, building view shares, median heights, footprint areas, and offset distance height ratios. The exact relation between the design variables and the perceived safety score is thus somewhat more difficult to explain solely based on the sensitivity analysis.

### Building height

The influence of the building height of single buildings on the overall human perception score is fairly limited, especially for, the finer parcellation category three. This, however, is not surprisingly as finer buildings cover less area and therefore less volume. When varying the building heights of all buildings, the building heights do have a relative strong influence on all human perception categories but especially on perceived safety. For the latter it is even the most dominant design variable category based on the precentral ability to change the human perception score.

Interesting to note is the large amount of insignificant correlation coefficients for the individual building height design variables. This is likely to be a consequence of among others a low number of observations. However, still this also means that the correlation found based on the small number of observations is mostly not strong enough to be found significant. Although, for perceived safety the correlation coefficient of the building height of the first building of the first and fourth plot has been found to be significant. These values also indicate a contradicting behavior, as increasing the height of the first building on the first plot has a negative influence on the perceived safety score whereas increasing the height of the first building on fourth plot has a positive influence on perceived safety. It is therefore difficult to say if the increase in building height of one building generally leads to lower or higher human perception scores. A potential explanation of this contradicting effect can be the requirement that the overall volume always needs to stay the same. Increasing one building in height thus results in decreasing other buildings in height if the footprints maintain the same. Also, the location of the points of analysis can be related to this. A building that is located within the buffer zone and within the line of sight of multiple points of analysis is likely to influence the score more strongly. Since all building heights together can influence human perception scores strongly, it can be stated that the exact composition of building heights is important in relation to human perception.

Reflecting on Table 27, higher buildings and building height variation generally influence the built environment attributes: 'height standard deviation relative', 'offset distance height ratio', 'absolute height difference', 'sky share', 'building share' and 'height median'. All human perception categories include at least two of these attributes so it could be expected that the general influence is quite high. However, for perceived beauty the dominance of the attribute 'tree share' could explain the fairly limited influence and because of the volume requirement the general influence of the 'offset distance height ratio' as a result of varying the building heights might be limited as well since reducing one building in height results in increasing another building in height. Furthermore, the limited influence of varying one building in height in relation to the relative high influence of varying all buildings for perceived liveliness could be the result of the attribute 'absolute height difference'. One building is likely to only affect a few points of analysis on this attribute whereas varying all buildings in height is able to affect all points of analysis on this attribute. The large influence of building heights on sky share can be explained by the attribute 'sky share' in relation to the attribute 'building share'. Minimizing sky share through increasing the building share in a view results in higher perceived safety scores, an optimal composition of the buildings by varying building height can influence this whereas for one building this influence is limited. Furthermore, increasing the height of the buildings laying in the buffer zone of most points of analysis positively contributes to the perceived safety score through the attribute 'height median'.

### Green strip

The green strip sensitivity analysis was only conducted on the parcellation three context. The reason for this is that the green strip width does not influence the building volumes of parcellation zero buildings different then parcellation three buildings and the other way around, the type of buildings varying per parcellation category do not influence the green strip width. From the sensitivity analysis, it can be seen that the combination of the inner and outer green strip width influences each of the human perception scores relatively strong but especially perceived beauty is influenced strongly.

For the width of the inner and outer green strip individually, it can be seen that the influence is relatively limited however a clear influence is visible in the correlation coefficients. The outer green strip most clearly influences perceived beauty positively whereas both the inner and outer green strip show the same clear influence for perceived liveliness (-) and perceived safety (+).

Reflecting on Table 27, the relative large influence of the green strip width on perceived beauty is in line with what can be expected from Table 27. The attribute 'tree share' namely is of large influence on perceived beauty and the green strip width is the only design variable influencing this. The attribute ‘tree share’ is less dominant in liveliness and influences perceived safety indirectly through the attributes ‘sky share’ and ‘building share’, explaining the lower influence of green strip width on perceived liveliness and safety. Furthermore, the maximum width of the street is constant so green strip width does not influence the other built environment attribute values. However, if the green strips are very narrow and the other street typology strips are relatively narrow as well, the total street width could be lower than the maximum street width. In this case, the distance between a building and the street centerline could become smaller. There is no indication from Table 28 that this dynamic influenced the human perception scores a lot.

### 5.2.5. Conclusion OAT sensitivity analysis

In conclusion, Table 28 provides a clear overview of the strength of the most relevant design variables on each human perception score. Perceived beauty is mostly influenced by the green strip widths, perceived liveliness is mostly influenced by the offset distances and perceived safety is mostly influenced by the building heights. Additionally, the offset and green strip width design variables show relative direct relationships with the human perception scores, showing the strongest and least fluctuating correlation coefficients, whereas the building heights of the individual buildings can have a strong collective influence if placed in a certain composition. The exact composition determines if an increase in building height leads to an in- or decrease in human perception score. Furthermore, it can be seen from the different contexts in which the sensitivity analysis is conducted that also the parcellation category can have quite a strong influence on the human perception scores. On general, parcellation category zero resulted in higher human perception scores then parcellation category three.

Finally, due to the nature of the OAT analysis, it remains unknown to which extent interactions between all design variables are able to influence the human perception scores and to which extent an individual design variable contributes to this overall influence.

## 5.3. Single objective optimization

For each of the three human perception categories a single objective optimization is run. The objective of these optimizations was to maximize the respective human perception score. Within this section, a subsection describes the results from the optimization runs per human perception category. In addition, a brief reflection on the sensitivity analysis is included per human perception category. As for the sensitivity analysis, the optimization runs have only been conducted for the high density relations in the high density context. Finally, the optimization results for optimizing for each of the human perception categories are related to each other. The overall results are not yet reflected on the literature, research phase one and two. This will be done in the conclusion, discussion and recommendation chapter.

### 5.3.1. Perceived beauty

Regarding perceived beauty, the following remarks can be made based on the optimization output: the output has the roughest parcellation category, zero. Furthermore, the street offset distance is fourteen meters and the adjacent building offset distance is twenty-one meters. These values result in the removal of the corner building on plot zero (see Figure 54 for the location of plot zero). The inner green strip is thinner than the outer green strip, being respectively seven and ten meters. There is no canal so the two inner green strips are laying adjacent to each other. Finally, there is a slight variation in building heights for the remaining three buildings.

In relation to the sensitivity analysis, the set rough parcellation category zero is in line with what could be expected as the roughest parcellation category in the sensitivity analysis shows higher minimum and maximum scores than the finest parcellation category. The adjacent building offset distance has a positive correlation with the perceived beauty score, as visible from the sensitivity analysis. The relative high value of 21 meters, 30 meters is the maximum offset distance, therefore is also as expected from the sensitivity analysis. There are likely to be many reasons that it has not been set to the maximum. For example this could have been caused by the volume requirement or the daylight requirement, both generally prevent buildings from becoming too thin and high. The street offset distance of fourteen is somewhat less straightforward based on the sensitivity analysis. For parcellation category zero it has a weak negative correlation (r=-0.07), so there does not seem to be a direct relation between the street offset distance and the perceived beauty score. The value of fourteen is likely to be a result of the dynamics in the design generation process influenced by the street offset distance value. The relative high green strip widths are also in line with the finding from the sensitivity analysis that the outer green strip width is positively correlating with the perceived beauty score (r=0.66). In addition, the influence of the two green strip widths combined is the highest from all design variable combination concerning perceived beauty. Therefore, the relative high values of seven and ten meters are as expected. Table 29 contains the design variables of the important design variables as well as the human perception scores and Figure 56 present visuals of the on perceived beauty optimized design.

*Table 29: Perceived beauty optimization output design variable values and human perception score values*

| Design variable | Value |
|---|---|
| **Percelation category** | 0 |
| **Street offset** | 14 |
| **Adjacent building offset** | 21 |
| **Inner green strip width** | 7 |
| **Outer green strip width** | 10 |
| **Human perception category score** | **Value** |
| **Perceived beauty score** | 2.39 |
| Perceived liveliness score | 1.92 |
| Perceived safety score | -1.88 |

