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Faculteit Bedrijfseconomische Wetenschappen

master handelsingenieur

Masterthesis

Deep learning for choice behavior analysis to assess the impact of urban features on perceived beauty and perceived safety

Laura Verboven

Scriptie ingediend tot het behalen van de graad van master handelsingenieur, afstudeerrichting technologie in business

PROMOTOR :
Prof. dr. Stephan BRUNS

BEGELEIDER :
De heer Ilias MOKAS

2020
2021

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This master thesis was written during the COVID-19 crisis in 2020-2021. This global health crisis might have had an impact on the (writing) process, the research activities and the research results that are at the basis of this thesis.

Preface

This Master thesis marks the end of my studies at Hasselt University in the program of Business Engineering – Technology in Business. During this thesis I learned many things about two topics I am interested in: developments in data analytics and the importance of urban planning and design. Once again, I noticed how valuable it is to collect and analyze big amounts of data. However, big amounts of data can only be transformed into actionable insights if one manages to analyze them in an interpretable way. I that regard, more traditional methods for analysis are still very effective. Also, I learned the importance of, and the opportunities for, urban planning and design using a social approach. In conclusion, I am very grateful to have conducted this research and completed this Master thesis.

This would have never been possible without the support of some people, so I would like to take this opportunity to express my deepest gratitude. First and foremost, I would like to thank Prof. dr. Stephan Bruns and my co-supervisor Mr. Ilias Mokas. They have guided me very well through the process of conducting my research and their feedback has been much appreciated. Thank you both for your flexibility and helpfulness, from beginning till the end.

Finally, I would like to thank my family and friends for their unconditional love, support and advice. Without my sister's jokes, the regular video calls with Aïcha and Kim, and the efforts of many others, the road to my destination would not have been as much fun as it has been.

Summary

Research purpose

Since 2007, the global share of people living in urban areas exceeds the share of people living in rural areas (WorldBank, 2018). The United Nations argue that this phenomenon, called *urbanization*, will not cease to grow. They expect this percentage to increase to roughly 68% by the mid-century (UN, 2019). This demographic megatrend is driven by factors such as natural population growth, migration from rural to urban areas, and migration from abroad (Lerch, 2017). Consequently, policymakers and urban planners have to take into account an increasing number of factors, including human perceptions regarding inclusive, safe, resilient, and sustainable cities (UN-General-Assembly, 2014). Therefore, developing a comprehensive body of knowledge about the built environment, for example, regarding perceived beauty and safety, is becoming more important than ever before. However, there is insufficient scientific research about how urban planners can design beautiful and safe cities. Consequently, this Master thesis addresses the following main research question:

Which urban attributes increase the probability of a city to be perceived as more beautiful and/or more safe?

Research design

In order to address this main research question, a "secondary research question" is analyzed: What is the optimal method to find the effect of urban attributes on perceived beauty and perceived safety? Traditionally, this was done by conducting interviews, questionnaires, and related methods referred to as stated preference methods (SP) (Louvière & Timmermans, 1990). These traditional techniques for data collection are quite costly and time consuming, as has been academically agreed upon (e.g., Zhang et al., 2018). However, big amounts of data should be collected and analyzed. This can be done using Deep Learning (DL). Also, the results should be interpretable for urban planners to take action. Choice Modelling (CM) is a suitable method in this regard. Choice modelling is theoretically based on the consumer theory of Kelvin J. Lancaster (Lancaster, 1966). This theory puts emphasis on the attributes of a commodity leading preferences instead of the commodity itself. To benefit from the perks of both DL and CM, this Master thesis applies a sequential approach of DL and CM to a dataset about urban scenery. This approach is similar to the one used by Rossetti et al. (2019).

Results

The dataset that is used for the CM in this Master thesis originates from the Place Pulse 2.0 dataset (Dubey et al., 2016). One of the supervisors of this Master thesis (Ilias Mokas) used DL in order to perform image segmentation on the images from the Place Pulse 2.0 dataset. As a result, the original dataset now contained information on the composition of the images. All urban attributes were classified under six groups of urban attributes: "Sky", "Green" (including trees, grass, mountains, plants, etc.), "Blue" (including rivers, fountains, lakes, etc.), "Impervious surface" (including runways, bridges, pavements, etc.), "Non-permanent objects" (including people, cars, busses, etc.) and "Grey" (including walls, fences, traffic lights, etc.). Eventually, this Master thesis performs a CM analysis on the resulting dataset.

On one hand, the impact of the six groups of urban attributes on perceived beauty is analyzed. Only for the groups "Sky" and "Grey" is there a negative effect on perceived beauty. This is consistent with previous literature, that says that walls, buildings, highway road signs and other urban features contribute negatively to perceived beauty (Quercia et al., 2014; Seresinhe et al., 2017; Zhang et al., 2018). Furthermore, this Master thesis shows that urban greenery contributes highly positive to perceived beauty. This too, is in line with the findings of previous literature. For example, Quercia et al. (2014) studied what urban features make the city of London look "beautiful, quiet and happy" and they found that public gardens and residential trees have a positive impact on perceived beauty. The other groups of urban attributes that were analyzed, "Blue", "Non-permanent objects" and "Impervious surface", also showed a positive association with perceived beauty.

On the other hand, the impact on perceived safety is analyzed. Urban attributes from the groups "Sky" and "Grey" have also a negative impact on perceived safety. Their model estimates are both significant at the 0.001 level, but their absolute values are remarkably smaller than their respective estimates in the model on perceived beauty. This means that urban attributes from "Sky" and "Grey" have a more negative impact on perceived beauty than on perceived safety. Previous literature mainly agrees with the findings of this Master thesis in this regard. The feeling of entrapment, which is usually caused by the presence of walls, buildings, etc., induces feelings of being unsafe in a city (Johansson et al., 2020; Rahm et al., 2020; Zhang et al., 2018). Further, urban greenery has, once again, the most significant positive impact in the choice model. This implies that people feel safer, the more urban vegetation around. This is consistent with some previous studies (Zhang et al., 2018), although there are exceptions where urban vegetation is not beneficial for people to feel safe in a city. For example, some women acknowledge that dense vegetation could be an incentive to avoid certain places or sidewalks (Gargiulo et al., 2020). Lastly, blue elements in the city, non-permanent objects and impervious surfaces have a positive impact on perceived safety. The fact that non-permanent objects, such as passing persons and vehicles, make people perceive a city as safe, confirms the "eyes on the street" theory of Jane Jacobs that was first published in 1961 (Jacobs, 1961). This theory says that people feel safer the more people around, because their eyes on the street provide informal surveillance.

There are no urban attributes that require a trade-off when it comes down to perceived beauty and perceived safety. All elements of an urban scene that add up positively to perceived beauty, also have a positive impact on perceived safety. And the other way around.

Reflection

As mentioned earlier, six groups were used to classify urban attributes. However, these categories might have been chosen too broad as too many different attributes belong to the same category. Consequently, the results were only limited to the impact of urban attribute *groups* on perceived beauty/safety instead of the impact of urban attributes *by themselves* on the perceptual indicators. Another limitation of this Master thesis is concerned with the utility functions that were developed in the CM step. The systematic components of these utility functions only contained information on the urban attributes of each alternative in the dataset, but there is no information included about the characteristics of respondents that participated in the survey (e.g., gender, nationality, age). Including more variables in the equations, would have made the estimates more accurate.

Regarding future research, I encourage researchers to further investigate which urban attributes make a city look beautiful and/or safe. Also, more research should be done regarding collecting and analyzing big data. The sequential approach that was used for this Master thesis showed that there is merit in combining more traditional methods (i.e., Choice Modelling) with more recently developed methods (i.e., Deep Learning).

Table of contents

List of figures

List of tables

1. Introduction

1.1 Contextual background

For most of their time on Earth, humans lived in small communities. However, over the past few decades, this way of life has dramatically changed, with a transition in 2007, when more people globally were living in urban areas instead of rural ones (WorldBank, 2018). Since then, the rural population has stagnated, while more people migrated to urban areas every year. In 2016, it was estimated that 55.3% of the global population lived in cities, a ratio that does not cease to grow (UN, 2016). Frankly, there is no doubt that *urbanization* is a real trend, which policymakers need to consider. The United Nations (UN) even gave birth to a foundation fully dedicated to urban development in the mid-70s, at the "Habitat I" conference in Vancouver, Canada (UN, 1976). However, urbanization then was not yet as evolved as it is today, so measures have become more urgent in recent years. On 1 January 2002, Habitat's mandate and status was truly strengthened and became "UN-Habitat", accelerating new strategies for achieving urban development and shelter goals and targets (UN-General-Assembly, 2002). Later, around 2015, the UN established a set of seventeen Sustainable Development Goals (SDGs), of which number eleven is called "Make cities and human settlements inclusive, safe, resilient and sustainable" (UN-General-Assembly, 2014). The discipline of *urban planning* is thus rooted deeply into modern policy making.

Urban planning takes into account many physical features: green walls, traffic lights, benches, residential trees, parking spots, stairs, bridges, urban canals, etc. These examples are only the top of the iceberg, there are many more. In the remainder of this Master thesis, the words *urban attributes* will be used to refer to all physical features in an urban area. Carefully planning and managing urban attributes is important because studies have shown that they affect the residents of a city in many aspects. Some studies show the interrelationship for urban greenery with both mental and physical well-being (Douglas et al., 2017; Lu, 2019; Wang, Helbich, et al., 2019; Wood et al., 2017), with urban greenery being for example parks, street green, green space for sporting activities, and so on. Other studies point out the effect that non-green urban elements have on perceived safety, beauty, or liveliness (De Silva et al., 2017; Verma et al., 2020; Wang, Liu, et al., 2019; Wang, Yuan, et al., 2019). Furthermore, numerous examples exist that show designing and planning urban attributes are turned into practice. For example, UN-Habitat's Toolkit for public space planning (UN-Habitat, 2016) inspired policy makers in urban areas all over the world: from a dangerous, problematic area that was turned into a safe, lively business center in South Africa (Dobson, 2007) to Miami's master plan to turn all its public spaces in a beautiful, green oasis (Miami-Dade-County-Parks-and-Recreation-Departement, 2007). However, it should be noted that this Master thesis is only interested in the impact of a city's physical appearance on (perceived) *beauty* and (perceived) *safety*.

The more people come to live in cities, the more adaptive and resilient cities should be. In other words, urban planners should try to design and manage sustainable urban living. This requires them to take on a systems approach, to see how a city and its urban attributes serve its residents. The interaction between a city, its urban attributes, and its residents could be referred to as an ecosystem. Ecosystems are communities of living organisms that interact with nonliving components in their environment, just like a system does (Costanza et al., 1997). Its services represent the benefits human populations derive, directly or indirectly, from those interactions. This is indeed the case for cities, where people constantly interact with their environment (e.g., city park) and each other (e.g., traffic). An example of ES in this Master thesis (i.e., with regard to (perceived) beauty and safety) is urban vegetation. Green in the city often stimulates its residents to participate in recreational activities (e.g., Zhang et al., 2013), but it could also evoke feelings of fear or entrapment when it hides paths from view (e.g., Gargiulo et al., 2020). This all suggests that urban planners should be able to measure people's perception on their environment in order to make proper decisions regarding urban development. In other words, urban planners should be able to elicit the value people attach to urban scenery that is made up from several urban attributes. This is a rather social perspective on the valuation of urban ES (Hubacek & Kronenberg, 2013).

1.2 Methodological background

For policymakers and urban planners to effectively design and manage an urban environment, more insights are needed on the *perception* of people on urban attributes. However, "perception" is an unobservable variable. It is needed to develop a method to estimate perceptual indicators, such as perceived beauty or perceived safety. Therefore, this Master thesis will assume perceptions can be modeled through latent variables (Bollen, 2002; Borsboom et al., 2003). Figure 1 visualizes this methodology – how perceptions will be estimated through observable parameters, in the context of urban areas. Consequently, data about urban attributes and their linkage with human perception has to be gathered. Traditionally, this was done by conducting interviews, questionnaires, choice modeling, and related methods referred to as stated preference methods (SP) (Louvière & Timmermans, 1990). As Louvière and Timmermans have shown in their research, all SP methods involve multiple steps and decisions to attain accurate results. Early research about measuring human perceptions on urban settings used this type of methodology to collect their data for analysis (Lynch, 1960; Nasar, 1990; Ulrich, 1983). These traditional techniques for data collection are quite costly and time consuming, as has been academically agreed upon (e.g., Zhang et al., 2018). With a steadily increasing urban population, developing a comprehensive body of knowledge about the built environment is becoming more difficult but more meaningful than ever before. More difficult because there are more residents, with different backgrounds, to take into account. More meaningful than ever before, because living in cities is becoming more and more a standard. All this suggests that a researcher in the field of urban planning should have access to methods and tools that support the collection and analysis of data at a larger scale. Big data has gained a lot of attention in recent years. Due to the emergence of crowdsourcing technology there is an enhanced opportunity to collect large amounts of data on the perception of urbanization, as proven by for example the MIT Media Lab program "Place Pulse" (Salesses et al., 2013) and the crowdsourcing website "UrbanGems" (Quercia et al., 2014). Due to the developments in *machine learning* (ML), also the analysis of large amounts of data can be done more efficiently, as has been shown in multiple research papers (Lau et al., 2019; Wang, Yuan, et al., 2019).

Modern techniques to collect and analyze big data have many advantages. However, they are often criticized for their lack of interpretability, which is referred to as the *black box* issue. This issue is especially the case for artificial neural networks (ANNs) in the discipline of *deep learning* (DL), a subdivision of ML (Rossetti et al., 2019; van Cranenburgh & Alwosheel, 2019). That is why many researchers seek to combine the interpretability perks of traditional SP methods with the strong accuracy and efficiency capabilities of DL. The traditional SP method that is used most often together with DL, is *discrete choice modelling* (DCM) (Barthélemy et al., 2018; Hensher & Ton, 2000; Paredes et al., 2017). The way in which both techniques (i.e., DL and DCM) are combined differs in the academic literature. For example, there are hybrid models that aim at employing ANNs' properties and techniques to enhance or augment SP methods (Sifringer et al., 2018; Wong & Farooq, 2019). Or, but only very seldom, there are models that aim at investigating the black box character of ANNs and therefore propose strategies and solutions to overcome that issue (Rossetti et al., 2019). As in the study of Rossetti (2019), this Master thesis will also develop a sequential approach, in which DL outputs will be used as the input for a DCM. More specifically, one of the supervisors of this Master thesis (Ilias Mokas) will process big data through a DL technique called *image processing*. Image processing gives computers the ability to process images in a way that simulates human vision. That is, computers are able to perform tasks on images, such as action recognition, attribute segmentation and decision making (Ibrahim et al., 2020). The output of the image processing step is a dataset that contains information on the segmentation of a large amount of images of urban scenery. This dataset is fed into a DCM model in order to measure perceived beauty and perceived safety.