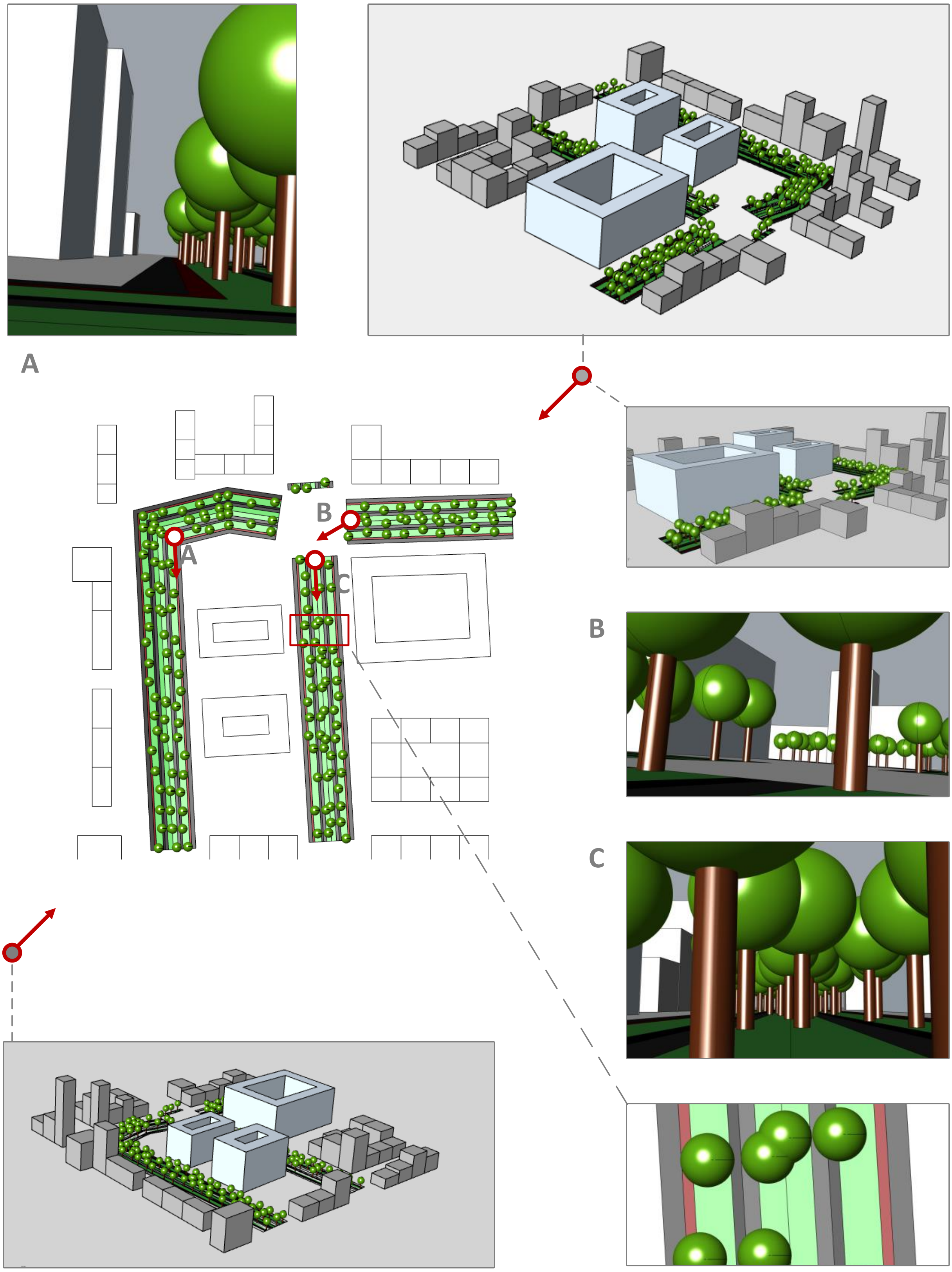



*Figure 56: Overview of beauty optimization output*

### 5.3.2. Perceived liveliness

Regarding perceived liveliness, the following remarks can be made on the retrieved output: The computer sets the parcellation category to one, sets a reasonable small street offset of three meters, an adjacent building offset of nine meters resulting in separated building blocks and wide green strips in which the outer green strip is set as the widest.

Reflecting this on the sensitivity analysis, it could have been expected that the parcellation category zero would have been selected when comparing the scores of the parcellation zero context with the parcellation three context, in which parcellation zero showed the highest minimum and maximum results. However, the sensitivity analysis is run in a context in which all building heights except of the varied one are equal. As can be seen in Figure 57, the building heights vary in the optimized output. This degree of variation would not have been possible with parcellation zero. The importance of height variation is in line with the relative high influence of building heights as visible from the sensitivity analysis. Table 30 contains the design variables of the important design variables as well as the human perception scores. Figure 57 presents visuals of the on perceived liveliness optimized design.

*Table 30: Perceived liveliness optimization output design variable values and human perception score values*

| Design variable | Value |
|---|---|
| Percelation category | 1 |
| Street offset | 3 |
| Adjacent building offset | 9 |
| Inner green strip width | 7 |
| Outer green strip width | 10 |
| **Human perception category score** | **Value** |
| Perceived liveliness score | 2.04 |
| Perceived beauty score | 2.31 |
| Perceived safety score | -1.80 |

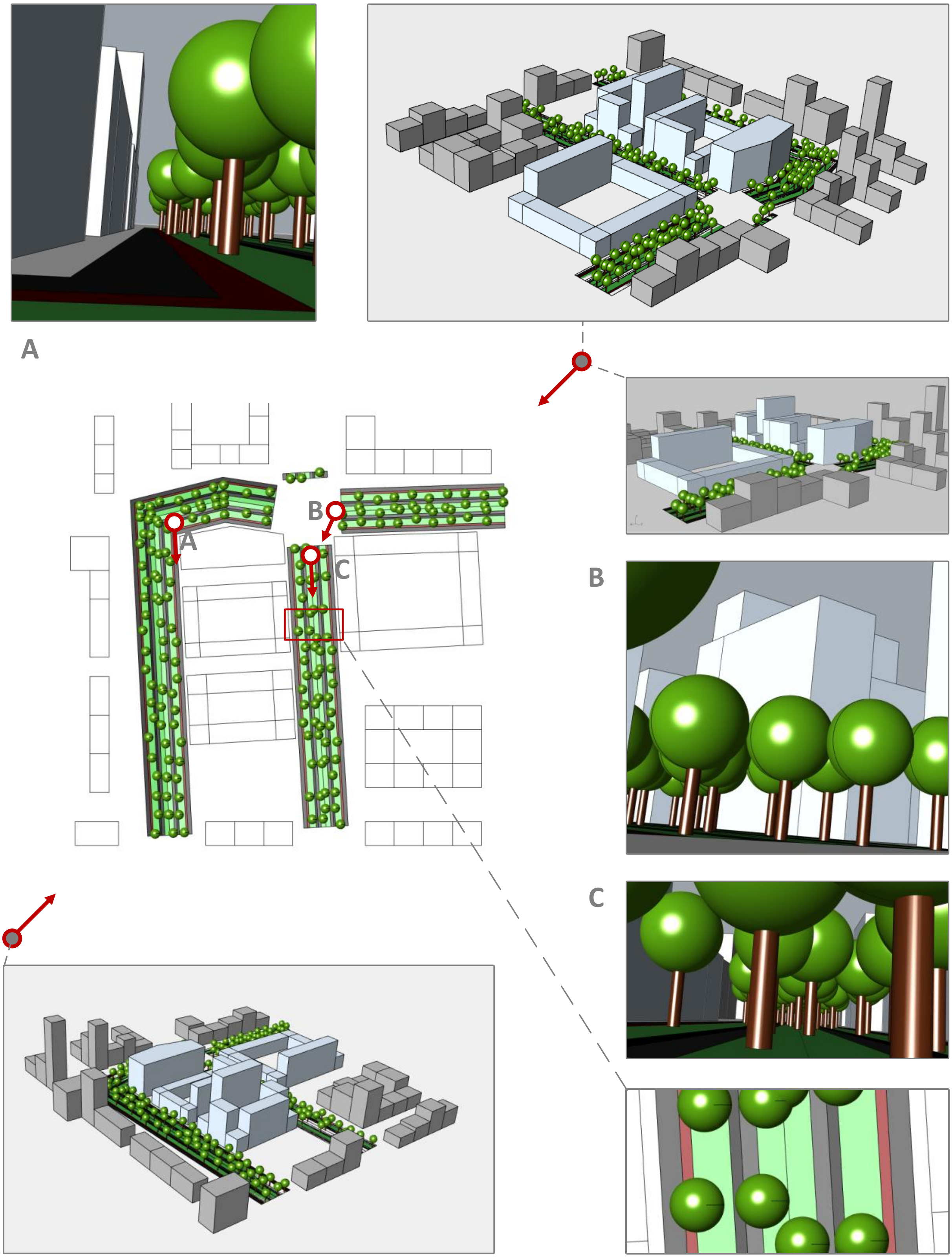



*Figure 57: Overview of liveliness optimization output*

### 5.3.3. Perceived safety

Regarding perceived safety, the following remarks can be made on the retrieved output: As for perceived liveliness, the computer has set the parcellation category to one. The street offset is somewhat higher in relation to perceived liveliness and beauty, being eight meters. The Adjacent building offset is ten meters, again resulting in the separation of the building plots. The, in relation to perceived beauty and liveliness, higher offset distances result in general higher average building heights. The green strip widths are again set to relative large values of nine meters for the inner strips and ten meters for the outer strips, making the outer strips again larger. Furthermore the inner green strips are separated by a canal. Finally, as can be seen from **Fout! Verwijzingsbron niet gevonden.**, the building heights of the individual buildings show quite some variation.

Reflecting these results on the sensitivity analysis, not setting the parcellation category to zero seems logical as, the finer parcellation category three shows higher perceived safety results. Although, not the finest parcellation category is set by the computer for maximum perceived safety scores as parcellation category one is selected. Furthermore, the positive correlation with the offset distances for the non parcellation zero category context in the sensitivity analysis is in line with the, in relation to perceived beauty and liveliness, higher offset distances. Finally, the large variation in building heights are likely to be a result from the relative high impact of building heights on the overall perceived safety score. Table 31 contains the design variables of the important design variables as well as the human perception scores. Figure 58 presents visuals of the on perceived safety optimized design.