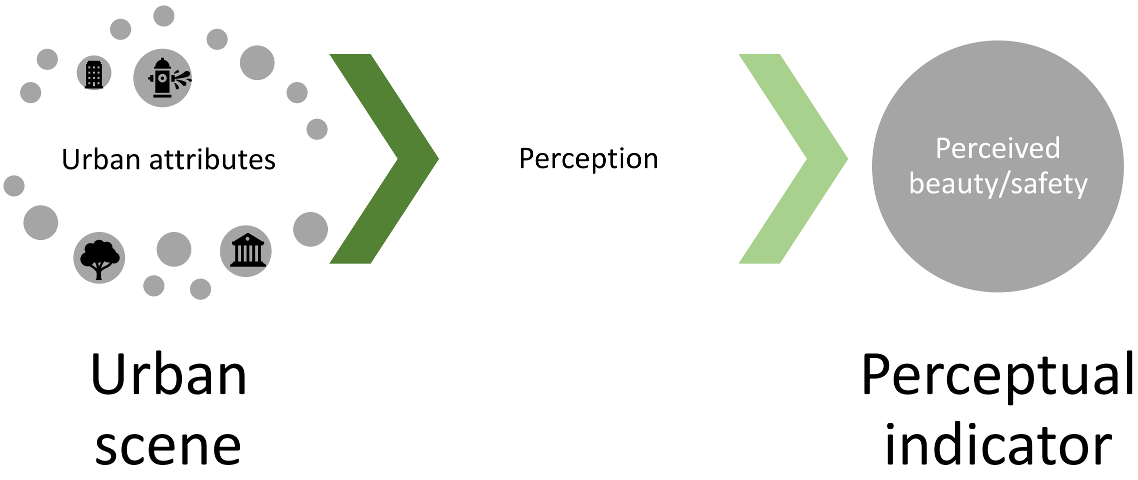


Figure 1 Framework that is used in this Master thesis to elicit information on two perceptual indicators from urban scenery. The left arrow (dark green) represents a structural relation, while the right arrow (light green) represents a measurement relation.

1.3 Research purpose

As mentioned in the previous sections, developing a comprehensive body of knowledge about the built environment is becoming more difficult but more meaningful than ever before due to urbanization. More and more people are migrating to cities, which means that there are more and more parameters and opinions that need to be taken into account in order to build sustainable cities. However, there is a lack of scientific articles in regard with urban planning using an approach of citizen involvement (i.e., a social approach). It is important that cities are designed in such a way that they are both scenic and that their citizens feel safe. If a city is attractive to work and/or live in, it could contribute to the eleventh SDG (i.e., "Make cities and human settlements inclusive, safe, resilient and sustainable"). However, there is insufficient scientific research about how urban planners can design and manage beautiful and safe cities. If there is such research, its scope is only very narrow because of the use of small amounts of data. For example, some articles have only a small geographical scope, limited to a certain region of a city (Gargiulo et al., 2020). But because of increasing urbanization, there is an urgent need for methods that can collect a big amount of data. Big amounts of data are important to take into account as many opinions of different citizens as possible. The main research question of this Master thesis is on urban planning:

Which urban attributes provide a higher probability for a city to be perceived as more beautiful and/or more safe?

Table 1 shows the main research question and some underlying sub research questions. Secondly, this study will look at which method is best suited to answer the main research question. Therefore, the secondary research question is:

Which method is the optimal approach to answer the main research question?

In the optimal scenario, answering the main research question can be done by collecting and analyzing big amounts of data. Traditionally, SP methods are used for this, but they are very time intensive and thus very costly. That is why DL techniques could be interesting, in order to analyze large amounts of data. Their results are very accurate, but their processing steps often lack interpretability. It thus would be optimal to combine the interpretability perks of traditional SP methods (e.g., DCM) with the opportunity of accurately analyzing big data of DL techniques. However, a research gap should be noted in this regard. There is simply not sufficient research about using DL together with DCM, and definitely not for studying urbanization. The combination of DL and DCM is mostly used in the context of transportation (Sifringer et al., 2020; Tortum et al., 2009). Moreover, the comparison of both techniques is more widely studied than their combination (Barthélemy et al., 2018; Hagenauer & Helbich, 2017; Hensher & Ton, 2000) . Therefore, this study will also contribute to the research field of DL for choice analysis. This Master thesis will apply a sequential method of DL and DCM and see whether this improves the interpretability of DL algorithms, while not comprising on their accuracy benefits. The sequential method will be applied to the framework shown in Figure 1. That is, the method should provide results that are interpretable regarding perceived safety and perceived beauty of urban scenery.

Main research question	**Which urban attributes provide a higher probability for a city to be perceived as more beautiful and/or more safe?**
Sub research questions	Which urban attributes is perceived beauty most sensitive to? Which urban attributes is perceived safety most sensitive to? Which urban attributes have a positive impact on perceived beauty but a negative impact on perceived safety? Which urban attributes have a positive impact on perceived safety but a negative impact on perceived beauty?

Table 1 Main research question and the underlying sub research questions.

1.4 Outline

This Master thesis contains a qualitative component and a quantitative one. Firstly, a thorough literature review was conducted using the search strategy (i.e., databases and search terms) that is mentioned in Appendix 1. The literature review is presented in section 2 and will guide the reader through all insights that are needed to know about the context of this thesis and that will help to understand the quantitative section. Section 2 will start with explaining the emergence of urbanization (section 2.1) and the growing importance of urban planning (section 2.1.3). Next in the literature review is the fact that urban attributes (e.g., urban greenery, traffic signs, bicycle paths) give rise to ecosystem services (ES) that impact human behavior (section 2.2). Therefore, if one is to perform urban planning properly, they should take on a social approach, involving a city's residents. This guides the reader to literature about economic valuation methods, which are used to understand people's preferences. First, some traditional methods will be discussed (section 2.3), with a focus on discrete choice experiments (DCMs) (section 2.3.2.1). Afterwards, the literature review will continue with more recent developments in economic valuation. Since, this Master thesis is only interested in deep learning (DL), we will only look at this technique (section 2.4).

After the literature review in section 2, the third section provides the quantitative component of this Master thesis. This section will first provide some insights on the way data was collected (section 3.1) and the methodology that was used for the analysis (section 3.2). The results will be presented in section 3.3. Last but not least, the analysis will be discussed in section 4, which also looks at the limitations of this Master thesis and recommendations for future research.

2. Literature review

2.1 The trend of urbanization

2.1.1 Concept

"Urbanization is the process through which cities grow, and higher and higher percentages of the population come to live in the city." (National Geographic, 2019)

Graphics about urbanization throughout time prove that there is reason to believe that higher percentages of the world population migrate to urban areas. Although there is no global consensus on the definition of "urban area" (UN, 2005), the differences would be negligible because of the high numbers that appear in all studies. Figure 2, visualized by Our World in Data (Ritchie & Roser, 2018), shows urbanization over the past 500 years for some of the biggest territorial entities in the world.

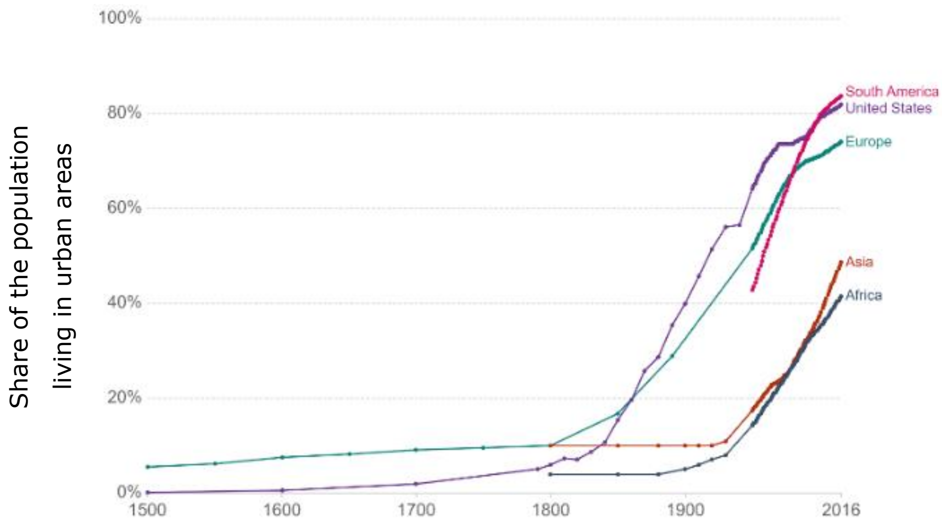


Figure 2 Urbanization from 1500 until 2016 in South America, United States, Europe, Asia and Africa.

Although the United Nations has only institutionalized regulations for urbanization in the 1970s, it is clear that it had been a phenomenon in earlier centuries. Rudolf Hartog published a study about the history of urbanization (Hartog, 1999). He describes when and why more people migrated to cities, both small and large, like Bielefeld and Berlin in Germany or like megacities such as London and Moscow. In pre-industrial times cities sought to cope with the increasing population through adding more stories to their existing houses. Density rose to half the land use per capita since the Middle Ages: from 100m² per person on average to 50m² per person. However, industrial developments in the middle of the 19th century accelerated urbanization. For example, Hartog shows that Berlin started with a population of 550,000 in 1861 and grew to 1.55 million in 1890, an annual increase of over 30,000 people. By 1950, most people in Europe and North America were living in urban areas, as Figure 3 confirms (Ritchie & Roser, 2018). However, urbanization took another pace in developing countries situated in Asia, Africa and South America, where urbanization only took off in the second half of the 20th century. There is a strong contrast with Figure 4, now that more than 50% of the world population lives in urban areas from 2007 onward (WorldBank, 2018).

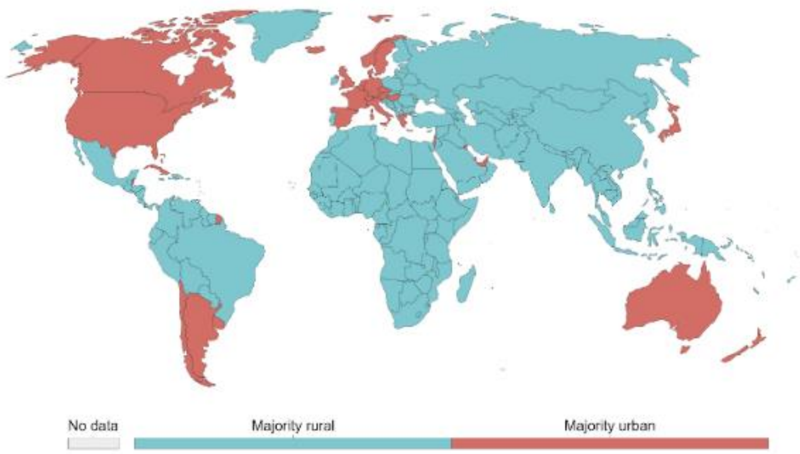


Figure 3 Share of the population which lives in urban versus rural areas in 1950.

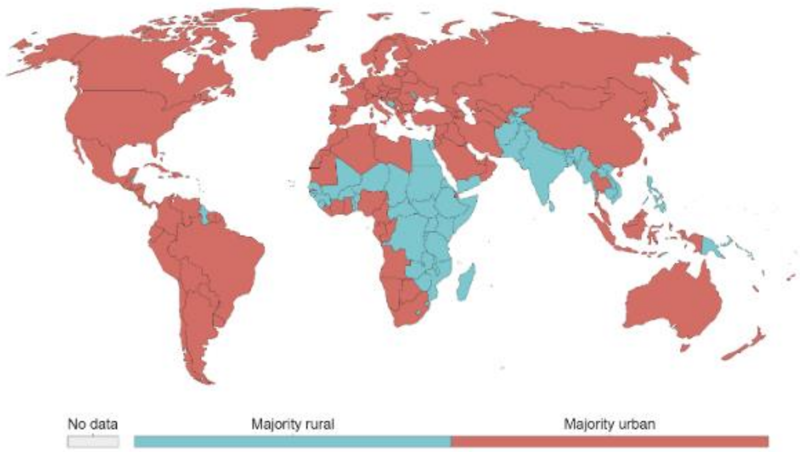


Figure 4 Share of the population which lives in urban versus rural areas in 2021.

The United Nations (UN) declares that urbanization will not cease to grow, they even expect the urban world population to increase to roughly 68% by the mid-century. This demographic megatrend is driven by factors among which natural population growth, migration from rural to urban areas and migration from abroad (Lerch, 2017).

2.1.2 Implications

Urbanization has strong ties with three dimensions of sustainable development, namely, economic, environmental and societal (UN, 2019). It thus induces changes in lifestyle, culture, behavior and so on, both in urban and rural areas. There are a couple of examples that show the positive side effects of urbanization. One of those examples is that urbanization generally has a positive impact on economic growth, although little inferences can be drawn between the speed of urbanization and the economic growth rate (Chen et al., 2014). This is a positive side effect that appears in the long run, so we should not be surprised to see accelerated urbanization without economic growth. Fact is that at present, urban economies account for approximately 80% of global GDP (WorldBank, 2020). Beside the positive effect of urbanization on economic growth, studies have shown that it might also have a positive effect on the environment. For example, Norman, MacLean and Kennedy have shown that living in cities could be more sustainable (Norman et al., 2006). Their study provides an empirical assessment of greenhouse gas (GHG) emissions and energy use related to more rural and more urban area development. The authors argue that low density area development tends to result in roughly 2.5 times the annual GHG emissions per capita in comparison with high density area development. Also, the annual energy use per capita is higher in rural regions than it is in urban regions. However, these insights highly depend on the geographical scope of the research. If the geographical scope of a study is limited to a city that is organized in such a way that most of its factories are located outside the city center, it makes perfect sense that GHG emissions are lower in the urban area than elsewhere. It could also be the other way around, which will probability result in a scenario that contradicts the findings of Norman, MacLean and Kennedy (Norman et al., 2006).

However, there are also disadvantages when urbanization comes into play. One of them being the higher infection ratio that diseases cause, because of the higher population density in urban areas (UN, 2019). We see the same pattern with the current COVID-19 pandemic, now that an estimated 90% of all reported COVID-19 cases come from urban areas, making them the epicenter of the pandemic (Guterres, 2020). Moreover, the pandemic can have a disproportionate impact on more vulnerable groups due to deep-rooted inequalities, including where in a city a person lives and works. A United Nations report says tackling COVID-19 seems to be more challenging for example in urban areas with high levels of crime and violence and poor infrastructure and housing. Most other research about the disadvantageous side effects of urbanization reflect on its environmental impact and on its relativeness with increased crime rates. Studies point out that urbanization comes with increased levels of CO_2-emissions and also a negative effect on biodiversity (Liu & Bae, 2018; UN, 2019). Also, related to crime rates, studies have shown that urbanization comes with increased opportunity for violence (Flango & Sherbenou, 1976; Stewart & Cantora, 2015).

2.1.3 Urban planning

"Urban planning is one of a number of designations for forms of spatial planning that encompass ways in which land, land use, spatial morphologies, resource distributions, and social interactions may be planned and managed." (Huxley, 2009)

Since more and more people are migrating to urban areas to make a living and build a home, it is of great importance to proactively prepare for sustainable cities. Urban planning is a process in which one can plan and manage a high-quality residential environment, which leads to esthetical, social, economic and ecological benefits. It has been studied that thoughtful design is required to create appealing public open spaces that encourage people to be actively involved in recreational or physical activities (Zhang et al., 2013). The cited study shows that the mere existence of public open space can already be associated with walking for recreation. But infrastructural enhancement, for example good paths to reach those open spaces, is further associated with walking as transportation mode for going from point A to point B. Urban planning/design is thus an effort that should be considered on both a macro- and a micro-level. Not only is urban planning important on different levels of scope, it is also important in different time frames. Planning for a sustainable urban area is planning for the long term. An urban planner should thus also consider the impact on, for example, elderly people, who increasingly prefer "aging in place". "Aging in place" is referred to the fact that people want to grow old in their own community, with some level of independence, rather than in residential care (Wiles et al., 2011). To assist elderly people staying at home, responsibility does not only lie with the architect who designs their houses, but responsibility also lies with the urban planner who takes care of transportation accessibility, recreational opportunities, and amenities that facilitate physical activity and social interaction.

2.1.4 Urban attributes

The discipline of urban planning involves a wide range of urban attributes: bridges, city parks, benches, fountains, pedestrian crossings, lakes, trees along the road, and many more. Urban attributes are present in different layers of a city (Figure 5).

For example, the built environment addresses cities from an architectural and urban design perspective in order to understand the level of physical appearance of the street-level or the level of safety within a certain neighborhood. Examples of urban attributes in this layer of the city are buildings, open spaces and sidewalks. Another layer, that of transportation and traffic, is a more complex layer that merges and interacts with other layers of the city and is concerned with transport modes, road safety and optimization of traffic. Typical urban attributes in this layer include traffic lights, street lighting, pedestrian crossings, vehicles etc. Furthermore, the natural environment is the layer at which green spaces, landscape, and other green urban attributes are present. The elements of this layer influence human perception of the visual appearance of the built environment and also affects mobility and human interaction in cities.

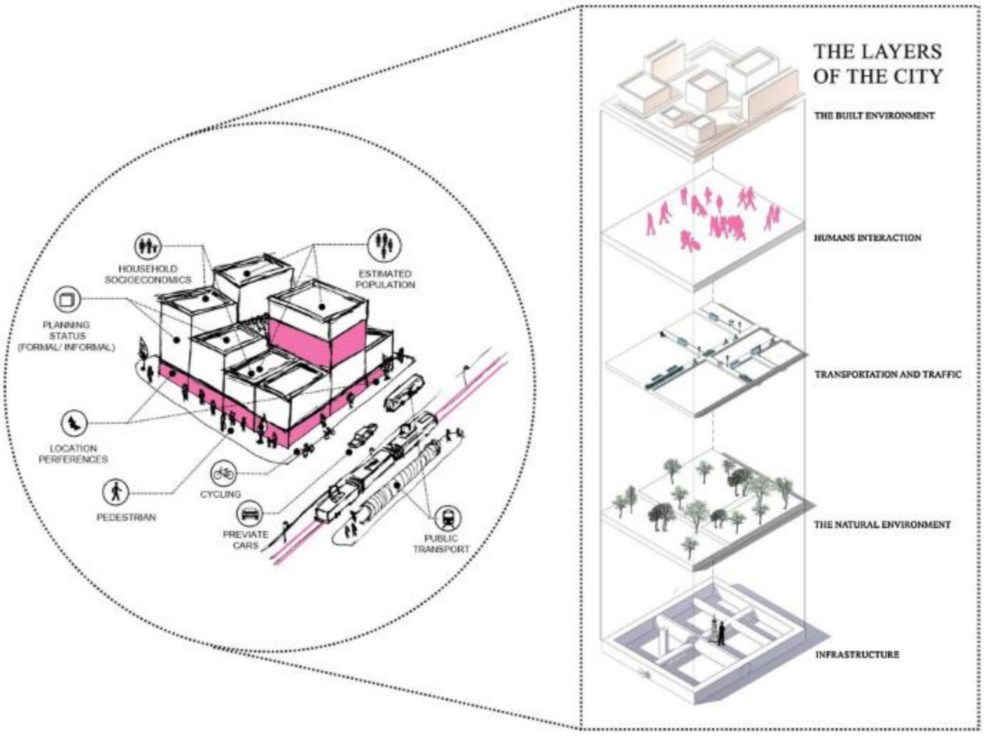


Figure 5 Five layers of the city as visualized by Ibrahim (2020) who used the layers of the city to explain urban analytics[1].

2.1.4.1 Impact of urban attributes on perceived beauty

This section briefly reviews literature on the correlation between urban attributes and perceived beauty (Table 2). Quercia (2014) researched what makes the city of London look beautiful, as well as quiet and happy. The authors found that Victorian houses, public gardens, red bricks and residential trees were positively correlated with perceived beauty. The opposite is true for council housing, bridges and highway road signs and guardrails. Another study about measuring human perceptions on the built environment is that of Zhang (2018). Their research shows that there is a highly significant positive correlation between urban attributes such as trees, grass and paths and perceived beauty. There are also some urban attributes for which they found a highly significant negative correlation with beauty, such as bridges and buildings. A third example is the study of Seresinhe (2017). They used ratings of over 200,000 images of Great Britain from the online game Scenic-Or-Not to understand what beautiful outdoor spaces are composed of. Their research resulted in an extensive list of urban attributes that are positively/negatively correlated with beautiful spaces. The most important examples of their complete list are integrated in table 2.

[1] Urban analytics is urban research that exploits big data resources, available from social media, crowd sourcing, and sensor networks, by means of data analysis and beyond.

Reference	(+) beauty	(-) beauty
Quercia et al.	Victorian houses, public gardens, red bricks, residential trees	Council housing, bridges, highway road signs and guardrails
Seresinhe et al.	Natural canals, historical man-made features (churches, castles, towers, viaducts, …), forest paths, cottages, ponds, rivers, urban green, etc.	Hospital, parking lot/garage, industrial area, construction site, highway, playground, gas station, fire station, motel, kennel, etc.
Zhang et al.	Trees, grass, paths	Bridges, trucks, floors, fences, walls, buildings, sky

Table 2 Literature on the correlation between urban attributes and perceived beauty.

Some visual examples of places that people perceived as beautiful can be consulted in Appendix B. Note that the academic literature contains many studies about urban design, but lacks detailed studies that research which urban attributes cause urban areas to be perceived as beautiful (i.e., the composition of beautiful cities).

2.1.4.2 Impact of urban attributes on perceived safety

In contrast with the previous section, more research has been done regarding the impact of urban attributes on perceived safety (Table 3). For example, the relationship between urban greenery and perceived safety is studied very frequently in academic literature. Some studies have demonstrated that green spaces might evoke feelings of fear, ranging from fear of physical dangers to social dangers, such as crime (Gargiulo et al., 2020). In this cited study the authors designed and implemented a safety map to visualize the perceived safety of women on green environments. They found that path lighting, open views, increased user density and presence of residential areas are positively correlated with perceived safety. As a logic consequence, high vegetation density (e.g., excessive trees and bushes) is negatively correlated with perceived safety as it tends to have a negative effect on visibility. Also views of industrial areas and parking areas are negatively correlated with perceived safety. Their results were consistent with the "eyes on the street" theory developed by Jane Jacobs in 1961, which says that people feel safer the more people around, because their eyes on the street provide informal surveillance (Jacobs, 1961).

Another study also focused on examining the relationship between urban greenery and perceived safety (Rahm et al., 2020). Participants of the study took part in a structured 300m walk representative of the pedestrian planning strategy of their district and afterwards gathered for a focus group. The authors found that participants' feeling towards urban greenery was different depending on whether they walk during daytime or after dark. During daytime they regarded greenery as a positive environmental factor, but after dark participants would frequently avoid environments with greenery. Urban greenery was also exposed to the feeling of entrapment, which induces feelings of unsafety. If the greenery was dense and too close to the path, participants felt not able to escape from potentially dangerous situations. However, just like Gargiulo (2020) found, this study showed evidence that the presence of other people contributed to the perceived safety of an urban area, even after dark.

There are also studies that focus on the correlation between other urban attributes and perceived safety. For example, Johansson (2020) researched the correlation between street lighting and perceived safety. This study reports on the development and evaluation of a method that analyses pedestrians' movements in an artificially lit outdoor environment. Previous literature namely suggests that lighting has an impact on people's walking behavior, both on their choice of travel as well as on their choice of route. The authors argue that different lighting conditions indeed lead to different behaviors of pedestrians, which gives relevant insights about topics like perceived safety.

The study of Zhang (2018) comprises of even more urban attributes and their effect on perceived safety. They concluded that the strongest contributions (both positive and negative) came from sidewalk, grass, car, road, path, fence, tree, wall, building and sky. The first five urban attributes (sidewalk – path) are positively correlated with the perception of a built environment being safe, while the other five attributes (fence – sky) are negatively correlated with the safe indicator. Some visual examples of places that people perceived as safe can be consulted in Appendix B.

Reference	(+) safety	(-) safety
Gargiulo et al.	Open views, people around, street lighting	Dense vegetation, parking areas
Johansson et al.	Daytime, street lighting	Entrapment
Rahm et al.	Daytime, people around, street lighting	Entrapment
Zhang et al.	Sidewalks, grass, cars, roads, paths	Fences, trees, walls, buildings, sky

Table 3 Literature on the correlation between urban attributes and perceived safety.

2.2 Ecosystem services

Urban attributes and their impact on human perception are very important to take into account for urban planning. Furthermore, some urban attributes even give rise to other benefits beside positive human perception. Specifically, urban greenery (natural urban attributes) give rise to ecosystem services (ES). This section will guide the reader through the concept of ES, its application in urban areas and why it is important to value them.

Ecosystems are communities of living organisms that interact with nonliving components in their environment, just like a system does. Ecosystem goods (such as food) and services (such as air purification) represent the benefits human populations derive, directly or indirectly, from those interactions (Costanza et al., 1997). In general, those goods and services are referred to as ecosystem services (ES). The notice of ES helps reframe the value of conserving nature, not as something that is extra or in conflict with human goals, but as a necessary partner in achieving those goals.

In the study of Costanza (1997) one can find ES grouped in seventeen categories, ranging from water regulation and biological control to recreational and cultural services (see Appendix C for all categories). All ecosystem services belong to four overarching functions: supporting, provisioning, regulating and cultural functioning (Haines-Young & Potschin, 2010). Furthermore, the total value of those ecological services can be built up from both market and non-market components. Take for example the total value of a forest: it adds value to both timber production (market component) and to the aesthetical appearance of an area (non-market component). Adding up both the market and non-market value of an ecosystem service results in its total value. In 1997, Costanza and others hinted at the total global value of ecosystem services (Costanza et al., 1997). They estimated that seventeen categories of global ecosystem services provided on average $33 trillion dollars worth of services annually (without even using the high ends of all value ranges and without taking into account the value of desert, tundra and rangelands). The majority of the value of services came from their non-market components, such as nutrient cycling ($17 trillion per year), waste treatment ($2.3 trillion per year), disturbance regulation ($1.8 trillion per year) and gas regulation ($1.3 trillion per year). Since natural capital and ecosystem services face a future in which they will become more scarce, Costanza and the other authors expect their value to increase even more.

2.2.1. Urban ES

The ES concept is frequently discussed with regard to air, land, and water resources in rural and natural landscapes. But also urban attributes give rise to ES and because of global urbanization, urban issues have also received more attention in reports on ecosystem services (Bolund & Hunhammar, 1999; Hubacek & Kronenberg, 2013; Kremer et al., 2015; Luederitz et al., 2015). Since the borders between different ecosystems are often diffuse, one could argue that a city is one single ecosystem, while others see the city as composed of several individual ecosystems. Table 4 provides an example of different urban ecosystems within the city of Stockholm, the ES they supply (Bolund & Hunhammar, 1999), and some examples of urban attributes that make up the urban ecosystem.

Ecosystem	Some urban attribute(s)	Ecosystem services
Cultivated land	Garden, food crops	- Air filtering - Micro climate regulation - Noise reduction - Rainwater drainage - Recreation
Lakes/Sea	Open water area	- Micro climate regulation - Recreation
Managed green areas (e.g., park, playground or golf course)	Grass, trees, plants	- Air filtering - Micro climate regulation - Noise reduction - Rainwater drainage - Recreation
Stream	Flowing water	- Micro climate regulation - Recreation
Street tree surrounded by paved ground	Tree	- Air filtering - Micro climate regulation - Noise reduction - Recreation
Urban forest	Trees	- Air filtering - Micro climate regulation - Noise reduction - Rainwater drainage - Recreation
Wetland (e.g., marsh or swamp)	Grass, bushes	- Air filtering - Micro climate regulation - Noise reduction - Rainwater drainage - Sewage treatment - Recreation

Table 4 Ecosystems in Stockholm, some examples of natural urban attributes that appear in those ecosystems, and the ES they provide.

Note that this Master thesis is only interested in the recreational and cultural value of urban ecosystem services. There is a subtle difference between recreational ecosystem services (RES) and cultural ecosystem services (CES). RES can be defined as the environment's contributions to the range of leisure and recreational opportunities and experiences that humans can benefit from (Hermes et al., 2018), while CES can be defined as the nonmaterial, intangible benefits people obtain from ecosystems in general (Cheng et al., 2019). Other urban ES (e.g., air filtering, noise reduction, sewage treatment, etc.) are out of the scope of this Master thesis.

2.2.2 Valuation of ES

However, measuring the (economic) value of ES is difficult. ES are not traded on any market, so one cannot simply look at commercial prices in order to know how people value some ES. Without market intervention of governments certain products or services would never be realized or would never be paid for, like benches in public parks, national defense, street lighting, air pollution, or ES. These are market failures referred to as public goods and externalities (Cornes & Sandler, 1996). Firstly, public goods are goods that are both nonrivalry and nonexcludable, which means that consumption of the good will not prevent the opportunity of using it again and that one cannot exclude others from using the same good, respectively. An urban park, such as Brussel's Jubelpark, is an example of an urban ecosystem that is a public good. Secondly, externalities exist when the action of one economic agent has an impact (either positive or negative) on the utility or production function of another economic agent, and no procedure for compensation exists (Cornes & Sandler, 1996). For example, person A has a green roof on his house, which not only reduces the air pollution he causes by himself, but also reduces the air pollution caused by his neighbors. Public goods and externalities have an important impact on people's day-to-day life (see for example Costanza, 1999; Costanza et al., 1997; Haines-Young & Potschin, 2010), as do ES. Therefore, governments are in desperate need of accurate valuation methods to account for products and services that are not automatically regulated by the market.

2.2.3 Economic valuation of ES

Classical economic theory presumes that consumers are maximizers of self-interest, and that self-interest consistently guides them across different decisions (McFadden, 2001). Later in the field of economic valuation, researchers looked at the consumer as a rational decision maker with preferences represented by a utility function $U(x)$ for a certain product or service x. The consumer would then maximize his or her utility subject to a budget constraint, a mapping that was assumed to hold at the market level with a disturbance ε applied to it in order to explain discrepancies in observed data. At first, standard economic theory was developed for the purpose of interpreting changes in prices and quantities of goods sold in markets.

However, the theory has been extended to public goods and other nonmarket goods and services (Freeman III et al., 2014). Since then it is assumed that consumers have preferences among alternative bundles of goods, consisting of various quantities of both market and nonmarket goods. Because of financial or other restrictions, consumers have to make trade-offs when deciding on the quantities they want of the goods or services within the bundle. Those tradeoffs that people make when choosing to substitute one or more good for another reveals important insights about the value that they attach to the goods and services at stake. Value measures based on substitutability are called willingness to pay (WTP) or willingness to accept (WTA) (Freeman III et al., 2014). WTP is defined as the maximum price a consumer is willing to pay for a certain quantity of goods or services (Gall-Ely, 2009), whereas WTA is defined as the minimum sum of money a consumer would require to voluntarily accept the loss of a certain quantity of goods or services (Freeman III et al., 2014).

Although the concept of economic valuation has only slightly evolved over time, its methods have transformed tremendously. Section 2.3 discusses the more traditional methods of doing economic valuation, through revealed preference methods and stated preference methods. The focus will be on one specific stated preference method: discrete choice modelling (DCM). Afterwards, section 2.4 continues with more recent developments in economic valuation, those of deep learning (DL).