*Table 31: Perceived safety optimization output design variable values and human perception score values*

| Design variable | Value |
|---|---|
| Percelation category | 1 |
| Street offset | 16 |
| Adjacent building offset | 0 |
| Inner green strip width | 12 |
| Outer green strip width | 15 |
| **Human perception category score** | **Value** |
| Perceived safety score | -0.23 |
| Perceived beauty score | 0.69 |
| Perceived liveliness score | 1.02 |

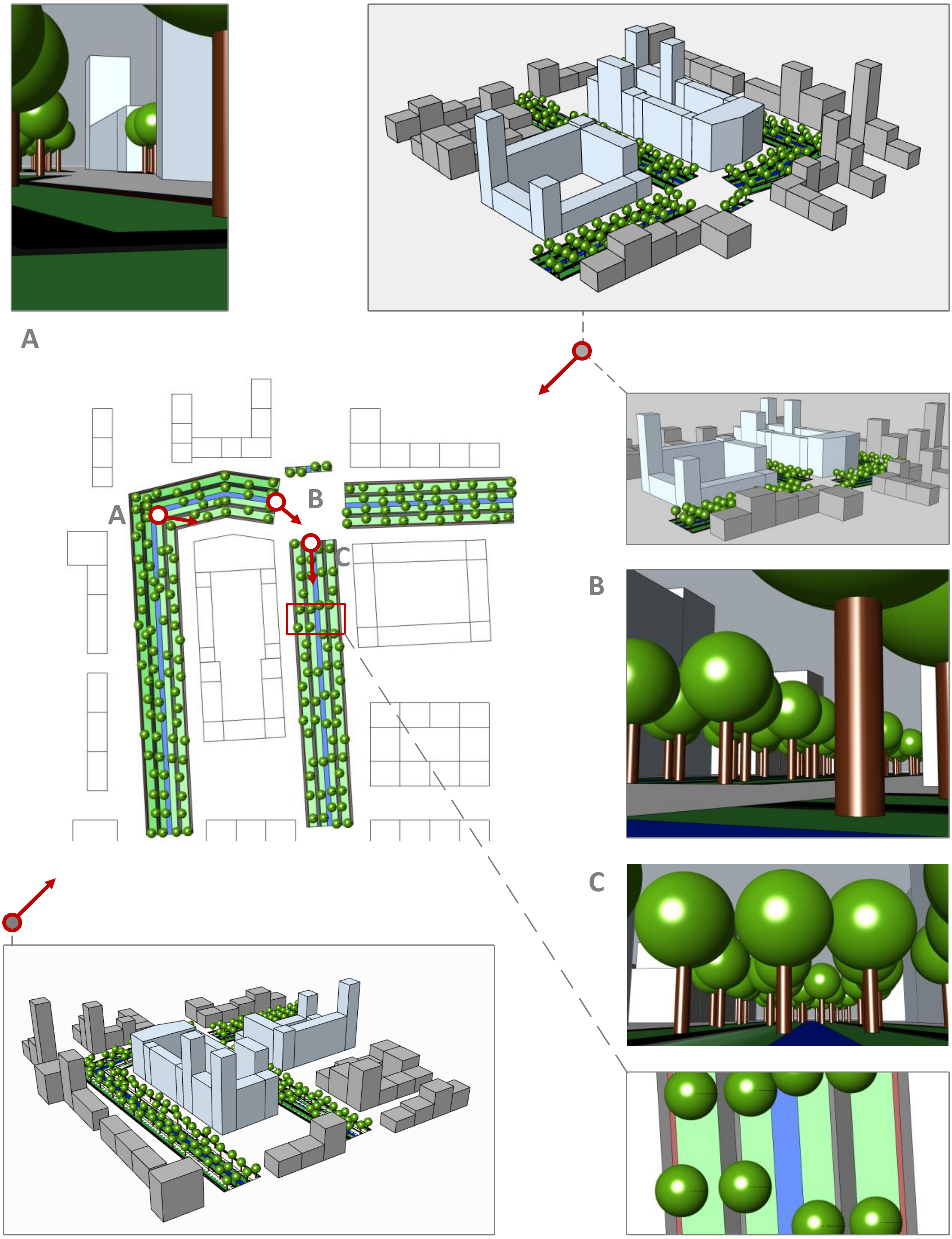



*Figure 58: Overview of safety optimization output*

### 5.3.4. Relating perceived beauty, liveliness, and safety to each other

Relating the design variable values of perceived beauty, liveliness, and safety results in the following remarks: First of all, only perceived beauty has parcellation category zero. In combination with the fewer variation in building heights, seen from Figures 56, 57 and 58 above, the perceived beauty optimal design can be considered as simpler and more uniform. Liveliness has the smallest offset distances so the building footprints are the largest but the mean height the lowest, liveliness does however show the most variation in building heights. Concerning the green strip widths, it can be seen that for perceived beauty and liveliness, the inner green strip is thinner than the outer green strip whereas this is the other way around for perceived safety. The perceived safety optimization output design is also the only one having a canal. This difference could be a consequence of the view share attributes included for the human perception relations. The equation calculating the perceived beauty and safety score include tree share, whereas the equation calculating perceived safety includes building share and sky share but not tree share. Here building and sky share do have a negative influence on perceived safety, so the tree share is likely to be maximized. However, sky share has a larger negative effect on perceived safety then building share. As a result, the way tree share is maximized for perceived safety could differ since not only tree share is maximized but also sky share is minimized. The preference of building share over sky share concerning perceived safety could be a reason why the adjacent building offset distance is set to zero, especially as the façade length index is not included in the calculation for perceived safety.

From the human perception score, specifically in relation to the above, it is interesting to see that the optimized output for perceived liveliness shows a very high perceived beauty score as well (2.31) which is slightly lower than the perceived beauty score for the optimized perceived beauty output (2.39). The other way around, this also applies but not as strongly as the perceived liveliness score of the optimal perceived beauty design is 1.92 whereas the perceived liveliness score for the optimal perceived liveliness design is 2.04. This could be the consequence of the, in relation to perceived liveliness and safety, high dependency of perceived beauty on the tree share. The green strip widths are namely the same in the optimal perceived beauty and optimal perceived liveliness design. Furthermore it is interesting to see that the optimal perceived safety score leads to relative low perceived beauty and liveliness scores. Table 32 provides on overview of the design variable values and human perception scores of the on all three different human perception categories optimized designs.

*Table 32: The design variable and human perception score values of perceived beauty, liveliness, and safety related to each other*

| Design variable | Beauty value | Liveliness value | Safety value |
|---|---|---|---|
| **Percelation category** | 0 | 1 | 1 |
| **Street offset** | 14 | 3 | 16 |
| **Adjacent building offset** | 21 | 9 | 0 |
| **Inner green strip width** | 7 | 7 | 12 |
| **Outer green strip width** | 10 | 10 | 15 |
| **Human perception category score** | **Value** | | |
| **Perceived beauty score** | **2.39** | 2.31 | 0.69 |
| **Perceived liveliness score** | 1.92 | **2.04** | 1.02 |
| **Perceived safety score** | -1.88 | -1.80 | **-0.23** |

## 5.4. Multi objective optimization

In this section, the output of a run multi objective optimization is provided and described. The above section, on the single optimization, already described several conflicts between the design variable values and the human perception scores.

The output of the multi objective optimization is presented by the Octopus plugin in Grasshopper through a 3D scatterplot. Here every point represents a design in the Pareto front, meaning that the in Figure 59 visualized points represent designs that cannot be improved on one human perception category without decreasing the score of another human perception category.

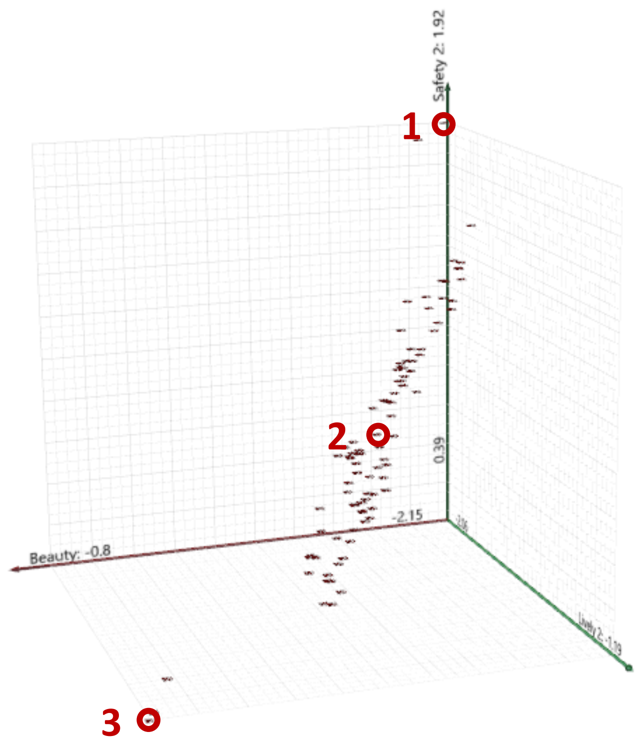



*Figure 59: Pareto front represented in the output 3D scatterplot*

The output has been generated based on 25 generations all consisting of 100 designs. The designs have been multi-objectively optimized using genetic optimization. In contradiction to the single objective optimization, generally fewer generations have been produced. More generations would likely result in a slightly higher score, however, would also require more computation time. In contradiction to the single objective optimization, the goal of the multi objective optimization is not to find the most optimal design but to demonstrate the results of a comprehensive optimization process considering more than one human perception category and considering the practical use of the created tool. In practice, the goal is to get supported during the design process and to get informed on potential design solutions aligning to human perception. The required time to do so is an important consideration here. Below, several designs have been highlighted from the Pareto front, in Figure 59 these designs have been marked by numbers one to three. Starting with the design that maximizes perceived safety while not considering perceived beauty and liveliness, this design is presented in Figure 60 (1 in Figure 59). Second, the design balancing the three human perception categories is presented in Figure 61 (2 in Figure 59). Third, the design aligning optimally to perceived beauty and liveliness but not to perceived safety is presented in Figure 62 (3 in Figure 59). Finally, the design variable values and human perception scores of t