2.3 Traditional methods

2.3.1 Revealed preferences

Revealed preferences methods (RP) are based on observing actual behavior, for further specifications we follow the definitions in the study of Cheng (2019). When studied in monetary terms, RP means observing the actual markets that are related to the ES of interest to assess its value. The following table (Table 5) will briefly describe some of the valuation methods based on RP that are used most often to assess the value of CES and RES in monetary terms (Cheng et al., 2019; Hermes et al., 2018).

Evaluation method	Description
Benefits/Value transfer	Measures economic values of ES by transferring and adjusting data (costs/benefits/…) from an existing study to a new study.
Hedonic pricing	Estimates economic values of changes in ES based on housing prices on the market. Namely, house prices are sensitive to their environment; whether they are close to an industrial area, a recreational park, a point of interest, etc. or not is reflected in their market price. This method cannot be applied for all ES, but is interesting if one wants to estimate the value of e.g., pollution, a scenic view or a recreational area (ConservationStrategyFund, 2015a).

Market price	Approaches economic values of ES based on the price of products that can be bought and sold on a commercial market. For instance, it looks at entrance fees paid to parks to calculate the park's value. This method can thus also be applied to fish, insects, nuts, water, timber and the like, because these are products that can be sold on a commercial market (ConservationStrategyFund, 2015b).
Travel cost	Estimates economic values of ES based on the travel costs that people are willing to pay for in order to get to a certain destination. There are no direct costs that can be measured, like with the market price method, but there are some indirect costs involved (e.g., bus ticket to travel and opportunity cost of time spent elsewhere) that can give meaningful insights about the value of an area (ConservationStrategyFund, 2015c).

Table 5 Monetary revealed preference methods that are most commonly used for valuing cultural and recreational ecosystem services.

Monetary valuation methods can be challenging to use for some CES or RES. For example, assessing the (perceived) aesthetic value of a scenery is too complex to express in monetary terms. Also, assessing the value someone attaches to a scenery with regard to (perceived) safety, is very hard to express in monetary terms. That is why non-monetary RP methods are emerging, which essentially comes down to observing behavior or analyzing documents to indirectly assess the value humans attach to the ES. The following table (Table 6) will describe some methods to extract data based on RP that are used most often to assess the value of CES and RES in non-monetary terms (Cheng et al., 2019; Hermes et al., 2018).

Data extraction method	Description
Document	Looks at texts, images, or other forms of a document to acquire information on human preferences. For instance, counting the number of photos taken from an area.
Observation	Looks directly at human actions and behavior to estimate the social value of ES. For instance, observing the number of visits to a park.
Social media-based	Based on social media data from various resources. For instance, uses the number of pictures on a photo-sharing website as a proxy for the value of an ES.

Table 6 Data extraction methods that are most commonly used for non-monetary revealed preference methods.

2.3.2 Stated preference methods

Stated preference methods (SP) are used when it is not possible to observe actual behavior, so people are provided with hypothetical scenarios. Like in section 2.3.1, we will follow once again definitions used in the study of Cheng (2019) to make further specifications of existing SP. When researchers want results in monetary terms, they will have to build hypothetical markets and ask respondents to directly state their willingness to pay or willingness to accept for some good or service. The following table (Table 7) will briefly describe some of the valuation methods based on SP that are used most often to assess the value of CES and RES in monetary terms (Cheng et al., 2019; Hermes et al., 2018).

Evaluation method	Description
Choice experiment	Analyzes respondents' choices between different bundles of ES which are described in terms of their attributes and attribute levels.
Contingent valuation	Estimates the values of ES by directly asking people their willingness to pay for a certain ES. This method is well known for its survey technique which simply asks people questions like "What would you pay to […]?", "Would you be willing to pay amount *X* for […]?" or "Tick off the amounts you are willing to pay for […]." etc. (ConservationStrategyFund, 2016).
Deliberative valuation	Integrates scientific or technical forms of analysis with deliberation to estimate the value of ES. It is an interactive valuation method to form value judgements.

Table 7 Monetary stated preference methods that are most commonly used for valuing cultural and recreational ecosystem services.

As with RP, it might not always be possible to describe the value of an ES in monetary terms. The same examples as in section 3.2.1 can be applied: assessing the (perceived) aesthetic value of a scenery is too complex to express in monetary terms. Also, assessing the value someone attaches to a scenery with regard to (perceived) safety, is very hard to express in monetary terms. For non-monetary techniques, SP is simply about directly asking about one's value related to an ES. Table 8 will describe some of the methods to extract data based on SP that are used most often to assess the value of CES and RES in non-monetary terms (Cheng et al., 2019; Hermes et al., 2018).

Data extraction method	Description
Expert-based	Uses experts' knowledge and experience to assess ES.
Interview or focus group*	Gains insights about how and why people value ES through face-to-face interaction or other similar techniques. The main difference between an interview and a focus group is that the former is usually performed one-on-one while the latter is performed in group and moderated by an expert.
Participatory mapping	Combines modern cartography tools with participant interaction to map ES.
Questionnaire*	Directly asks questions to respondents as in the contingent valuation method, but not necessarily related to money. For instance, researchers could use a Likert scale[2] or ask respondents to select from given options in order to learn about respondents' internal valuation processes.
Scenario simulation	Simulates future scenarios with different attributes to provide advice to policy makers and planners.
Volunteered geographic data	Based on user-generated content, which Goodchild calls volunteered geographic information (VGI) in his work "Citizens as sensors: the world of volunteered geography" (Goodchild, 2007), others refer to it as participatory geographic information systems (PPGIS/PGIS) (Hermes et al., 2018). VGI is the extension of participatory mapping with geographic information systems (GIS). One of the more captivating examples of VGI or PGIS is Wikimapia, where anyone with an Internet connection can select an area on planet Earth and add a description to it, including links to other sources.

*Table 8 Data extraction methods that are most commonly used for non-monetary stated preference methods. (*By far most used)*

2.3.2.1 Discrete choice modelling

A discrete choice model (DCM) usually results in a survey in which the researcher asks respondents to choose between a finite number of scenario's in a choice set (Figure 6). Each scenario has different levels of the attributes the researcher wants to learn about. The choice a respondent makes, provides insights about how the different attributes of the choice sets are valued. In other words, a researcher will learn more about the willingness to pay (WTP) for each attribute, instead of only learning about the WTP for the overall ecosystem.

[2] Likert scale is a rating scale (e.g. 1-5 or 1-10) used to assess preferences, opinions or behaviors.

	Campground A	Campground B	Status quo alternative
Picnic Shelters	Yes	Yes	Stay at home: I would not choose either campground ☐
Boat ramps	Yes	Yes	
Camping fee	$20	$25	
I would choose:	☐	☐	

Choice set

Choice attributes

Some attribute levels of *"Camping fee"*

Figure 6 Example of a choice set, as copied from the DCM by Holmes (2017).

2.3.2.1.1 Consumer theory of Kelvin J. Lancaster

The conceptual foundation for DCM lies within the hedonic method, which states that the demand for goods is actually derived from the demand for attributes (Holmes et al., 2017). Consumers evaluate items and then use these evaluations when choosing between products. Although conventional consumer theory had already been opposed to a newer, attribute-based approach in previous studies, Kelvin J. Lancaster's 'A new approach to consumer theory' is referred to as the main study for this topic (Lancaster, 1966).

For instance, if one would intend to value a recreational site and use the results in a cost-benefit analysis, why not opt for e.g., the travel cost method and use a DCM instead? Peter J. Greig did exactly that. He explains that the travel cost method is based on a consumer theory in which the consumption of a commodity, such as a recreational site, is a utility function of its own, substitutes' prices and consumer income and taste (Greig, 1983). However, in a cost-benefit analysis it might be useful to compare the same commodity with itself, albeit with other characteristics. That is why researchers might reside to evaluation methods supported by Lancaster's theory which puts emphasis on the attributes of a commodity leading preferences instead of the commodity itself (Lancaster, 1966).

2.3.2.1.2 Random utility maximization by J. Marschak

If a person *A* chooses commodity *X* and rejects commodity *Y*, this behavior is interpreted as an indication that commodity *X* yields a higher utility than commodity *Y* does (decision-utility theory of Böckenholt (2006)). Lancaster's consumer theory would argue that it is not the commodities themselves, but their attributes, that constitute utility measures. More specifically, any good can be described in terms of its characteristics (or attributes) and the levels that these attributes can take.

But what if person *B* chooses differently, or what if person *A* chooses differently next time? Lancaster's consumer theory does not explain this kind of behavior in economic choices. There might be attributes internal or external to a commodity that cannot be observed by the researcher, but that impact choice behavior (Holmes et al., 2017).

In the field of psychometrics[3], Louis L. Thurstone investigated decision-utility theory in his work 'A law of comparative judgment' (Thurstone, 1927). Thurstone explains that a single observer judges options by the method of paired comparisons and all choice options can be represented along a utility continuum through stochastic variability that explains unobserved parameters (Böckenholt, 2006). The stochastic variability is driven by randomness and can be explained by the normal distribution, which provides a probabilistic version of decision utility. Thurstone's work was introduced into economics in 1960 by Jacob Marschak, who studied the concept of choice probabilities in utility maximization when random elements are present (Marschak, 1960). He called this Random Utility Maximization (RUM) models. RUM models are models where utility of commodity i for a respondent k is the sum of a systematic (v) and a random (ε) component:

$$(1) \qquad U_{ik} = v_{ik}(Z_i, y_k - p_i) + \varepsilon_{ik},$$

where $v_{ik}(Z_i, y_k - p_i)$ is the systematic component constituted by a vector of attributes associated with commodity i (Z_i), income (y_k) and the cost of commodity i (p_i) and ε_{ik} is the random component that incorporates unobserved factors that make respondent k choose for commodity i (Holmes et al., 2017). The "*Utility Maximization*" part in RUM models reflects on the fact that the respondent will choose the alternative with the highest utility, i.e., he will choose alternative i if and only if

$$(2) \qquad v_{ik}(Z_i, y_k - p_i) + \varepsilon_{ik} \; > \; v_{jk}(Z_j, y_k - p_j) + \; \varepsilon_{jk},$$

for all j, i.e., all alternatives, available in the choice set. The error term is a stochastic variable in the random utility function and thus allows one to make probabilistic statements about choice behavior. Namely, the probability that a respondent will choose commodity i from the presented choice set can be expressed as

$$(3) \qquad P_{ik} = P[v_{ik}(Z_i, y_k - p_i) + \varepsilon_{ik} \; > \; v_{jk}(Z_j, y_k - p_j) + \; \varepsilon_{jk}],$$

for all j, i.e., all alternatives, available in the choice set.

[3]Psychometrics is the science of measuring an individual's mental capacities and processes.

2.3.2.1.3 The multinomial logit model of Daniel McFadden

It was Daniel McFadden who developed an econometric model that is widely used in discrete choice modelling. His *conditional logit model* or *multinomial logit model* (MNL) is based on hedonic analysis – as in Lancaster's consumer theory – and random utility maximization (McFadden, 1972). I would like to refer to McFadden's work for deeper mathematical understanding of his model and continue with the most important result of his work. More specifically, he proved that the probability of person k choosing for alternative i in choice set t is given by

(4) $$P_{i,k,t} = \frac{e^{v_{i,k,t}}}{\sum_{j=1}^{J} e^{v_{j,k,t}}},$$

where $v_{i,k,t}$ is the systematic component of the utility of alternative i for person k in choice set t. By using MNL one thus has a predictive model to support decision making.

2.4 More recent method: Deep Learning

Deep Learning (DL) is a subset of ML, which on its turn is a subset of Artificial Intelligence (AI). AI refers to techniques that enable computers to mimic human behavior and ML represents a set of algorithms trained on data to make AI's purposes possible (Hargrave, 2020). DL inherits from ML its aim to make accurate predictions based on pattern-recognition, but it does so in a more hierarchical way (LeCun et al., 2015). Namely, DL processes data in a multi-layered way, passing on information from one layer of *neurons* to another layer of *neurons*, like the human brain does. Consequently, DL is often referred to as *Deep Neural Networks (DNN)* or *Artificial Neural Networks (ANN).* Although there exists a small difference between these two terms (i.e., DNN are ANN with many layers), they will be used interchangeably in this Master thesis. LeCun, Bengio and Hinton (2015) published a very clear and comprehensive paper on the fundamentals of DL. For instance, they explain in which different stages an artificial neural network processes images, which is summarized in Figure 7. Images start at the so called *input layer,* go through a finite number of *hidden layers*, and end the DL program in an *output layer*. The representation in Figure 7 is often referred to as the *(traditional) feedforward deep neural network* (LeCun et al., 2015). Beside DL beating records in image recognition and speech recognition, the authors point out many more successes of this technique: natural language understanding (e.g., topic classification, sentiment analysis, question answering and language translation), reconstructing brain circuits, predicting gene expression and disease, etc. (LeCun et al., 2015).

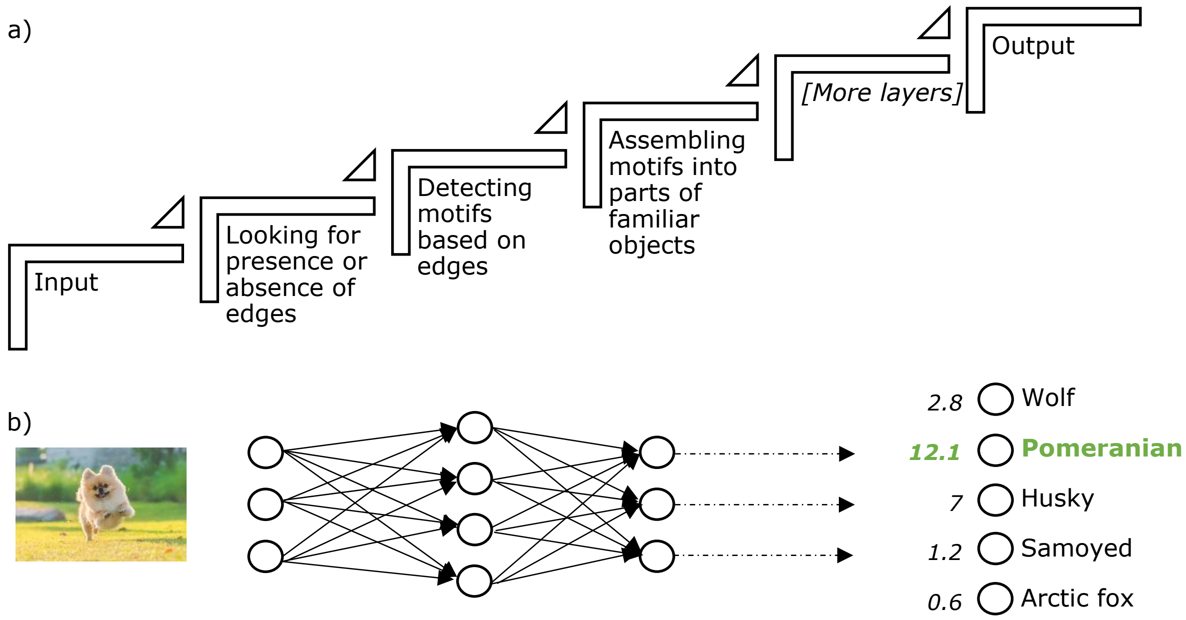


Figure 7 A) Simplified visual representation of the different stages (i.e. layers) an artificial neural network operates in order to process images. B) Simplified visual representation of a fictive example of an artificial neural network, based on the one used by LeCun (2015).