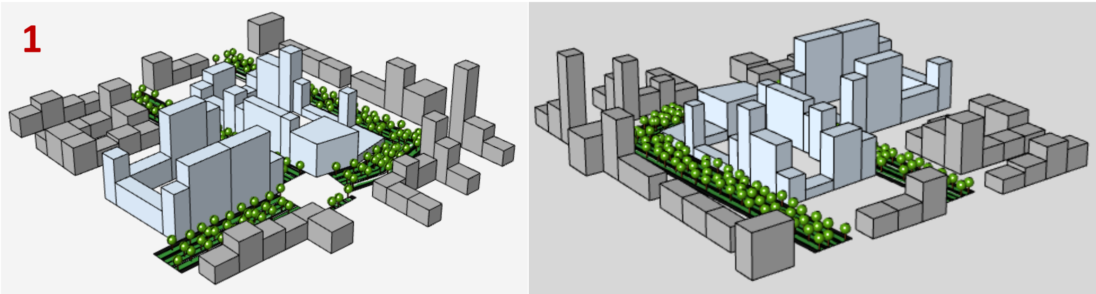



*Figure 60: Pareto front optimized design perceived safety*

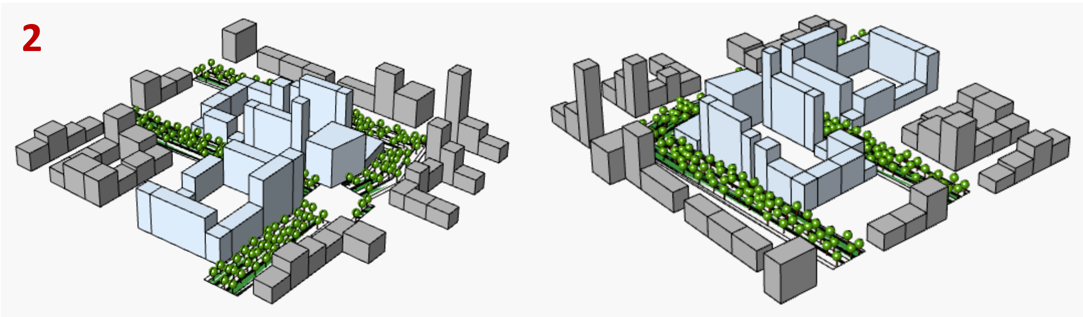



*Figure 61: Pareto front optimized design balance of the three human perception categories*

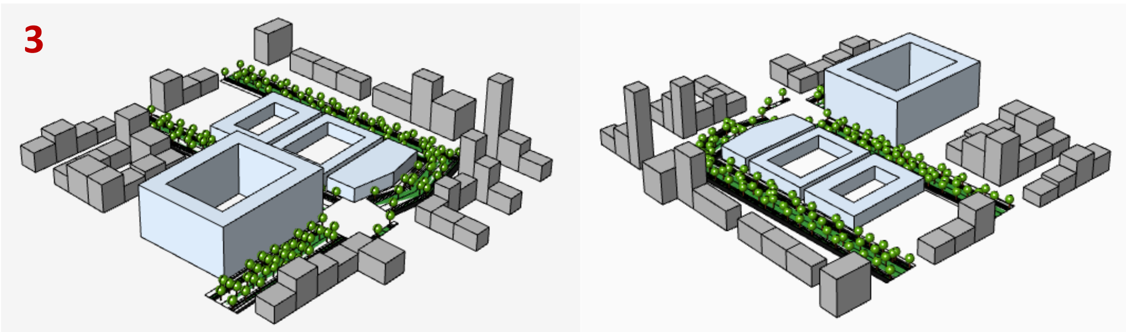



*Figure 62: Pareto front optimized design perceived beauty and liveliness*

From the multi-objective optimization it appears that perceived beauty and liveliness seem to go hand in hand when optimizing for one of them as there are only slight variations in the perceived beauty and safety scores for the designs in the Pareto front. Perceived safety seems to be conflicting with perceived beauty and liveliness in the Pareto front. This is also visible in the three highlighted designs, the designed marked by one shows a relative high perceived safety but relative low perceived beauty and liveliness scores. The design marked by three shows relative high perceived beauty and liveliness scores but a relative low perceived safety score.

*Table 33: Design variable values and human human perception scores for output one to three in the Pareto Front*

| **Design variable** | **1** | **2** | **3** |
|---|---|---|---|
| **Percelation category** | 2 | 2 | 0 |
| **Street offset** | 1 | 2 | 2 |
| **Adjacent building offset** | 0 | 3 | 3 |
| **Inner green strip width** | 16 | 12 | 15 |
| **Outer green strip width** | 17 | 20 | 4 |
| **Human perception category score** | | | |
| **Perceived beauty score** | 0.80 | **1.72** | **2.14** |
| **Perceived liveliness score** | 1.19 | **1.72** | **2.06** |
| **Perceived safety score** | **-0.39** | **-0.94** | -1.92 |

## 5.5. Conclusion Results

Using a test scenario, being a part of an TUDPUD output design surrounded by a high density context, the created computational urban design tool has been tested on its outcomes. The results have been presented first in the form of a sensitivity analysis, after which the single objective optimization result for each human perception category was presented and finally several results of the conducted multi-objective optimization have been presented. From this set of analysis and optimization runs the following conclusions can be drawn:

Concerning perceived beauty, the single objective optimization on perceived beauty includes wide green strips. From the street views it can be seen that the street view is dominated by trees as a result of this. Furthermore, the optimized result has parcellation category zero. The adjacent building distance is that large, in combination with the street offset distance, that the plot zero building is removed. The removal of this building on its hand leads to higher mean building heights. This is all in accordance with the sensitivity analysis showing the green strip width to be most influential, a positive correlation between perceived beauty and the adjacent building offset distance and higher scores for parcellation category zero. Furthermore, the behavior and tradeoffs that had to be made to steer the design towards having a high median height, relative equal building heights and a minimal distance to street is in line with the findings from the multinomial logit analysis.

Interesting to see in the single optimization is the behavior of the scores for perceived beauty and liveliness whereas perceived safety scores do not seem to increase or decrease simultaneously with perceived beauty or liveliness. Perceived liveliness shows more variation in building heights in relation to perceived beauty which can be expected based on the sensitivity analysis and the multinomial logit analysis results. This variation is only possible with finer parcellation categories, explaining the finer parcellation category. Furthermore, comparable street typologies can be found for perceived liveliness and beauty, likely to be the consequence of maximizing tree share in the street view.

The perceived safety single optimization output shows a different street typology, likely to be the result of the attributes building share and sky share instead of tree share to be present in the for perceived safety incorporated relationship. The buildings are clustered without space between the individual parcels, maximizing the building share while minimizing the sky share in the street view. The relatively large street offset distance for perceived safety can be explained by the consequence that it decreases the offset distance height ratio whereas it increases the median building height.

The multi-objective optimization highlights that indeed perceived beauty and liveliness are related to each other. Probably due to the dominance of the tree share attribute in the incorporated formulas calculating the human perception scores. The multi-objective optimization furthermore has shown to be a fast and insightful optimization tool enabling the user to make insightful tradeoffs between designs having different impacts on different human perception scores. The optimal outcomes for each individual human perception category are approaching the optimal outcomes as found from the single objective optimization runs while requiring significant less computation time.

Altogether, the results of the created computational urban design tool show explainable and understandable outcomes based on the found relations between the human perception categories and the volumetric built environment. The incorporated requirements and relationships have been able to implement trade-offs that had to be made by the computer during the optimization process. This results in a dynamic design generation process, generating predominantly green volumetric urban designs that are positively aligned to how humans perceive the built environment.

# 6. Conclusion, discussion & recommendation

Within this thesis, an attempt to incorporate human perception in computational urban design has been described. This attempt was successfully completed, resulting in computationally generated designs that have been optimized to maximally align to perceived beauty, liveliness, and safety. Based on the process of this attempt, many lessons have been learned on how to incorporate human perception in computational urban design. Using the demonstrated approach to incorporate human perception in computational urban design and the lessons learned from this approach, incorporating human perception in computational urban design will be able to strengthen computational urban design as supportive tool in the conceptual design phase of an urban development.

Figure 63 visualizes how this chapter relates to the overall research design. It can be seen how this chapter reflects upon, and uses, the findings from all main parts of this thesis. Including the findings from the literature, the findings from research phase one and two but specifically also the overall results of this research as described in chapter five.

Within this chapter, first a conclusion will be drawn formulating an answer to the main research question: How can the perception of humans be included in computational urban design? Followed by a discussion, identifying the most important remarks that have to be made on the research process, decisions and results. Finally, this chapter ends with a section including recommendations for future research on incorporating human perception in computational urban design.

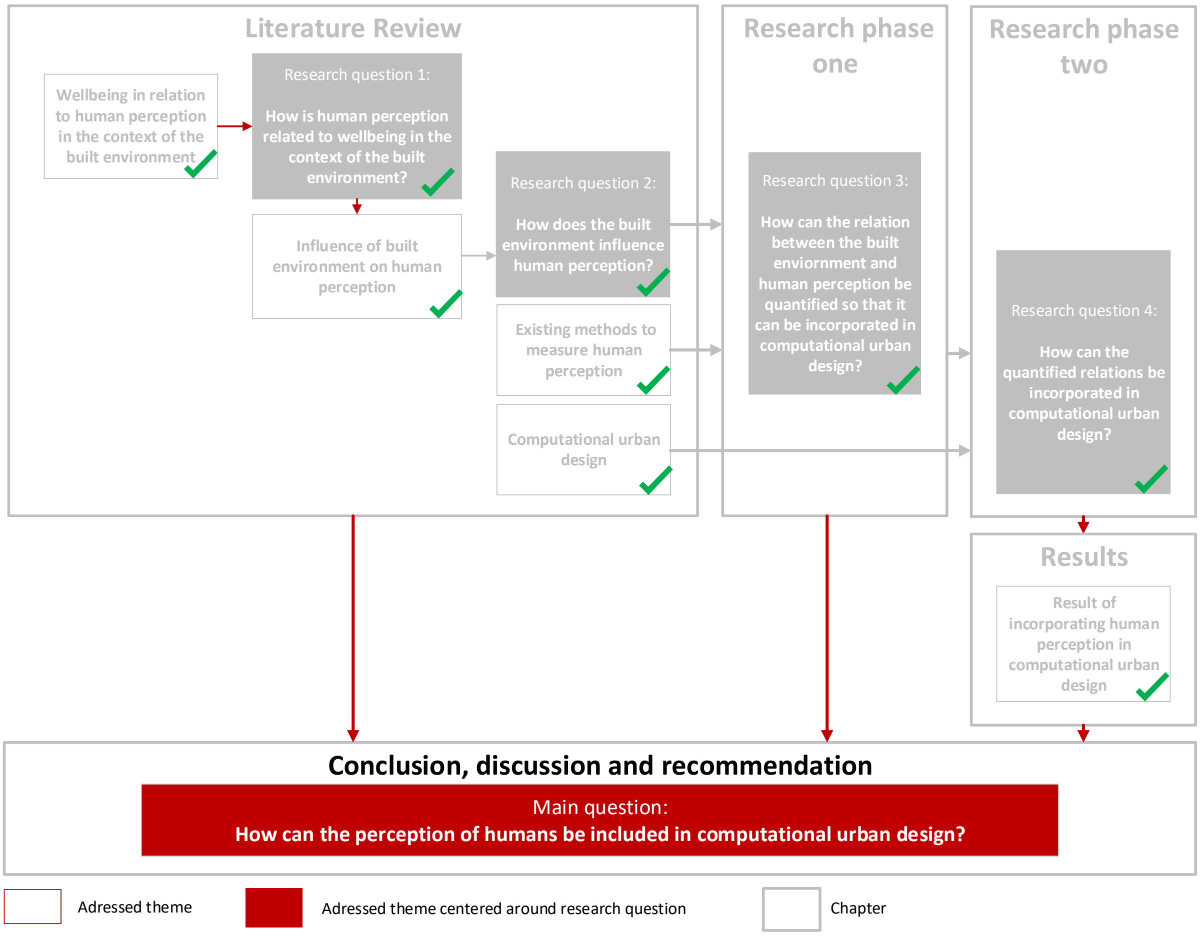



*Figure 63: Conclusion, discussion and recommendation chapter in relation to the overall research design*

## 6.1. Conclusion

In order to provide an answer to the question: How can the perception of humans be included in computational urban design, first a brief reflection on the four main phases of this research is provided below.

Based on a conducted literature review on the question: How is human perception related to wellbeing in the context of the built environment, it was found that perceived beauty, liveliness, and safety influence human wellbeing. Literature mentions many built environment elements that influence these three human perception categories. Relating these relations to computational urban design, it can be stated that specifically the volumetric built environment elements influencing human perception are relevant in this research as computational urban design is strongest in generating conceptual designs.

Formulating an answer to the question: How can the relation between human perception and the built environment be quantified so that it can be incorporated in computational urban design? Using multinomial logit analysis applied on a dataset retrieved using a big data approach was found to result in understandable and quantified relationships between the volumetric built environment and each of the three human perception categories. The big data approach includes street view images, respondent choices between street view images regarding human perception and open built environment data. As a result of the analysis, the presence of trees is found to have a strong positive influence on each human perception category. However, also the building composition, height and street width have been found to influence perceived beauty, liveliness, and safety.

In research phase two, it has been demonstrated that these found and quantified relationships can be incorporated in computational urban design. The Grasshopper implementation script created in this research concerned a generative design component built on top of a parametric urban design component, resulting in an overall computational urban design tool. As a result, the user is able to implement important design considerations manually first after which the design can be optimized on human perception.

In computational urban design, a design is generated based on design variables. The human perception scores and the design variable values of the optimized design can be related to the incorporated relationship, among others through the results of a sensitivity analysis. However, the results also highlight that the design generation process and the set of requirements have a strong influence on the output designs. The requirements and limitations from the design generation process guarantee the incorporation of other design aspects. Preventing the design variables to reach values leading to non-realistic designs that are purely based on the incorporated relationships, containing for example buildings not receiving enough daylight. As a result, it can be concluded that it is important for a computational urban design tool to comply to multiple design aspects, especially when implementing quantitative relationships concerning human perception.

Altogether, the following answer to the research question can be formulated: human perception can be incorporated in computational urban design by implementing understandable and proven functions describing the relation between human perception and the built environment. However, the design freedom should be limited by requirements in order to make sure that design aspects are included as well.

As a result, this research contributes to knowledge and research in the field of computational urban design by demonstrating a method to incorporate human perception in computational urban design. Based on this research, human wellbeing can be addressed in computational urban design through the incorporation of human perception. Although the demonstrated method requires improvement in accuracy, current practice can benefit from this research as the applied methodology results in useful insights regarding the perception of humans in computationally generated designs. Altogether, strengthening computational urban design as supportive tool in the urban design and development process.

## 6.2. Discussion

Throughout this thesis, the applied methods and the implications of these methods on the intermediate results have been discussed already per research phase. From the literature review, it has become clear that the volumetric built environment measured on the objective perception of humans is likely to only explain a part of an individual's perception on the built environment. Findings from research phase one confirmed this, as the found relationships between the volumetric built environment and human perception was relative weak. However, it was also discussed that this could also be partially caused by the applied methodology, being a big data approach including not fully consistent and accurate data. As a result, other methods such as measuring human perception through virtual environments, would likely have resulted in stronger relationships as the environment is controlled minimizing the non-captured built environment influence on human perception. Also, the data describing the captured built environment elements is more accurate and consistent in created virtual environments. However, virtual environments are less realistic, making the potentially found relationships less reliable. Furthermore, the used approach of using street view images of existing environments also contributes to the understanding of the importance of the volumetric built environment on human perception in relation to non-volumetric built environment elements on human perception. Based on the results, the influence of the volumetric built environment on human perception is likely to be limited. However, in order to understand this thoroughly, research is needed that enables a comparison between the strength of the relations between human perception and non-volumetric built environment elements and human perception and volumetric built environment elements. Only when this comparison is accurately made, it can be stated to which extent human perception can be incorporated in computational urban design that focusses on generating volumetric urban designs.

Furthermore, human perception in relation to the built environment is a complex relationship, involving many different elements. In order to accurately relate the built environment to human perception, not only built environmental characteristics should be known but also socio-demographical characteristics of the respondents should be known. Additionally, the composition of the built environment elements is likely to be relevant as well. As a result, many different interactions between the built environment elements could result in completely different types of built environments, associated with different perceptions that vary per individual. Discrete choice models enable the incorporation of many different attributes, built environment elements or socio-demographic characteristic, including interactions between them. However, correlations between the variables may become a problem. Furthermore, many less influential attributes are likely to be insignificant in discrete choice models. However, since human perception in relation to the built environment is a complex relationship, there might be many less influential attributes influencing human perception. Individually these attributes could seem insignificant but collectively the influence might be relative strong. For quantifying human perception in relation to the built environment more accurately, it would be relevant to further study the potential of other analysis methods on more extensive datasets. Including socio demographic data on the respondents and methods for inclusion of a large pool of attributes and combinations of attributes for which the individual influence is limited but the collective influence could be significant.

Yet, the multinomial logit model has shown to be a suitable model for this research, providing insight in the relation between human perception and the built environment by pointing out the most dominant attributes and enabling the incorporation of these attributes in computational urban design.

## 6.3. Recommendation

As mentioned in the conclusion, the in this thesis described methodology for incorporating human perception in computational urban design can be considered as a suitable methodology based on the described execution of this methodology. Yet, many things can be improved so that it is possible to generate urban designs with computational urban design, that are aligned to human perception, faster, more accurate and more comprehensive.

It was found that different urban densities result in different relations between human perception and the volumetric built environment. As the data availability was too scarce to distinguish between more urban environment categories in the analysis, it was not possible to study the relation between human perception and the built environment for specific urban typologies. Although, it was shown that it is possible to classify locations based on the urban typology in the surrounding using volumetric built environment characteristics. Studying the relations between human perception and the volumetric built environment for every urban typology could result in interesting and more accurate relations. If more volumetric building data becomes openly available, more of these classifications can be made to study the relation between the volumetric built environment and human perception for different urban environments. Furthermore, using crowdsourcing to gather human perception choices can result in large datasets such as the Place Pulse 2.0 dataset. However, in order to understand the perception of humans in relation to the built environment better, future research could focus on extending the data gathering process by asking respondents socio-demographic information. When different relations between human perception and the built environment can be quantified for different socio-demographic groups, a computational urban design tool is able to optimize a design for the target group of the area.

Furthermore, there are many built environment elements that can be studied more extensively or that can be added. This research again highlights the importance of greenery in urban environments in relation to human perception. However, here only the share of trees visible in the street view has been included. Since greenery is of such importance, more detailed but yet volumetric greenery elements could be included in future research that incorporates human perception in computational urban design. For example, the height and width of the trees.

In addition, other volumetric built environment elements can be included, for example attributes describing significant variations in the shape of a building. Within this research, solely the total area and one reference height is used. Since the height, offset and area of buildings all have an influence on human perception, a difference can be expected between a rectangular building with a straight façade in relation to a circular building of which the highest floors are set back further away from the street. However, in order to describe variations in these shapes additional open building data is needed, describing the shape of buildings more detailed and accurate. Furthermore, concerning the street typology, within this research only the width of the green strip directly influences the human perception score through the number of streets. Future research could focus on describing the street typology more detailed by including directly related attributes in the analysis, such as the presence of a parking strip, the car road width, the pedestrian path width, etcetera.