The most common form of DL is supervised learning, which involves training the DL algorithm with labeled data (LeCun et al., 2015). For instance, assume that we would like to program a DL algorithm that is able to categorize street view images containing traffic lights, pedestrian crossings, thresholds and other urban attributes. The first step is to collect a large data set of images of traffic lights, pedestrian crossings, thresholds, etc. labelled with the correct category. During training, the DL program is shown an image and produces an output in the form of a vector with scores for each category (cf. Figure 7b). The given output vector is compared to the desired output vector in an objective function that calculates the error (or distance) that the DL program made. The DL program then adjusts its internal parameters (i.e., weights that define the input-output function of the DL) and by repeating this exercise *learns* how to categorize the images correctly (LeCun et al., 2015). This procedure actually refers to a specific methodology that has a wide range of applications: *backpropagation*. At its core, backpropagation is simply a structured and exact method for quantifying all the derivatives of a single target quantity (e.g., the error an ANN made in categorizing images), while taking into account a large set of input quantities (e.g., the ANN weights) (Werbos, 1990). As mentioned earlier in this section, its purpose is that the predictions (i.e., vector outputs) of an DL algorithm should be as close as possible to (or the same as) some target prediction for a provided training set with data that is new to the algorithm.

2.4.1 Deep Learning for visual understanding

Since we are interested in DL for image processing (i.e., computer vision) in the quantitative part of this Master thesis, it is important to have a good understanding of previous literature related to the topic. In his paper, Ibrahim (2020) summarized eight fundamental tasks of computer vision, upon which other tasks can be framed and built (Figure 8).

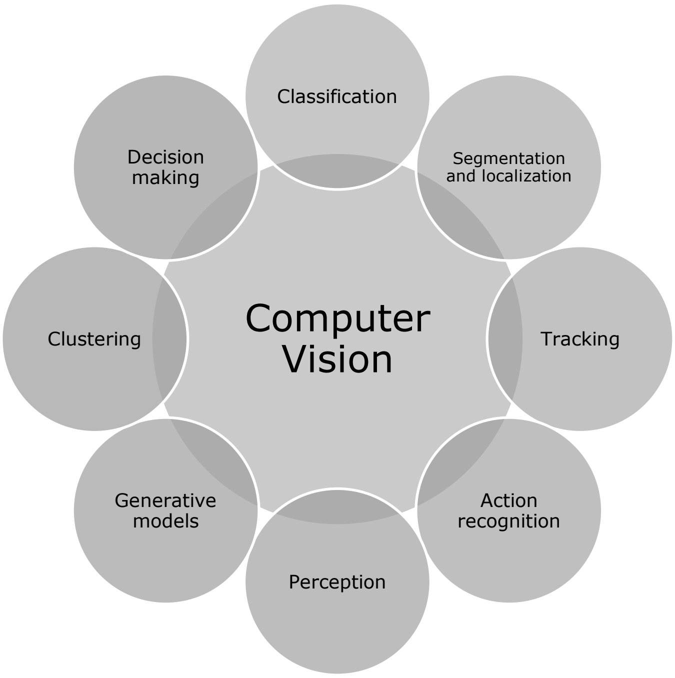


Figure 8 Visualization of eight computer vision tasks, content of the figure created by Ibrahim (2020).

We will be using DL for a 'Segmentation and localization' task: the process of identifying multiple objects in a single image (Zou et al., 2019). The objective of object detection is to develop computational models and techniques that provide an answer to a frequent question in computer vision: *What objects are where?* Convolutional Neural Networks (CNN) have been used most often to develop those computational models and techniques (Zou et al., 2019). Therefore, we will look at this type of network a little more in depth in the next section.

2.4.1.1 Convolutional Neural Networks

The Convolutional Neural Network (CNN) is one of the most notable deep learning approaches, and also the most commonly used one in various computer vision applications (Guo et al., 2016), especially for the task of image segmentation (Zou et al., 2019). The general CNN architecture is shown in Figure 9. A CNN is constructed from three types of layers, each with its own role to play: convolutional, pooling and fully-connected layers. Often a CNN configuration contains five convolutional layers, each followed by a pooling layer, and three fully-connected layers (Guo et al., 2016).

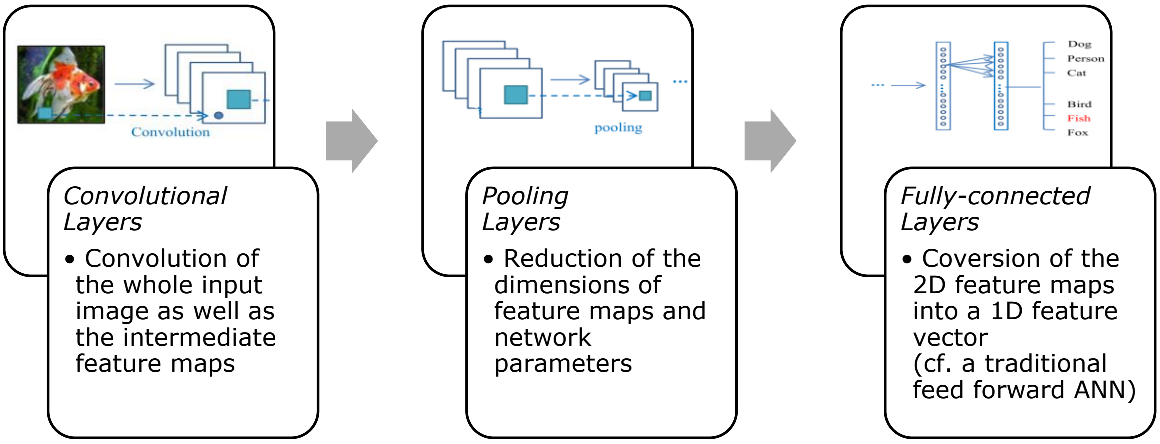


Figure 9 General configuration of a CNN, consisting of three different types of layers (source of the pictures in the graphic is Guo (2016)).

Numerous alternative versions of the general configuration exist. For instance, GoogleNet replaced the fully-connected layer for a sparsely-connected architecture in order to reduce the computational effort needed for training its ANN (Szegedy et al., 2015). Other examples are the Dropout (Srivastava et al., 2014) and DropConnect (Wan et al., 2013) networks in order to overcome overfitting[4] of an ANN. Also derived models have emerged, such as RCNNs (Regions with CNN features) and FCNs (Fully Convolutional Neural Networks), to make CNN more suitable for object detection and semantic segmentation instead of image classification (Girshick et al., 2014; Long et al., 2015).

2.4.1.2 Applications for urban planning

An increasing number of research is conducted about Deep Learning-based computer vision for advancement in urban planning. Ibrahim (2020) published a systematic and comprehensive literature review about this topic. In respect of their systematic approach, the authors categorized the application areas of urban analytics into five layers of the city, which we have already seen in section 2.1.4 of this Master thesis: the built environment, human interaction, transportation and traffic, the natural environment, and infrastructure. Table 9 shows the applications of computer vision to these five layers.

City layer	Application category
1. The built environment	Urban components Land use classification Urban perception Urban safety

[4] Overfitting is when a ANN is too closely fit to a dataset (usually its training dataset) so that it might provoke errors when trying to use it on another dataset. Source: Dietterich, T. (1995). Overfitting and undercomputing in machine learning. *ACM computing surveys (CSUR)*, *27*(3), 326-327.)

2. Human interaction	No specific categorization
3. Transportation and traffic	Traffic surveillance Safety / Accidents
4. The natural environment	Flora and fauna Environmental and weather conditions
5. Infrastructure	Concrete condition Pavement / Road condition Bridge component recognition

Table 9 Applications of computer vision to the five layers of the city as by Ibrahim (2020).

In general, the layer of the built environment is studied most (Ibrahim et al., 2020). This Master thesis will also contribute to this city layer, by performing an image classification task and predicting urban perception based on the presence of certain urban attributes (i.e., composition of urban attributes on beautiful/safe cities). Assessing urban perception (in general) through image classification has been researched by others too (Table 10). Table 10 provides an overview of previous literature related to this topic together with a brief explanation of each paper.

Reference	Contribution
(De Nadai et al., 2016)*	The authors of this paper explore the connection between the levels of activity and the perception of safety in neighborhoods of two Italian cities. They combined mobile phone data, as a proxy for activity level or liveliness, with scores of perceived safety from a crowdsourced visual perception survey.
(Doersch et al., 2015)	In *What makes Paris looks like Paris?* the authors argued that the “look and feel” of a city rests not only on the few famous landmarks it has, but largely on a set of stylistic urban elements. Given some geographic region *R*, the authors aim to find visual elements that are both 1) repeating, and 2) geographically discriminative, through computer vision techniques.
(Dubey et al., 2016)*	In this paper, the authors introduced a crowdsourced dataset of global urban appearance with pairwise image comparisons and proposed an ANN for predicting the human-labeled comparisons (i.e., what makes a place look safe / lively / beautiful / wealthy / boring / depressing)?
(Joglekar et al., 2020)	This study goes beyond predicting perceived beauty of a place, by proposing a framework to *generate* beautiful places through

	computer vision techniques. Their deep learning framework is called *FaceLift*.
(Law et al., 2020)*	This study demonstrates the classification of urban street frontage quality and shows that it can be an important component to help understand aspects of urban planning, such as perceived scenicness.
(Naik et al., 2016)*	The authors of this paper describe Streetscore: a computer vision algorithm that predicts the perceived safety of streetscapes.
(Ordonez & Berg, 2014)	The main contributions of this paper are image classification and regression models to predict human perceptions of safety, uniqueness, and wealth at a certain place.
(Quercia et al., 2014)*	This study used image processing techniques to determine visual cues that may cause a street in London to be perceived as being beautiful, quiet, or happy.
(Seresinhe et al., 2017)*	The authors of this study provide insights about what makes outdoor places are perceived as being beautiful by demonstrating the combination of online survey data with deep neural networks for image classification.
(Zhang et al., 2019)*	This study has provided evidence that street-level imagery can reveal socio-economic behavior, such as mobility patterns. The main contribution is that it sheds light on the connections between the physical urban settings and human activities.
(Zhao et al., 2018)*	The main contribution of this paper is providing a more complete perspective to urban valuation estimations, by integrating scattered sources of information (e.g., urban level features such as criminal rates, building level features such as housing prices, etc.) and implanting those into available images.

Table 10 Overview of scientific papers that contribute to academic literature about assessing urban perception based on image classification.
(References with an '' were also in the literature review of Ibrahim (2020))*

2.4.2 Deep Learning for choice behavior analysis

There is a growing number of choice behavior analysts that use ANN to enhance their research. The motivation for this trend is that the modelling techniques used for ANN emulate behavioral actions through similar neurological functions measured in the human brain (Friston & Stephan, 2007). The multi-layered architecture in ANNs represents the pattern in brain neuron activity when making decisions. This is very promising, but ANNs are still not mainstream for analyzing choice behavior.

That is why research is currently ongoing about scrutinizing, comparing and combining all possible techniques for choice behavior analysis. Since we are solely interested in the methods of DCM and DL/ANN, we will narrow this literature review down to these two topics. Alwosheel (2020) conducted a brief literature review on research efforts made in the light of ANNs used for choice behavior analysis. He used the categorization below for reviewed articles.

- *Comparative studies*: Have a focus on the comparison of ANNs to their counterpart traditional DCM for choice behavior analysis.
- *Enhancement and hybrid studies*: Aim at either employing ANNs' properties and techniques to enhance or augment DCMs, or at proposing a hybrid ANN-DCM approach.
- *Capitalization studies*: Want to use or improve the use of ANNs to analyze aspects of human choice behavior that are difficult to analyze with DCM.
- *Illuminating ANN black-box studies*: Aim at investigating the black-box character of ANNs and therefore proposes strategies and solutions to overcome that issue.

(Alwosheel, 2020) provides two interesting observations. First of all, although many reviewed articles noted that ANNs have a significant black-box issue (i.e., ANNs are difficult to interpret), there is very little attempt to overcome this issue. Secondly, most studies seem to focus on choice behavior within the field of transportation. Possibly, this is due to the availability of a few relatively large datasets of RP mode choices that can be used for free (Cranenburgh et al., 2021). As of 2017, a growing number of studies about choice behavior analysis has emerged in other research fields. These findings are also supported by Cranenburgh (2021) who conducted a literature review on the topic of *"Choice modelling in the age of machine learning"*. They used the following distinction for reviewed papers, based on methodological objective.

- *Compare studies*: Studies that focus on making comparisons in terms of model fit and prediction accuracy.
- *Beyond compare studies*: Studies that, for instance, try to integrate discrete choice models and machine learning models, and studies that try to extend machine learning approaches such that they become useful to tackle challenges of choice modelers.

The study of Cranenburgh (2021) resulted in some additional interesting findings about machine learning for choice behavior analysis. First, in terms of the type of machine learning model, most studies use ANNs, followed by support vector machines (SVMs) and decision trees. Second, concerning the data that is used, most research studied RP data. Only a fifth of all papers that were reviewed (25 in total) studied SP data. Third, regarding software packages, python is most widely used, although R and MATLAB also attain considerable market shares.

In subsection 2.4.2.1 we will look at some *comparative studies* in order to have a better understanding of the differences and similarities between DL and DCM models. Afterwards, in subsection 2.4.2.2, we will discuss studies that combine both techniques, which are often called *hybrid models*. Last, but not least, we will look at illuminating ANN black-box studies in section 2.4.2.3, the category of studies this Master thesis contributes to.

2.4.2.1 Deep Learning versus Discrete Choice Models

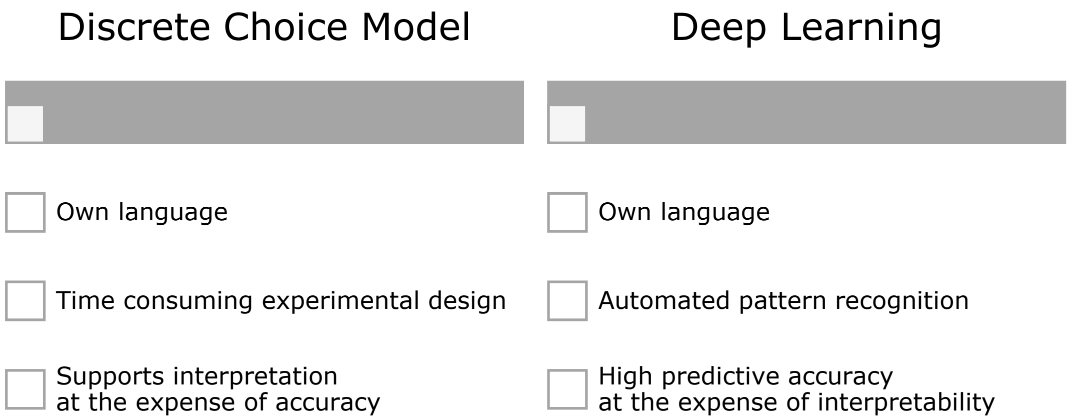


Figure 10 Differences between DCM-based method and DL-based method.