Concerning the computational urban design process, the following recommendations can be made for future research incorporating human perception in computational urban design: first of all, more design freedom can be incorporated in the computational urban design tool concerning the shape of the building. For example, allowing a building to have a different offset for the higher levels or allowing the footprint of the buildings to be set independently per building. Secondly, there is still room for improvement on the pace of the design generation and analysis process. The current optimization tool requires generally many hours to find an optimal design and since a fast optimization process is preferred in relation to its potential use in practice, the time of one design generation and analysis run should be minimized in order to lower the cost, expressed in time, of increasing the design freedom. In relation to this, increasing the design freedom should always be well considered as it is directly related to an increase in computation time as more design freedom simply results in more options to be explored.

Finally, looking further into the future, a computational urban design tool is preferred that is able to incorporate the perception of the target group of an area when computationally generating an urban design. It should do so very accurately in order to become useful in practice, considering the objective of computational urban design to be a supportive tool by speeding up development processes and improving the quality of the outcome of computationally generated designs. The current methodology, although there is room for improvement, could lack in accuracy to become as supportive as desired to be useful in practice. This could be a result of the lack of influence of the volumetric built environment on human perception in relation to the influence of the non-volumetric built environment on human perception, limiting the potential of the incorporation of human perception in computational urban design. However, this could also be a result of the lack of accuracy of the applied methods. Therefore, the most important focus of future studies attempting to incorporate human perception in computational urban design should be to increase the accuracy of the incorporated relationships. Here, other methods then using a big data approach including multinomial logit analysis could be considered. Including an analysis on the relation between human perception and the built environment for different target groups and for different urban environments.

## References


Agugiaro, G., González, F. G. G., & Cavallo, R. (2020). The city of tomorrow from . . . The data of today. *ISPRS International Journal of Geo-Information*, *9*(9). https://doi.org/10.3390/ijgi9090554

Al Mushayt, N. S., Dal Cin, F., & Barreiros Proenca, S. (2021). New Lens to Reveal the Street Interface . A Morphological-Visual Perception Methodological Contribution for Decoding the Public / Private Edge of Arterial Streets. *Sustainability*, *13*. https://doi.org/https://doi.org/10.3390/su132011442

Alhasoun, F., & Gonzalez, M. (2019). Streetify: Using Street View Imagery and Deep Learning for Urban Streets Development. *2019 IEEE International Conference on Big Data*, 2001–2006. https://doi.org/10.1109/BigData47090.2019.9006384

Alkhresheh, M. M. (2007). *Influence on user's sense of comfort and safety* [University of Florida]. http://ufdc.ufl.edu/UFE0019676/00001

Altomonte, S., Allen, J., Bluyssen, P. M., Brager, G., Heschong, L., Loder, A., Schiavon, S., Veitch, J. A., Wang, L., & Wargocki, P. (2020). Ten questions concerning well-being in the built environment. *Building and Environment*, *180*. https://doi.org/10.1016/J.BUILDENV.2020.106949

Austin, D. M., Furr, L. A., & Spine, M. (2002). The effects of neighborhood conditions on perceptions of safety. *Journal of Criminal Justice*, *30*(5), 417–427. https://doi.org/10.1016/S0047-2352(02)00148-4

Batool, A., Rutherford, P., McGraw, P., Ledgeway, T., & Altomonte, S. (2020). View preference in urban environments. *Lighting Res. Technol*, 613–636. https://doi.org/10.1177/1477153520981572

Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning*, *215*. https://doi.org/10.1016/j.landurbplan.2021.104217

Birenboim, A. (2018). The influence of urban environments on our subjective momentary experiences. *Environment and Planning B: Urban Analytics and City Science*, *45*(5), 915–932. https://doi.org/10.1177/2399808317690149

Birenboim, A., Bloom, P. B. N., Levit, H., & Omer, I. (2021). The study of walking, walkability and wellbeing in immersive virtual environments. *International Journal of Environmental Research and Public Health*, *18*(2), 1–18. https://doi.org/10.3390/ijerph18020364

Birenboim, A., Dijst, M., Ettema, D., de Kruijf, J., de Leeuw, G., & Dogterom, N. (2019). The utilization of immersive virtual environments for the investigation of environmental preferences. *Landscape and Urban Planning*, *189*(April), 129–138. https://doi.org/10.1016/j.landurbplan.2019.04.011

Boeing, G. (2017). OSMnx : New Methods for Acquiring , Constructing , Analyzing , and Visualizing Complex Street Networks. *Computers, Environment and Urban Systems*, *65*, 126–139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004

Bonaiuto, M., Fornara, F., & Bonnes, M. (2003). Indexes of perceived residential environment quality and neighbourhood attachment in urban environments : a confirmation study on the city of Rome. *Landscape and Urban Planning*, *65*(1–2), 41–52. https://doi.org/10.1016/S0169-2046(02)00236-0

Boston Planning and Development Agency. (2021). *3D Smart Model*. http://www.bostonplans.org/3d-data-maps/3d-smart-model/3d-data-download

BuildZero. (2021). *Opencitymodel*. https://github.com/opencitymodel/opencitymodel

Byoung-Suk, K., Rosenblatt Naderi, J., Praveen, M., & Shin, W.-H. (2004). *CORRELATES OF ENVIRONMENTAL CONSTRUCTS AND PERCEIVED SAFETY ENHANCEMENTS IN PEDESTRIAN CORRIDORS ADJACENT TO URBAN STREETS.*

ÇalıŞKan, O. (2017). Parametric design in urbanism: A critical reflection. *Planning Practice and Research*, *32*(4), 417–443. https://doi.org/10.1080/02697459.2017.1378862

Çalışkan, O., & Barut, Y. B. (2022). Pluralist production of urban form: towards a parametric development control for unity in diversity. *Journal of Urban Design*, *00*(00), 1–26. https://doi.org/10.1080/13574809.2022.2050892

Chamilothori, K., Chinazzo, G., Rodrigues, J., Dan-Glauser, E., Wienold, J., & Andersen, M. (2019). Subjective and physiological responses to façade and sunlight pattern geometry in virtual reality. *Building and Environment*, *150*, 144–150. https://doi.org/https://doi.org/10.1016/j.buildenv.2019.01.009

Chen, C., Li, H., Luo, W., Xie, J., Yao, J., Wu, L., & Xia, Y. (2022). Predicting the effect of street environment on residents' mood states in large urban areas using machine learning and street view images. *Science of the Total Environment*, *816*. https://doi.org/10.1016/j.scitotenv.2021.151605

Chi, D. A., González, M. E., Valdivia, R., & Gutiérrez, J. E. (2021). Parametric design and comfort optimization of dynamic shading structures. *Sustainability*, *13*(14). https://doi.org/10.3390/su13147670

City of Chicago. (2021). *Building Footprints*. https://data.cityofchicago.org/Buildings/Building-Footprints-current-/hz9b-7nh8

City of Toronto. (2021). *3D Massing*. https://open.toronto.ca/dataset/3d-massing/

de Boissieu, A. (2021). Introduction to Computational Design: Subsets, Challenges in Practice and Emerging Roles. In *Industry 4.0 for the Built Environment* (Vol. 20, pp. 55–75). Springer International Publishing. https://doi.org/10.1007/978-3-030-82430-3_3

De Nadai, M., Vieriu, R. L., Zen, G., Dragicevic, S., Naik, N., Caraviello, M., Hidalgo, C. A., Sebe, N., & Lepri, B. (2016). Are safer looking neighborhoods more lively? A multimodal investigation into urban life. *MM 2016 - Proceedings of the 2016 ACM Multimedia Conference*, 1127–1135. https://doi.org/10.1145/2964284.2964312

Di Filippo, A., Lombardi, M., Marongiu, F., Lorusso, A., & Santaniello, D. (2021). Generative design for project optimization. *Proceedings - DMSVIVA 2021: 27th International DMS Conference on Visualization and Visual Languages*, *June 2021*, 110–115. https://doi.org/10.18293/dmsviva21-014

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national indexNo Title. *American Psychologist*, *55*, 34–43. https://doi.org/https://doi.org/10.1037/0003-066X.55.1.34

Doan, Q. (2021). *Testing and extension of a GIS-supported design tool for new urban development areas* [Delft University of Technology]. http://resolver.tudelft.nl/uuid:b38588b1-1854-4ffa-976e-d87db3036b71

Dodge, R., Daly, A., Huyton, J., & Sanders, L. (2012). The challenge of defining wellbeing.

*International Journal of Wellbeing*, *2*(3), 222–235. https://doi.org/10.5502/ijw.v2i3.4

Dogan, T., Yang, Y., Samaranayake, S., & Saraf, N. (2020). Urbano: A tool to promote active mobility modeling and amenity analysis in urban design. *Architecture + Design*, *4*, 92–105.

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Idalgo, C. A. (2016). Deep Learning the City: Quantifying Urban Perception at a Global Scale. *Eccv*, *3*, 398–413. https://doi.org/10.1007/978-3-319-46448-0

Duin, van C., te Riele, S., & Stoeldraijer, L. (2018). Huishoudensprognose 2018-2060: opmars eenpersoonshuishoudens zet door. *Centraal Bureau Statistiek*, *December*, 1–32.