Prediction in choice behavior analysis is often performed using either statistics (e.g., DCM), which is theory-driven, or computational intelligence (e.g., DL), which is data-driven. Both techniques have strengths and weaknesses, but neither of them is perfect (Figure 10). First of all, they use different terminology for referring to the same or similar concepts: for instance, talking to statisticians one would say "independent variables and the predicted variable", while in a conversation with researchers of neural networks the terms "input and output" are preferred (Karlaftis & Vlahogianni, 2011). The table in Appendix D shows some examples of shared concepts in both methods that come under different names (Cranenburgh et al., 2021).

Further, there are differences between DCM and DL in terms of their philosophy, model development, and knowledge acquisition (Karlaftis & Vlahogianni, 2011). The way DCM does model development and knowledge acquisition is one of its main drawbacks. The first steps of its procedure are 1) identifying and describing attributes, and 2) developing an experimental design (Holmes et al., 2017). Step one, characterizing attributes, regularly involves holding structured conversations, such as focus groups, with stakeholders of the research outcomes. For instance, Koemle & Morawetz (2016) used a former paper, rigorous literature research and interviews in the mountain biking community to identify the most important trail attributes for their DCM to assess mountain biker trail preferences in Austria. Step two intends to determine the number of alternative scenarios to present in each choice set, and the number of choice sets to present to the respondents (Holmes et al., 2017). Both steps are very time sensitive and they should be, because they have a significant impact on the success of the DCM, and so it has gained much attention in the literature on choice modelling (Coast et al., 2012; Louviere et al., 2011; Norman et al., 2019). DL can overcome this problem. We saw in the previous sections that image processing could automatically perform tasks such as clustering, segmentation, localization, action recognition, etc. (Figure 8). This makes DL more attractive than DCM from a time perspective.

However, the most "famous" difference between DL and DCM might well be their goals. Theory-driven methods such as DCM, aim at providing a model and offering insights on the data and its structure – their results are backed by an interpretable theory (Cranenburgh et al., 2021; Paredes et al., 2017). On the other hand, computational intelligence techniques, such as DL, do not target interpretation, they just aim for offering good predictions of the situation under study (Karlaftis & Vlahogianni, 2011). This is why the predictive accuracy of DL methods usually outperform those of DCM models (Paredes et al., 2017), also in situations with missing data (Barthélemy et al., 2018).

2.4.2.2 Hybrid model

In the literature review of Alwosheel (2020), only two studies were mentioned that aim at either employing ANNs' properties and techniques to enhance or augment DCM, or at proposing a hybrid ANN-DCM approach. In the study of Wong & Farooq (2019) the authors propose a ResLogit model. Their model is built on the pillars of ResNet (i.e., Residual Neural Networks), whose strategy it is to overcome some ANN problems by skipping connections between layers, and of MNL (i.e., Multinomial Logit), albeit relaxing some of the very strict prerequisites of choice models (e.g., Independence of Irrelevant Alternatives axiom[5]). More specifically, the ResLogit model is a tractable method combining the structures of an ANN with the Generalized Extreme Value (GEV) choice model. The ResLogit model accomplished to resolve two shortcomings in ANN for choice behavior analysis, namely, overfitting due to systematic error of biased model estimates in ANN and lack of economic interpretability. At the same time, it benefits from the accurate prediction performance of ANNs. A second example of hybrid models between ANN and DCM, is the study of Sifringer (2018). They combined intuition from the field of DCM with the predictive strength of ANN by adding one term, an estimator for uncaptured decision-making information, to each utility function of an MNL model.

2.4.2.3 Deep Learning enhanced Discrete Choice Models

There are a couple of papers that "go beyond comparing" (following the terminology used by Cranenburgh (2021)). These are studies that, for instance, try to extend machine learning approaches such that they become useful to tackle challenges of choice modelers. For this particular study, we are only interested in ANN, not in machine learning in general. Research that studies the enhancement of DCM through other machine learning techniques than ANN are not within the scope of this literature review. Table 15 shows studies that go beyond comparing ANN with DCM. To the best of my knowledge, these are the only studies with regard to the topic at hand that are published up to date.

[5] Independence of Irrelevant Alternatives (IIA) assumes that the probabilities of each pair of alternatives are uncorrelated with the presence of other alternatives. (Source: McFadden, D. (2001). Economic choices. *American Economic Review*, *91*(3), 351-378.)

Reference	Data	ANN enhanced…
(Alwosheel et al., 2018)	SP	Multinomial Logit
(Alwosheel et al., 2019)	RP	Multinomial Logit
(Antonini et al., 2006)	RP	Multinomial Logit
(Rossetti et al., 2019)	SP	Multinomial Logit
(van Cranenburgh & Alwosheel, 2019)	SP	Latent Class – Mixed Logit
(Wang et al., 2020)	RP, SP	Multinomial Logit

Table 11 Papers about ANN enhanced choice modelling methods.

This study will also apply an ANN enhanced multinomial logit model, based on SP data. The model will be sequential: images will first be processed through DL and the resulting parameters will be put into a multinomial logit model. The following section, the quantitative part of this study, will demonstrate this sequential approach applied to data about urban scenery.

3. Empirical Analysis

3.1 Data collection

Figure 11 visualizes the flow of data that resulted in the input dataset for this section. More specifically, data used for this research's analysis originates from the Place Pulse 2.0 dataset (Dubey, 2016), which is the result of a large-scale crowdsourcing effort. Its developers gathered data about urban perception through surveying people worldwide. Respondents were given pairs of Google Street View images and were asked to evaluate them against a perceptual indicator – "Beautiful", "Boring", "Depressing", "Lively", "Safe", and "Wealthy". This effort resulted in a dataset, free for anyone to use, containing a total of 1.17 million pairwise comparisons for 110,988 images from 56 cities from 28 countries, scored by 81,630 volunteers along the six perceptual indicators mentioned earlier. The original dataset was then transformed by one of the supervisors of this Master thesis (Ilias Mokas) through DL. In his research he used a pretrained PSPNet, trained on the labeled images from the ADE20K segmentation database (Zhou et al., 2017), to process the images of the Place Pulse 2.0 dataset. All spatial landscape attributes in the images were semantically represented into six generic classes: 'Blue', 'Green', 'Grey', 'Impervious surfaces', 'Non-permanent objects', and 'Sky' (Table 11). His efforts resulted in a cleaned set of big data that was used as the input for this Master thesis's quantitative section.

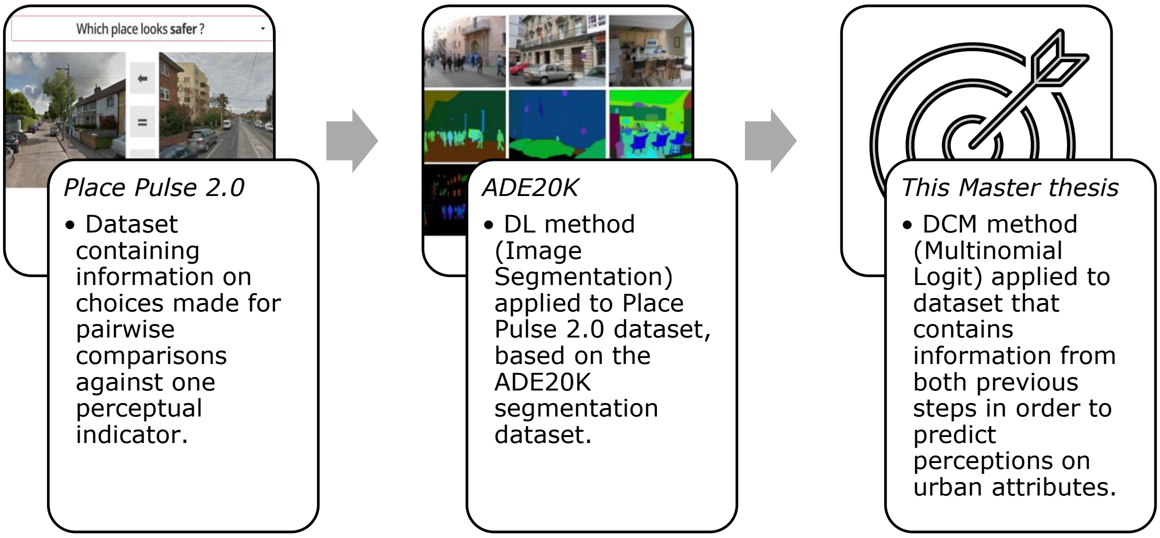


Figure 11 Visualization of the data flow from the Place Pulse 2.0 dataset to the dataset used for this Master thesis.

Category	Urban attributes
Sky	Sky
Green	Tree, Grass, Earth, Mountain, Plant, Path, Field, Rock, Hill, Flower, …
Blue	Water, Sea, River, Fountain, Pool, Waterfall, Lake
Impervious surface (I.S.)	Runway, Bridge, Road, Sidewalk, Pavement, Route, Span
Non-permanent objects (N.P.O.)	Person, Animal, Car, Bus, Motortruck, Bicycle, Van, …
Grey	Wall, Building, Fence, Screen, Flag, Light source, Traffic Light, Tower, House, Skyscraper, …

Table 12 Urban attributes and their overarching categories after image segmentation.

Table 12 shows the length and number of variables of the original (complete) dataset. The original dataset contains information on all six perceptual indicators of the Place Pulse 2.0 dataset. However, this Master thesis only focuses on data related to how beautiful/safe a place is perceived to be, so data about the other perceptual indicators was dropped. Also, some variables were not relevant for the current analysis (e.g., latitudinal and longitudinal coordinates of where the pictures were taken), so these variables were omitted too. It is necessary to perform two separate MNL models, one for measuring perceived beauty and one for measuring perceived safety. Therefore, two subsets were drawn from the original dataset: one containing only information on perceived beauty, and the other containing only information on perceived safety. In Table 13, the original dataset is compared with its subsets for the analyses of interest.

Parameter	Complete dataset	'Beauty' subset	'Safety' subset
Length	794,024 observations	107,129 observations	240,304 observations
Variables	31	17	17

Table 13 Summarizing parameters of the original dataset and the subsets that were consequently used for analysis.

3.2 Methodology

A MNL model was applied in order to predict people's perception on the urban environment built up from varying urban attributes. People were asked questions of the form "Which place looks safer/more beautiful?" and were given two Google Street View images to choose from. Based on equation (1) one thus needed to establish two utility functions for the MNL model, one for each alternative (picture) a respondent could choose from. Equation (5) and (6) represent those utility functions.

(5) $$U_{alt1,k} = V_{alt1,k} + \varepsilon_{alt1,k} \quad ,$$

(6) $$U_{alt2,k} = V_{alt2,k} + \varepsilon_{alt2,k} \quad ,$$

where $V_{alti,k}$ is the systematic component constituted by a vector of attributes associated with alternative i and $\varepsilon_{alti,k}$ is the random component that incorporates unobserved factors that make respondent k choose for alternative i. The vector of attributes in the systematic component corresponds to the landscape categories that are captured through DL (Table 11). Each picture, each one of both alternatives, consists of pixels that are part of one of the landscape categories. Which alternative respondent k chooses to answer the question "Which place looks safer/more beautiful?" with, depends on the composition of both pictures. For that reason, the observable (systematic) components of both utility functions can be written as follows:

(7) $$\begin{aligned} V_{alt1,k} = asc_{alt1} &+ \beta_{orange} * orange_{alt1} \\ &+ \beta_{green} * green_{alt1} \\ &+ \beta_{grey} * grey_{alt1} \\ &+ \beta_{blue} * blue_{alt1} \\ &+ \beta_{yellow} * yellow_{alt1} \\ &+ \beta_{red} * red_{alt1} \end{aligned}$$

(8) $$\begin{aligned} V_{alt2,k} = asc_{alt2} &+ \beta_{orange} * orange_{alt2} \\ &+ \beta_{green} * green_{alt2} \\ &+ \beta_{grey} * grey_{alt2} \\ &+ \beta_{blue} * blue_{alt2} \\ &+ \beta_{yellow} * yellow_{alt2} \\ &+ \beta_{red} * red_{alt2} \end{aligned}$$

where:

$orange_{alti}$ = # of pixels in alternative (picture) i that represent the "sky" category

$green_{alti}$ = # of pixels in alternative (picture) i that represent the "green" category

$grey_{alti}$ = # of pixels in alternative (picture) i that represent the "grey" category

$blue_{alti}$ = # of pixels in alternative (picture) i that represent the "blue" category

$yellow_{alti}$ = # of pixels in alternative (picture) i that represent the "non-permanent objects" category

red_{alti} = # of pixels in alternative (picture) i that represent the "impervious surfaces" category

The asc_{alti} parameters are the Alternative Specific Constants. These represent the average effect on utility of all factors that are not dependent on attribute levels and are thus not included in the equations. In order to know the impact of each landscape category on someone's landscape perception, we need to estimate the β-coefficients in the equations above. As mentioned earlier, this needs to be done separately for the beauty and the safety indicator, each with its own subset of the original dataset. Consequently, four utility functions were formulated for this Master thesis: two for both alternatives in the MNL model for beauty, and two for both alternatives in the MNL model for safety. Coefficient estimation was performed in RStudio with the Apollo package (Hess & Palma, 2019b). Apollo is a free package for conducting discrete choice models which does not rely on commercial statistical software as a host environment. Therefore, it was very suitable for this Master thesis. The website of the Apollo package provides its users with an extensive user manual so to guide them through their programming process (Hess & Palma, 2019a). For this Master thesis, the same user manual was used to write all necessary code for the MNL model. The complete R code can be found in Appendix E.

3.3 Results

Table 13 shows the standard errors, the estimates of the β-coefficients and a statistical interpretation for the beauty MNL model. All estimates were found to be significantly different from zero at a 0.001 significance level, except for the coefficient representing the "non-permanent objects" category, which was significant at the 0.01 level. Applying the estimates to equations (5) - (8) would result in the following two utility functions of person k on perceived beauty.

(9) $$U_{alt1,k} = -0.087707 * orange_{alt1} + 0.161584 * green_{alt1} - 0.104616 * grey_{alt1} + 0.026272 * blue_{alt1} + 0.005390 * yellow_{alt1} + 0.013721 * red_{alt1} + \varepsilon_{alt1,k}$$

(10) $$U_{alt2,k} = 0.047103 - 0.087707 * orange_{alt2} + 0.161584 * green_{alt2} - 0.104616 * grey_{alt2} + 0.026272 * blue_{alt2} + 0.005390 * yellow_{alt2} + 0.013721 * red_{alt2} + \varepsilon_{alt2,k}$$

The utility functions tell us that urban greenery, blue urban attributes, non-permanent objects and impervious surfaces have a positive effect on perceived beauty. It is also possible to compare their estimates to each other since all variables are measured in the same metric (i.e., pixels). Doing so, it is obvious that urban greenery is the strongest contributor to perceived beauty, with a β-coefficient estimated to be 0.161584. Also, non-permanent objects, such as vehicles or pedestrians, only have a very low contribution to perceived beauty, with a β-coefficient estimated to be 0.005390. On the other hand, the more one sees "sky" or urban attributes from the "grey" category, the less beautiful this place is perceived to be. Comparing both estimates, one could say that urban attributes from the "grey" category have the strongest negative impact on perceived beauty.

Beauty		
Attribute	**Estimate**	**Standard Error**
Sky	-0.087707	0.002227
Green	0.161584	0.002961
Grey	-0.104616	0.004812
Blue	0.026272	0.002607
N.P.O.	0.005390*	0.001792
I.S.	0.013721	0.002852
ASC alt1	0	
ASC alt2	0.047103	

Table 14 Results of the MNL for perceived beauty.
(indicates significance at the 0.01 level instead of the 0.001 level)*

Table 14 shows similar measures for the safety MNL model. All estimates are significantly different from zero at a 0.001 significance level. Applying the estimates to equations (5) - (8) results in the following two utility functions of person k on perceived safety.

(11)
$$U_{alt1,k} = -0.032984 * orange_{alt1} + 0.113797 * green_{alt1} - 0.032870 * grey_{alt1} + 0.013863 * blue_{alt1} + 0.035639 * yellow_{alt1} + 0.056321 * red_{alt1} + \varepsilon_{alt1,k}$$

(12)
$$U_{alt2,k} = 0.007643 - 0.032984 * orange_{alt2} + 0.113797 * green_{alt2} - 0.032870 * grey_{alt2} + 0.013863 * blue_{alt2} + 0.035639 * yellow_{alt2} + 0.056321 * red_{alt2} + \varepsilon_{alt2,k}$$

Once again, urban greenery, blue urban attributes, non-permanent objects and impervious surfaces contribute positively to the dependent variable (i.e., perceived safety). Urban greenery is the strongest positive contributor to perceived safety. Also, it can be noted that non-permanent objects contribute much more to perceived safety (β = 0.035639) than to perceived beauty (β = 0.005390). Further, urban scenery that exhibits more of the sky or contains more "grey" urban attributes, is likely to be perceived as less safe. However, "grey" urban attributes have a much more negative impact on perceived beauty (β = 0.104616) than on perceived safety (β = 0.032770).

Safety		
Attribute	Estimate	Standard Error
Sky	-0.032984	0.001396
Green	0.113797	0.001865
Grey	-0.032870	0.003028
Blue	0.013836	0.001759
N.P.O.	0.035639	0.001170
I.S.	0.056321	0.001863
ASC alt1	0	
ASC alt2	0.007643	

Table 15 Results of the MNL for perceived safety.

4. Discussion

4.1 Summary of findings

The physical setting of urban scenery, its urban attributes, influence human's perception on beauty, safety and other parameters (see section 2.1.4). Those urban attributes include a wide range of physical elements, varying over different layers of a city. For example, the city layer of the built environment addresses cities from an architectural and urban design point of view, in order to understand the level of physical appearance of the street-level or its level of safety. This Master thesis applies a big data approach to measure the impact of urban attributes, subdivided in six overarching categories, on perceived beauty and perceived safety. The six groups of urban attributes are the following: "Sky", "Green" (including trees, grass, mountains, plants, etc.), "Blue" (including rivers, fountains, lakes, etc.), "Impervious surface" (including runways, bridges, pavements, etc.), "Non-permanent objects" (including people, cars, busses, etc.) and "Grey" (including walls, fences, traffic lights, etc.). Consequently, a dataset processed through DL was implemented in a DCM analysis in order to answer main research question of this Master thesis:

Which urban attributes increase the probability of a city to be perceived as more beautiful and/or more safe?

Table 1 showed four sub research questions in order to provide a profound answer to the main research question. First of all, the impact of the six groups of urban attributes on perceived beauty is analyzed. Only for the groups "Sky" and "Grey" is there a negative effect on perceived beauty. This is consistent with previous literature, that says that walls, buildings, highway road signs and other urban features contribute negatively to perceived beauty (Quercia et al., 2014; Seresinhe et al., 2017; Zhang et al., 2018). Furthermore, this Master thesis shows that urban greenery contributes highly positive to perceived beauty. This too, is in line with the findings of previous literature. For example, Quercia et fal. (2014) studied what urban features make the city of London look "beautiful, quiet and happy" and they found that public gardens and residential trees have a positive impact on perceived beauty. The other groups of urban attributes that were analyzed, "Blue", "Non-permanent objects" and "Impervious surface", also showed a positive association with perceived beauty. Lastly, comparing the absolute values of all estimates, one can see that perceived beauty is most sensitive to urban greenery.

The next sub research question in Table 1 is about the impact of urban attributes on perceived safety. As in the previous DCM model, the urban attributes from the groups "Sky" and "Grey" have negative estimates. This means they have a negative impact on perceived safety. Their absolute values are remarkably smaller than their respective estimates in the model on perceived beauty. This suggests that urban attributes from "Sky" and "Grey" have a more negative impact on perceived beauty than on perceived safety. Previous literature mainly agrees with the findings of this Master thesis in this regard. The feeling of entrapment, which is usually caused by the presence of walls, buildings, etc., induces feelings of being unsafe in a city (Johansson et al., 2020; Rahm et al., 2020; Zhang et al., 2018). Further, urban greenery has, once again, the most significant positive impact in the choice model. This implies that people feel safer, the more urban vegetation around. This is consistent with some previous studies (Zhang et al., 2018), although there are exceptions where urban vegetation is not beneficial for people to feel safe in a city. For example, some women acknowledge that dense vegetation could be an incentive to avoid certain places or sidewalks (Gargiulo et al., 2020). Lastly, blue elements in the city, non-permanent objects and impervious surfaces have a positive impact on perceived safety. The fact that non-permanent objects, such as passing persons and vehicles, make people perceive a city as safe, confirms the "eyes on the street" theory of Jane Jacobs that was first published in 1961 (Jacobs, 1961). This theory says that people feel safer the more people around, because their eyes on the street provide informal surveillance. Once again, one can see that the perceptual indicator (i.e., perceived safety) is most sensitive to urban greenery.

Finally, there are no urban attributes that require a trade-off when it comes down to perceived beauty and perceived safety. All elements of an urban scene that add up positively to perceived beauty, also have a positive impact on perceived safety, and the other way around.

4.2 Limitations

Six categories were used to classify urban attributes. However, these categories might have been chosen too broad, too much different attributes belong to the same category. Therefore, the contribution that this study makes to the research field of urban design is only moderate. The inferences that could be made in section 4.1 were only limited to the impact of urban attribute *groups* on perceived beauty/safety instead of the impact of urban attributes *by themselves* on the perceptual indicators.

Two utility functions were developed in section 3.3. They only contained information on the urban attributes (i.e., segmented pixels) of each alternative (i.e., picture), there is no information included about the characteristics of respondents (e.g., gender, nationality, age). Including more variables in the equation, would have made the estimates more accurate, and consequently, would have made the error term smaller. Now all characteristics of respondents are regarded as "unobservable components", while they could have been included in the utility functions, if they were available.

4.3 Recommendations for future research

Following the limitations of this work, presented in the previous section, future research could be conducted for individual urban attributes instead of urban attribute groups. This is possible by doing the image processing task in such a way that more than six segments are identified, if possible, even for individual urban attributes. Another recommendation for future research is to include characteristics of respondents (e.g., age, gender) to study whether there are significant ethnographic differences when estimating perceptual indicators. Last but not least, it would also be interesting to use the developed method for prediction, i.e., to construct utility functions, fill in the number of pixels in each segment, and calculate the probability that the respondent would choose a certain alternative when being asked "Which urban scene is more beautiful/safe?".

5. Conclusion

People are more and more attracted to the vibrating environments of cities, whether their purpose is to work or live there, or do both. Therefore, the percentage of the global population that is living in urban areas instead of rural ones is increasing more than ever before. This phenomenon is called urbanization. It requires a lot of good urban planning and management in order to ensure sustainable living conditions in those growing urban areas. People constantly interact with each other, but also with their environment, in many different situations (e.g., traffic, recreational activities, construction, etc.). In this Master thesis, research is conducted on how urban attributes impact residents' feelings of perceived beauty and perceived safety.

To answer the main research question, a sequential approach of DL and DCM is applied. First, DL is used for segmenting the composition of urban scenery images, and afterwards the output of the DL process is fed into a DCM. This has shown that perceived beauty and perceived safety are both most sensitive to urban greenery. Urban greenery has a positive effect on both perceptual indicators. This means that the more vegetation is implemented in urban design, the more likely it is that people perceive the city to be beautiful and safe. Also water elements, non-permanent objects and impervious surfaces have a positive effect on perceived beauty and perceived safety in the city. However, "grey" urban attributes, such as walls, fences, and traffic lights, have a negative effect on perceived beauty and perceived safety.

Since urban population all over the world continues to grow, it is becoming more important than ever before to analyze human perceptions on the built environment. This Master thesis shows that using a sequential approach of DL and DCM is a promising method in order to find accurate and interpretable results. Furthermore, the importance of urban greenery is shown for policymakers and urban planners who are aiming at designing cities that are perceived as more beautiful and more safe.

References

Alwosheel, A., van Cranenburgh, S., & Chorus, C. G. (2018). Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis. *Journal of Choice Modelling*, *28*, 167-182.

Alwosheel, A., van Cranenburgh, S., & Chorus, C. G. (2019). ‘Computer says no’ is not enough: Using prototypical examples to diagnose artificial neural networks for discrete choice analysis. *Journal of Choice Modelling*, *33*.

Alwosheel, A. S. A. (2020). Trustworthy and Explainable Artificial Neural Networks for Choice Behaviour Analysis.

Antonini, G., Sorci, M., Bierlaire, M., & Thiran, J.-P. (2006). Discrete choice models for static facial expression recognition. *Lecture Notes in Computer Science*, 710-721.

Barthélemy, J., Dumont, M., & Carletti, T. (2018). Comparison of Discrete Choice Models and Artificial Neural Networks in Presence of Missing Variables.

Böckenholt, U. (2006). Thurstonian-based analyses: Past, present, and future utilities. *Psychometrika*, *71*(4), 615-629.

Bollen, K. A. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology*, *53*(1), 605-634.

Bolund, P., & Hunhammar, S. (1999). Ecosystem services in urban areas. *Ecological Economics*, *29*(2), 293-301.

Borsboom, D., Mellenbergh, G. J., & Van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, *110*(2), 203.

Chen, M., Zhang, H., Liu, W., & Zhang, W. (2014). The Global Pattern of Urbanization and Economic Growth: Evidence from the Last Three Decades. *PLoS ONE*, *9*(8).

Cheng, X., Van Damme, S., Li, L., & Uyttenhove, P. (2019). Evaluation of cultural ecosystem services: A review of methods. *Ecosystem Services*, *37*.

Coast, J., Al-Janabi, H., Sutton, E. J., Horrocks, S. A., Vosper, A. J., Swancutt, D. R., & Flynn, T. N. (2012). Using qualitative methods for attribute development for discrete choice experiments: issues and recommendations. *Health Economics*, *21*(6), 730-741.

ConservationStrategyFund. (2015a). *Valuation of Ecosystem Services: Hedonic Pricing Method* [Video file]. https://youtu.be/LkXVCQam5kw

ConservationStrategyFund. (2015b). *Valuation of Ecosystem Services: Market Based Valuation Method* [Video file]. https://youtu.be/M0ZdV5WU5K4

ConservationStrategyFund. (2015c). *Valuation of Ecosystem Services: Travel Cost Method* [Video file]. https://youtu.be/AjcQpzIBu1I

ConservationStrategyFund. (2016). *Valuation of Ecosystem Services: Contingent Valuation* [Video file]. https://youtu.be/__xzmIG4L8s

Cornes, R., & Sandler, T. (1996). *The theory of externalities, public goods, and club goods*, Cambridge University Press.

Costanza, R. (1999). The ecological, economic, and social importance of the oceans. *Ecological Economics*, *31*(2), 199-213.

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'neill, R. V., & Paruelo, J. (1997). The value of the world's ecosystem services and natural capital. *Nature*, *387*(6630), 253-260.

De Nadai, M., Vieriu, R. L., Zen, G., Dragicevic, S., Naik, N., Caraviello, M., Hidalgo, C. A., Sebe, N., & Lepri, B. *Are safer looking neighborhoods more lively? A multimodal investigation into urban life*, Proceedings of the 24th ACM international conference on Multimedia.

De Silva, C. S., Warusavitharana, E. J., & Ratnayake, R. (2017). An examination of the temporal effects of environmental cues on pedestrians' feelings of safety. *Computers, Environment and Urban Systems*, *64*, 266-274.

Dietterich, T. (1995). Overfitting and undercomputing in machine learning. *ACM Computing Surveys (CSUR)*, *27*(3), 326-327.

Dobson, R. (2007). Urban regeneration as a crime prevention strategy: The experience of Warwich Junction, Ethekwini (Durban), South Africa. In *Strategies and Best Practices in Crime Prevention in Particular in Relation to Urban Areas and Youth at Risk: Workshop at the 11th Congress on Crime Prevention and Criminal Justice (Bangkok, Thailand, 18-25 April 2005), proceedings.* International Centre for the Prevention of Crime.

Doersch, C., Singh, S., Gupta, A., Sivic, J., & Efros, A. A. (2015). What makes Paris look like Paris. *Communications of the ACM*, *58*(12), 103-110. https://doi.org/10.1145/2830541

Douglas, O., Lennon, M., & Scott, M. (2017). Green space benefits for health and well-being: A life-course approach for urban planning, design and management. *Cities*, *66*, 53-62. https://doi.org/10.1016/j.cities.2017.03.011

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016, 10/8/2016). *Deep Learning the City: Quantifying Urban Perception at a Global Scale.* European Conference on Computer Vision.

Flango, V. E., & Sherbenou, E. L. (1976). POVERTY, URBANIZATION, AND CRIME. *Criminology*, *14*(3), 331-346. https://doi.org/https://doi.org/10.1111/j.1745-9125.1976.tb00027.x

Freeman III, A. M., Herriges, J. A., & Kling, C. L. (2014). *The measurement of environmental and resource values: theory and methods*. Routledge.

Friston, K. J., & Stephan, K. E. (2007). Free-energy and the brain. *Synthese*, *159*(3), 417-458. https://doi.org/10.1007/S11229-007-9237-Y

Gargiulo, I., Garcia, X., Benages-Albert, M., Martinez, J., Pfeffer, K., & Vall-Casas, P. (2020). Women's safety perception assessment in an urban stream corridor: Developing a safety map based on qualitative GIS. *Landscape and Urban Planning*, *198*, 103779. https://doi.org/https://doi.org/10.1016/j.landurbplan.2020.103779

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014, 6/23/2014). *Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation* Computer Vision and Pattern Recognition. www.computer.org/csdl/proceedings/cvpr/2014/5118/00/5118a580.pdf

Goodchild, M. F. (2007). Citizens as sensors: the world of volunteered geography. *GeoJournal*, *69*(4), 211-221. https://doi.org/10.1007/s10708-007-9111-y

Greig, P. J. (1983). Recreation Evaluation Using a Characteristics Theory of Consumer Behavior. *American Journal of Agricultural Economics*, *65*(1), 90-97. https://doi.org/10.2307/1240341

Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., & Lew, M. S. (2016). Deep learning for visual understanding: A review. *Neurocomputing*, *187*, 27-48. https://doi.org/https://doi.org/10.1016/j.neucom.2015.09.116

Guterres, A. (2020). *COVID-19 in an urban world*. UN. https://www.un.org/en/coronavirus/covid-19-urban-world

Hagenauer, J., & Helbich, M. (2017). A comparative study of machine learning classifiers for modeling travel mode choice. *Expert Systems with Applications*, *78*, 273-282. https://doi.org/10.1016/j.eswa.2017.01.057

Haines-Young, R., & Potschin, M. (2010). The links between biodiversity, ecosystem services and human well-being. *Ecosystem Ecology: a new synthesis*, *1*, 110-139.