Echevarria Sanchez, G. M., Van Renterghem, T., Sun, K., De Coensel, B., & Botteldooren, D. (2017). Using Virtual Reality for assessing the role of noise in the audio-visual design of an urban public space. *Landscape and Urban Planning*, *167*(June), 98–107. https://doi.org/10.1016/j.landurbplan.2017.05.018

Eid, M., & Diener, E. (2004). Global judgments of subjective well-being: Situational variability and long-term stability. *Social Indicators Research*, *65*(3), 245–277. https://doi.org/10.1023/B:SOCI.0000003801.89195.bc

Fathi, S., Sajadzadeh, H., Sheshkal, F. M., Aram, F., Pinter, G., Felde, I., & Mosavi, A. (2020). The role of urban morphology design on enhancing physical activity and public health. *International Journal of Environmental Research and Public Health*, *17*(7), 1–29. https://doi.org/10.3390/ijerph17072359

Ferguson, M. J., & Bargh, J. A. (2004). How social perception can automatically influence behavior. *Trends in Cognitive Sciences*, *8*(1), 33–39. https://doi.org/10.1016/j.tics.2003.11.004

Foster, S., Wood, L., Christian, H., Knuiman, M., & Giles-corti, B. (2013). Social Science & Medicine Planning safer suburbs : Do changes in the built environment in fl uence residents ' perceptions of crime risk ? *Social Science & Medicine*, *97*, 87–94. https://doi.org/10.1016/j.socscimed.2013.08.010

Fusero, P., Massimiano, L., Tedeschi, A., & Lepidi, S. (2013). Parametric Urbanism: A New Frontier for Smart Cities. *Planum The Journal of Urbanism*, *2*(27), 1–13. http://www.planum.net/planum-magazine/themes-online/parametric-urbanism-a-new-frontier

García González, F. G. (2019). An interactive design tool for urban planning using the size of the living space as unit of measurement. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives* (Vol. 42, Issue 4/W15). https://doi.org/10.5194/isprs-archives-XLII-4-W15-3-2019

Google Maps. (2021). *Street View*. https://www.google.nl/maps

Groenemeijer, L., Gopal, K., Omtzigt, D., & Van Leeuwen, G. (2020). *Huishoudens en woningmarkt*. https://abfresearch.nl/publicaties/vooruitzichten-bevolking-huishoudens-en-woningmarkt-2020-2035/

Hakak, A. M., Bhattacharya, J., Biloria, N., de K. R., & Shah-Mohammadi, F. (2016). Navigating abstract virtual environment an eeg study Navigating abstract virtual environment : an eeg study. *Cognitive Neurodynamics*. https://doi.org/10.1007/s11571-016-9395-z

Hamers, D., Kuiper, R., van der Wouden, R., van Dam, F., van Gaalen, F., van Hoorn, A., van Minnen, J., Pols, L., & van Eck, J. R. (2021). *Grote Opgaven in Een Beperkte Ruimte*.

Harvey, C., Aultman-Hall, L., Hurley, S. E., & Troy, A. (2015). Effects of skeletal streetscape design on perceived safety. *Landscape and Urban Planning*, *142*, 18–28.

https://doi.org/10.1016/j.landurbplan.2015.05.007

Heffernan, E., Heffernan, T., & Pan, W. (2014). The relationship between the quality of active frontages and public perceptions of public spaces. *Urban Design International*, *19*(1), 92–102. https://doi.org/10.1057/udi.2013.16

Helsingin kaupunginkanslia. (2021). *3D models of Helsinki*. https://www.opendata.fi/data/en_GB/dataset/helsingin-3d-kaupunkimalli

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015a). Choice and utility. In *Applied Choice Analysis* (2nd ed., pp. 30–79).

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015b). Families of discrete choice models. In *Applied Choice Analysis* (2nd ed., pp. 80–116).

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015c). Getting started modeling : the workhorse – multinomial logit. In *Applied Choice Analysis* (2nd ed., pp. 437–471).

Heurkens, E. (2012). *Private Sector-led Urban* (Issue October 2012).

Iglesias, P., Greene, M., & de Dios Ortúzar, J. (2013). On the perception of safety in low income neighbourhoods: using digital images in a stated choice experiment. *Choice Modelling*, 193–210. https://doi.org/10.4337/9781781007273.00014

Jansson, C. (2019). *Factors important to street users' perceived safety on a main street*. KTH Royal Institute of Technology.

Jiang, B., Mak, C. N. S., Zhong, H., Larsen, L., & Webster, C. J. (2018). From broken windows to perceived routine activities: Examining impacts of environmental interventions on perceived safety of urban alleys. *Frontiers in Psychology*, *9*, 1–16. https://doi.org/10.3389/fpsyg.2018.02450

Joglekar, S., Quercia, D., Redi, M., Aiello, L. M., Kauer, T., & Sastry, N. (2020). Facelift: A transparent deep learning framework to beautify urban scenes. *Royal Society Open Science*, *7*(1). https://doi.org/10.1098/rsos.190987

Johnson, A., Thompson, E. M., & Coventry, K. R. (2010). Human perception, virtual reality and the built environment. *Proceedings of the International Conference on Information Visualisation*, 604–609. https://doi.org/10.1109/IV.2010.88

Kalantari, S., & Shepley, M. (2020). Psychological and social impacts of high-rise buildings: a review of the post-occupancy evaluation literature. *Housing Studies*, *36*(8), 1147–1176. https://doi.org/10.1080/02673037.2020.1752630

Karayazi, S. S., Dane, G., & de Vries, B. (2021). Utilizing urban geospatial data to understand heritage attractiveness in amsterdam. *ISPRS International Journal of Geo-Information*, *10*(4). https://doi.org/10.3390/ijgi10040198

Karimi, K. (2012). A reflection on'Order and Structure in Urban Design'. *Journal of Space Syntax*, *3*(1), 38–48.

Karimimoshaver, M., & Winkemann, P. (2018). A framework for assessing tall buildings' impact on the city skyline: Aesthetic, visibility, and meaning dimensions. *Environmental Impact Assessment Review*, *73*, 164–176. https://doi.org/10.1016/j.eiar.2018.08.007

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, *220*, 671–680. https://doi.org/10.1126/science.220.4598.671

Latkin, C. A., & Curry, A. D. (2003). *Stressful Neighborhoods and Depression : A Prospective Study of the Impact of Neighborhood Disorder*. *44*, 34–44. https://www.jstor.org/stable/1519814

Lee, H., & Kim, S. N. (2021). Perceived safety and pedestrian performance in pedestrian priority streets (Ppss) in Seoul, Korea: A virtual reality experiment and trace mapping. *International Journal of Environmental Research and Public Health*, *18*(5), 1–16. https://doi.org/10.3390/ijerph18052501

Leite, S., Dias, M. S., Eloy, S., Freitas, J., Marques, S., Pedro, T., & Ourique, L. (2019). Physiological arousal quantifying perception of safe and unsafe virtual environments by older and younger adults. *Sensors*, *19*(11). https://doi.org/10.3390/s19112447

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2015). Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry and Urban Greening*, *14*(3), 675–685. https://doi.org/10.1016/j.ufug.2015.06.006

Liu, Q., Zhu, Z., Zeng, X., Zhuo, Z., Ye, B., & Fang, L. (2021). The impact of landscape complexity on preference ratings and eye fixation of various urban green space settings. *Urban Forestry & Urban Greening*, *66*. https://doi.org/10.1016/j.ufug.2021.127411

Loewen, L. J., Steel, G. D., & Suedfeld, P. (1993). Perceived safety from crime in the urban environment. *Journal of Environmental Psychology*, *13*(4), 323–331. https://doi.org/10.1016/S0272-4944(05)80254-3

Lu, X., Tomkins, A., Hehl-lange, S., & Lange, E. (2021). Finding the difference : Measuring spatial perception of planning phases of high-rise urban developments in Virtual Reality. *Computers, Environment and Urban Systems*, *90*. https://doi.org/10.1016/j.compenvurbsys.2021.101685

Mehta, V. (2007). Lively Streets Determining Environmental Characteristics to Support Social Behavior. *Journal of Planning Education and Research*, *27*, 165–187. https://doi.org/10.1177/0739456X07307947

Michailidou, G. (2019). *The Influence of the Visible Views on Cyclists' Route Choices*. Delft University of Technology.

Middel, A., Lukasczyk, J., Zakrzewski, S., Arnold, M., & Maciejewski, R. (2019). Urban form and composition of street canyons : A human-centric big data and deep learning approach. *Landscape and Urban Planning*, *183*, 122–132. https://doi.org/10.1016/j.landurbplan.2018.12.001

Ministerie van Binnenlandse Zaken en Koningkrijksrelaties. (2020). *Nationale omgevingsvisie*.

Ministerie van Binnenlandse Zaken en Koninkrijksrelaties. (n.d.). *Leefbaarometer*. https://www.leefbaarometer.nl/home.php

Mouratidis, K. (2018). Rethinking how built environments influence subjective well-being: a new conceptual framework. *Journal of Urbanism*, *11*(1), 24–40. https://doi.org/10.1080/17549175.2017.1310749

Mouratidis, K. (2019a). Compact city, urban sprawl, and subjective well-being. *Cities*, *92*, 261–272. https://doi.org/10.1016/j.cities.2019.04.013

Mouratidis, K. (2019b). The impact of urban tree cover on perceived safety. *Urban Forestry and Urban Greening*, *44*, 126434. https://doi.org/10.1016/j.ufug.2019.126434

Mouratidis, K. (2021). Urban planning and quality of life : A review of pathways linking the built environment to subjective well-being. *Cities*, *115*. https://doi.org/https://doi.org/10.1016/j.cities.2021.103229 Received

Nabielek, K., Boschman, S., Harbers, A., Piek, M., & Vlonk, A. (2012). *Stedelijke verdichting: een ruimtelijke verkenning van binnenstedelijk wonen en werken*.

Naghibi Rad, P., Shahroudi, A. A., Shabani, H., Ajami, S., & Lashgari, R. (2019). Encoding Pleasant and Unpleasant Expression of the Architectural Window Shapes : An ERP Study. *Frontiers in Behavioral Neuroscience*, *13*(186). https://doi.org/10.3389/fnbeh.2019.00186

Nagy, D., Villaggi, L., & Benjamin, D. (2018). Generative urban design: Integrating financial and energy goals for automated neighborhood layout. *SimAUD*. https://doi.org/10.22360/simaud.2018.simaud.025

OpenStreetMap contributors. (2021). *OpenStreetMap*. https://www.openstreetmap.org

Pauwels, P. (2020). *Parametric Design [powerpoint slides]*. Eindhoven University of Technology.

Perez-Martinez, I., Martinez-Rojas, M., & Soto-Hidalgo, J. M. (2020). A preliminary approach to allocate categories of buildings into lands based on generative design. *IEEE International Conference on Fuzzy Systems*. https://doi.org/10.1109/FUZZ48607.2020.9177853

Quercia, D., O'Hare, N., & Cramer, H. (2014a). Aesthetic capital: What makes london look beautiful, quiet, and happy? *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*, 945–955. https://doi.org/10.1145/2531602.2531613

Quercia, D., O'Hare, N., & Cramer, H. (2014b). Aesthetic capital: What makes london look beautiful, quiet, and happy? *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*. https://doi.org/10.1145/2531602.2531613

Rahm, J., Sternudd, C., & Johansson, M. (2021). " In the evening , I don ' t walk in the park ": The interplay between street lighting and greenery in perceived safety. *URBAN DESIGN International*, *26*(1), 42–52. https://doi.org/10.1057/s41289-020-00134-6

Rakha, T., & Reinhart, C. (2012). *GENERATIVE URBAN MODELING : A DESIGN WORK FLOW FOR WALKABILITY-OPTIMIZED CITIES*. https://web.mit.edu/sustainabledesignlab/publications/SimBuild2012_WalkableCityConcept.pdf

Redi, M., Aiello, L. M., Schifanella, R., & Quercia, D. (2018). The Spirit of the City: Using Social Media to Capture Neighborhood Ambiance. *Proc. ACM Hum.-Comput. Interact. 2, CSCW*, *2*(144). https://doi.org/https://doi.org/10.1145/3274413 Proceedings

Rossetti, T., Lobel, H., Rocco, V., & Hurtubia, R. (2019). Explaining subjective perceptions of public spaces as a function of the built environment : A massive data approach. *Landscape and Urban Planning*, *181*, 169–178. https://doi.org/10.1016/j.landurbplan.2018.09.020

Roudsari, M. S., & Pak, M. (2013). Ladybug: A parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design. *Proceedings of BS 2013: 13th Conference of the International Building Performance Simulation Association*.

Rutten, D. (2013). Galapagos: On the logic and limitations of generic solvers. *Architectural Design*, *83*(2), 132–135. https://doi.org/10.1002/ad.1568

Saltelli, A. (2002). Sensitivity analysis for importance assessment. *Risk Analysis*, *22*(3), 579–590. https://doi.org/10.1111/0272-4332.00040

Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., & Wu, Q. (2019). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. *Environmental Modelling and Software*, *114*, 29–39. https://doi.org/10.1016/j.envsoft.2019.01.012

Shaffer, G. S., & Anderson, L. M. (1985). Perceptions of the security and attractiveness of urban parking lots. *Journal of Environmental Psychology*, *5*(4), 311–323. https://doi.org/10.1016/S0272-4944(85)80001-3

Simpson, J., Freeth, M., Simpson, K. J., & Thwaites, K. (2022). *Street edge subdivision : Structuring ground floor interfaces to stimulate pedestrian visual engagement*. *0*(0). https://doi.org/10.1177/23998083211068050

Smith, N. R., Lewis, D. J., Fahy, A., Eldridge, S., Taylor, S. J. C., Moore, D. G., Clark, C., Stansfeld, S. A., & Cummins, S. (2015). Individual socio-demographic factors and perceptions of the environment as determinants of inequalities in adolescent physical and psychological health : the Olympic Regeneration in East London ( ORiEL ) study. *BMC Public Health*, *15*(150). https://doi.org/10.1186/s12889-015-1459-1

Stamps, A. E. (2005). Enclosure and safety in urbanscapes. *Environment and Behavior*, *37*(1), 102–133. https://doi.org/10.1177/0013916504266806

Statistics Canada. (2021). *Autobuilding Ville Montreal*. https://www.statcan.gc.ca/en/lode/databases/odb

Steinø, N., Karima, B., & Obeling, E. (2013). Using Parametrics to Facilitate Collaborative Urban Design: An Attempt to Overcome some Inherent Dilemmas. *Planum. The Journal of Urbanism*, *1*(26). http://vbn.aau.dk/en/publications/using-parametrics-to-facilitate-collaborative-urban-design(fac621f3-cb5c-41ba-bf12-8b41093ad719).html

Stockholms Stad. (2021). *3D Buildings LOD2*. https://kartor.stockholm/kartor-geodata/

Tao, Y., Wang, Y., Wang, X., Tian, G., & Zhang, S. (2022). Measuring the Correlation between Human Activity Density and Streetscape Perceptions: An Analysis Based on Baidu Street View Images in Zhengzhou, China. *Land*, *11*(3). https://doi.org/10.3390/land11030400

TU Delft 3D geoinformation group. (2021). *3D BAG 21.09.8*. https://3dbag.nl/nl/download

United Nations Department of Economic and Social Affairs Population Division. (2019). *World Urbanization Prospects: The 2018 Revision*.

Verma, D., Jana, A., & Ramamritham, K. (2020). Predicting human perception of the urban environment in a spatiotemporal urban setting using locally acquired street view images and audio clips. *Building and Environment*, *186*. https://doi.org/10.1016/j.buildenv.2020.107340

Vidmar, J., & Koželj, J. (2013). Adaptive urbanism: a parametric maps approach. *THE CREATIVITY GAME Theory and Practice of Spatial Planning*, *3*(148), 44–52. https://doi.org/10.15292/iu-cg.2015.03.044-052

Vierlinger, R., Zimmel, C., & Schneider, G. (2018). *Octopus* (0.4). https://www.food4rhino.com/en/app/octopus

Vinnikov, M., Hamilton, L. I., Motahari, K., & Ozludil Altin, B. (2021). Understanding Urban Devotion through the Eyes of an Observer. *ETRA '21 Short Papers*. https://doi.org/https://doi.org/10.1145/3448018.3458003 Permission

Wang, Y. (2007). On the Cognitive Processes of Human Perception with Emotions, Motivations, and Attitudes. *International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, *1*(4). https://doi.org/10.4018/jcini.2007100101

Wang, Y., Wang, Y., Patel, S., & Patel, D. (2006). A layered reference model of the brain (LRMB). *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, *36*(2), 124–133. https://doi.org/10.1109/TSMCC.2006.871126

Weber, R. (2008). *Aesthetics o f streetscapes: influence o f fundamental properties o n aesthetic judgments o f urban space ",."* 128–146.

Weber, R., Schnier, J., & Jacobsen, T. (2008). Aesthetics of streetscapes: influence of fundamental properties on aesthetic judgments of urban space. *Perceptual and Motor Skills*, *106*, 128–146. https://doi.org/DOI10.2466/PMS.106.1.128-146

Weijs-Perrée, M., Dane, G., & van den Berg, P. (2020). Analyzing the relationships between citizens' emotions and their momentary satisfaction in urban public spaces. *Sustainability*, *12*(7921). https://doi.org/10.3390/SU12197921

Weijs-Perrée, M., Dane, G., van den Berg, P., & van Dorst, M. (2019). A multi-level path analysis of the relationships between the momentary experience characteristics, satisfaction with urban public spaces, and momentary- and long-term subjective wellbeing. *International Journal of Environmental Research and Public Health*, *16*(3621). https://doi.org/10.3390/ijerph16193621

White, E. V, & Gatersleben, B. (2011). Greenery on residential buildings : Does it affect preferences and perceptions of beauty ? *Journal of Environmental Psychology*, *31*(1), 89–98. https://doi.org/10.1016/j.jenvp.2010.11.002

Wilson, L., Danforth, J., Davila, C. C., & Harvey, D. (2019). How to generate a thousand master plans: A framework for computational urban design. *SIMAUD '19: Proceedings of the Symposium on Simulation for Architecture and Urban Design*, *28*, 113–120.

Ye, Y., Zeng, W., Shen, Q., Zhang, X., & Lu, Y. (2019). The visual quality of streets: A human-centred continuous measurement based on machine learning algorithms and street view images. *Environment and Planning B: Urban Analytics and City Science*, *46*(8), 1439–1457. https://doi.org/10.1177/2399808319828734

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning*, *180*(October 2017), 148–160. https://doi.org/10.1016/j.landurbplan.2018.08.020

Zhang, L., Ye, Y., Zeng, W., & Chiaradia, A. (2019). A systematic measurement of street quality through multi-sourced Urban data: A human-oriented analysis. *International Journal of Environmental Research and Public Health*, *16*(10). https://doi.org/10.3390/ijerph16101782

Zhang, Y., & Liu, C. (2021). Parametric urbanism and environment optimization: Toward a quality environmental urban morphology. *International Journal of Environmental Research and Public Health*, *18*(7). https://doi.org/10.3390/ijerph18073558

Zhao, H., Shi, J., Qi, X., Wang, X., & Jia, J. (2017). Pyramid Scene Parsing Network. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 6230–6239. https://doi.org/10.1109/CVPR.2017.660