Hartog, R. (1999). Growth without limits: Some case studies of 20th-century urbanization. *International Planning Studies*, *4*(1). https://doi.org/10.1080/13563479908721728

Hensher, D. A., & Ton, T. T. (2000). A comparison of the predictive potential of artificial neural networks and nested logit models for commuter mode choice. *Transportation Research Part E: Logistics and Transportation Review*, *36*(3), 155-172.

Hermes, J., Van Berkel, D., Burkhard, B., Plieninger, T., Fagerholm, N., von Haaren, C., & Albert, C. (2018). Assessment and valuation of recreational ecosystem services of landscapes. *Ecosystem Services*, *31*, 289-295.

Hess, S., & Palma, D. (2019a). Apollo (version 0.1. 0). *User manual, Choice Modeling Centre, University of Leeds, Leeds*.

Hess, S., & Palma, D. (2019b). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, *32*, 100170. https://doi.org/10.1016/j.jocm.2019.100170

Holmes, T., Adamowicz, W., & Carlsson, F. (2017). Choice Experiments. In (Vol. 13, pp. 133-186). https://doi.org/10.1007/978-94-007-7104-8_5

Hubacek, K., & Kronenberg, J. (2013). Synthesizing different perspectives on the value of urban ecosystem services. *Landscape and Urban Planning*, *109*(1), 1-6.

Huxley, M. (2009). Planning, Urban. In R. Kitchin & N. Thrift (Eds.), *International Encyclopedia of Human Geography* (pp. 193-198). Elsevier. https://doi.org/https://doi.org/10.1016/B978-008044910-4.01097-X

Ibrahim, M. R., Haworth, J., & Cheng, T. (2020). Understanding cities with machine eyes: A review of deep computer vision in urban analytics. *Cities*, *96*, 102481. https://doi.org/https://doi.org/10.1016/j.cities.2019.102481

Jacobs, J. (1961). *The death and life of great American cities*, Vintage

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), 190987. https://doi.org/doi:10.1098/rsos.190987

Johansson, M., Laureshyn, A., & Nilsson, M. (2020). Video analysis of pedestrian movement (VAPM) under different lighting conditions—method exploration. *Energies*, *13*(6), Article 4141. https://doi.org/10.3390/en13164141

Karlaftis, M. G., & Vlahogianni, E. I. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. *Transportation Research Part C Emerging Technologies*, *19*(3), 387-399. https://doi.org/10.1016/J.TRC.2010.10.004

Koemle, D. B. A., & Morawetz, U. B. (2016). Improving mountain bike trails in Austria: An assessment of trail preferences and benefits from trail features using choice experiments. *Journal of Outdoor Recreation and Tourism*, *15*, 55-65. https://doi.org/10.1016/J.JORT.2016.04.003

Kremer, P., Andersson, E., McPhearson, T., & Elmqvist, T. (2015). Advancing the frontier of urban ecosystem services research. *Ecosystem Services*, *12*, 149-151.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *The Journal of Political Economy*, *74*(2), 132-157.

Lau, E. T., Sun, L., & Yang, Q. (2019). Modelling, prediction and classification of student academic performance using artificial neural networks. *SN Applied Sciences*, *1*(9), 982. https://doi.org/10.1007/s42452-019-0884-7

Law, S., Seresinhe, C. I., Shen, Y., & Gutierrez-Roig, M. (2020). Street-Frontage-Net: urban image classification using deep convolutional neural networks. *International Journal of Geographical Information Science*, *34*(4), 681-707. https://doi.org/10.1080/13658816.2018.1555832

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444. https://doi.org/10.1038/NATURE14539

Le Gall-Ely, M. (2009). Definition, measurement and determinants of the consumer's willingness to pay: a critical synthesis and avenues for further research. Recherche et Applications en Marketing (English Edition), 24(2), 91-112.

Lerch, M. (2017). International migration and city growth. *United Nations Population Division*, *Technical Paper* (10).

Liu, X., & Bae, J. (2018). Urbanization and industrialization impact of CO2 emissions in China. *Journal of Cleaner Production*, *172*, 178-186. https://doi.org/10.1016/j.jclepro.2017.10.156

Long, J., Shelhamer, E., & Darrell, T. (2015, 6/7/2015). *Fully convolutional networks for semantic segmentation.* Computer Vision and Pattern Recognition.

Louvière, J., & Timmermans, H. (1990). Stated preference and choice models applied to recreation research: A review. *Leisure Sciences*, *12*(1), 9-32.

Louviere, J. J., Pihlens, D., & Carson, R. (2011). Design of Discrete Choice Experiments: A Discussion of Issues That Matter in Future Applied Research. *Journal of Choice Modelling*, *4*(1), 1-8. https://doi.org/https://doi.org/10.1016/S1755-5345(13)70016-2

Lu, Y. (2019). Using Google Street View to investigate the association between street greenery and physical activity. *Landscape and Urban Planning*, *191*, 103435.

Luederitz, C., Brink, E., Gralla, F., Hermelingmeier, V., Meyer, M., Niven, L., Panzer, L., Partelow, S., Rau, A.-L., Sasaki, R., Abson, D. J., Lang, D. J., Wamsler, C., & von Wehrden, H. (2015). A review of urban ecosystem services: six key challenges for future research. *Ecosystem Services*, *14*, 98-112. https://doi.org/https://doi.org/10.1016/j.ecoser.2015.05.001

Lynch, K. (1960). *The image of the city*, (11) MIT press.

Marschak, J. (1960). 1974). Binary-choice constraints and random utility indicators. *Marschak (1974)*, 218-239.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

McFadden, D. (2001). Economic choices. *American Economic Review*, *91*(3), 351-378.

Miami-Dade-County-Parks-and-Recreation-Departement. (2007). *The Miami-Dade County Parks and Open Space System Master Plan*.

Naik, N., Raskar, R., & Hidalgo, C. A. (2016). Cities Are Physical Too: Using Computer Vision to Measure the Quality and Impact of Urban Appearance. *The American Economic Review*, *106*(5), 128-132. https://doi.org/10.1257/AER.P20161030

Nasar, J. L. (1990). The evaluative image of the city. *Journal of the American Planning Association*, *56(1)*, 41-53.

National Geographic. (2019, 22 October 2019). *Urbanization*.
https://www.nationalgeographic.org/encyclopedia/urbanization/#:~:text=urbanization-,Noun,a%20city%20or%20metropolitan%20area.

Norman, J., MacLean, H. L., & Kennedy, C. A. (2006). Comparing High and Low Residential Density: Life-Cycle Analysis of Energy Use and Greenhouse Gas Emissions. *Journal of Urban Planning and Development*, *132*(1), 10-21.

Norman, R., Craig, B. M., Hansen, P., Jonker, M. F., Rose, J., Street, D. J., & Mulhern, B. (2019). Issues in the design of discrete choice experiments. *The Patient-Patient-Centered Outcomes Research*, *12*(3), 281-285.

Ordonez, V., & Berg, T. L. (2014, 9/6/2014). *Learning High-Level Judgments of Urban Perception* European Conference on Computer Vision.

Paredes, M., Hemberg, E., O'Reilly, U. M., & Zegras, C. (2017). Machine Learning or Discrete Choice Models for Car Ownership Demand Estimation and Prediction? *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transporation Systems*, 780-785.

Quercia, D., O'Hare, N. K., & Cramer, H. (2014). Aesthetic capital: what makes london look beautiful, quiet, and happy? *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 945-955. https://doi.org/10.1145/2531602.2531613

Rahm, J., Sternudd, C., & Johansson, M. (2020). "In the evening, I don't walk in the park": The interplay between street lighting and greenery in perceived safety. *Urban Design International*. https://doi.org/10.1057/s41289-020-00134-6

Ritchie, H., & Roser, M. (2018). *Urbanization*. Our World In Data.

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

Salesses, P., Schechtner, K., & Hidalgo, C. A. (2013). The Collaborative Image of The City: Mapping the Inequality of Urban Perception. *PLoS ONE*, *8*(7), e68400.

Seresinhe, C. I., Preis, T., & Moat, H. S. (2017). Using deep learning to quantify the beauty of outdoor places. *Royal Society Open Science*, *4*(7). https://doi.org/10.1098/RSOS.170170

Sifringer, B., Lurkin, V., & Alahi, A. *Enhancing discrete choice models with neural networks*, Proceedings of the 18th Swiss Transport Research Conference (STRC), Monte Verità/Ascona, Switzerland.

Sifringer, B., Lurkin, V., & Alahi, A. (2020). Enhancing discrete choice models with representation learning. *Transportation Research Part B: Methodological*, *140*, 236-261.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. J*ournal of Machine Learning Research*, *15*(1), 1929-1958.

Stewart, K., & Cantora, A. (2015). Urban Crime. In *The Encyclopedia of Crime & Punishment* (pp. 1-3). https://doi.org/https://doi.org/10.1002/9781118519639.wbecpx204

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015, 6/7/2015). *Going deeper with convolutions.* Computer Vision and Pattern Recognition.

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(4), 273.

Tortum, A., Yayla, N., & Gökdağ, M. (2009). The modeling of mode choices of intercity freight transportation with the artificial neural networks and adaptive neuro-fuzzy inference system. *Expert Systems with Applications*, *36*(3), 6199-6217.

Ulrich, R. S. (1983). Aesthetic and Affective Response to Natural Environment. *Behavior and the Natural Environment*, 85-125. http://link.springer.com/10.1007/978-1-4613-3539-9_4

UN-General-Assembly. *Strengthening the mandate and status of the Commission on Human Settlements and the status, role and functions of the United Nations Centre for Human Settlements (Habitat): Resolution adopted by the General Assembly*, 26 February 2002, A/RES/56/206.

UN-General-Assembly. *Open Working Group proposal for Sustainable Development Goals*, 12 August 2014, A/68/970.

UN-Habitat. (2016). *Gobal Public Space Toolkit: From Global Principles to Local Policies and Practice*.

UN. *The Vancouver declaration on human settlements*, United Nations Conference on Human Settlements, Vancouver.

UN. (2005). Definition of "Urban". *Demographic Yearbook*.

UN. (2016). *The World's Cities in 2016*, Statistical Papers - United Nations (Ser. A), Population and Vital Statistics Report, UN New York.

UN. (2019). *World urbanization prospects: the 2018 revision*, Department of Economic Social Affairs Population Division.

van Cranenburgh, S., & Alwosheel, A. (2019). An artificial neural network based approach to investigate travellers' decision rules. *Transportation Research Part C: Emerging Technologies*, *98*, 152-166. https://doi.org/10.1016/j.trc.2018.11.014

Van Cranenburgh, S., Wang, S., Vij, A., Pereira, F., & Walker, J. (2021). Choice modelling in the age of machine learning. arXiv preprint arXiv:2101.11948.

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*, 107340.

Wan, L., Zeiler, M., Zhang, S., Le Cun, Y., & Fergus, R. *Regularization of neural networks using dropconnect*. International Conference on Machine Learning.

Wang, R., Helbich, M., Yao, Y., Zhang, J., Liu, P., Yuan, Y., & Liu, Y. (2019). Urban greenery and mental wellbeing in adults: Cross-sectional mediation analyses on multiple pathways across different greenery measures. *Environmental Research*, *176*, 108535.

Wang, R., Liu, Y., Lu, Y., Zhang, J., Liu, P., Yao, Y., & Grekousis, G. (2019). Perceptions of built environment and health outcomes for older Chinese in Beijing: A big data approach with street view images and deep learning technique. *Computers, Environment and Urban Systems*, *78*, 101386. https://doi.org/10.1016/j.compenvurbsys.2019.101386

Wang, R., Yuan, Y., Liu, Y., Zhang, J., Liu, P., Lu, Y., & Yao, Y. (2019). Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. *Health & Place*, *59*, 102186.

Wang, S., Wang, Q., & Zhao, J. (2020). Deep neural networks for choice analysis: Extracting complete economic information for interpretation. *Transportation Research Part C: Emerging Technologies*, *118*, 102701. https://doi.org/https://doi.org/10.1016/j.trc.2020.102701

Werbos, P. J. (1990). Backpropagation through time: what it does and how to do it. *Proceedings of the IEEE*, *78*(10), 1550-1560.

Wiles, J. L., Leibing, A., Guberman, N., Reeve, J., & Allen, R. E. S. (2011). The Meaning of "Aging in Place" to Older People. *The Gerontologist*, *52*(3), 357-366.

Wong, M., & Farooq, B. (2019). ResLogit: A residual neural network logit model. *ArXiv: Econometrics*.

Wood, L., Hooper, P., Foster, S., & Bull, F. (2017). Public green spaces and positive mental health – investigating the relationship between access, quantity and types of parks and mental wellbeing. *Health & Place*, *48*, 63-71. https://doi.org/10.1016/j.healthplace.2017.09.002

WorldBank. (2018). Number of people living in urban and rural areas, World, 1960 to 2017. *Our World in Data*. https://ourworldindata.org/urbanization#number-of-people-living-in-urban-areas.

WorldBank. (2020, 2020/04/20). *Urban Development*. https://www.worldbank.org/en/topic/urbandevelopment/overview

Zhang, F., Wu, L., Zhu, D., & Liu, Y. (2019). Social sensing from street-level imagery: A case study in learning spatio-temporal urban mobility patterns. *ISPRS Journal of Photogrammetry and Remote Sensing*, *153*, 48-58. https://doi.org/10.1016/J.ISPRSJPRS.2019.04.017

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*, 148-160. https://doi.org/10.1016/j.landurbplan.2018.08.020

Zhang, H., Chen, B., Sun, Z., & Bao, Z. (2013). Landscape perception and recreation needs in urban green space in Fuyang, Hangzhou, China. *Urban Forestry & Urban Greening*, *12*(1), 44-52. https://doi.org/https://doi.org/10.1016/j.ufug.2012.11.001

Zhao, J., Liu, X., Kuang, Y., Chen, Y. V., & Yang, B. (2018, 6/18/2018). *Deep CNN-Based Methods to Evaluate Neighborhood-Scale Urban Valuation Through Street Scenes Perception* IEEE International Conference on Data Science in Cyberspace.

Zhou, B., Zhao, H., Puig, X., Fidler, S., Barriuso, A., & Torralba, A. (2017, 7/21/2017). *Scene Parsing through ADE20K Dataset.* Computer Vision and Pattern Recognition.

Zou, Z., Shi, Z., Guo, Y., & Ye, J. (2019). Object Detection in 20 Years: A Survey. *arXiv preprint arXiv: 1905.05055*.

Appendices

Appendix A

Used search engines / databases	
Name	**Why**
Google Scholar	Google Scholar has the power of Google searches applied to research papers and patents. For relevant papers it shows related articles, references and links to full text. This way, it is easy to do forward - and backward citation search.
Microsoft Academic	This is Microsoft's response to Google Scholar, which has the same perks. The most relevant publications of your research can be easily found because there are many filters that can be applied to do an advanced search. Furthermore, one can find additional relevant articles through a search by author, by topic or by other attributes.
Search terms	
'Choice model' **'Choice modelling'** **'DCE'** **'Multinomial Logit Model'**	All terms were used interchangeably, so the OR operator could be applied.
'DL' **'Deep learning'** **'Deep neural network'** **'Artificial neural network'**	All terms were used interchangeably, so the OR operator could be applied.
'Urbanisation' **'Urbanization'** **'Urban planning'** **'Urban development'** **'Urban design'** **'Urbanizing'** **'Urbanising'**	All terms were used interchangeably, so the OR operator could be applied.
'Built environment' **'Urban attributes'** **'Urban visual elements'** **'Urban features'** **'City design'**	All terms were used interchangeably, so the OR operator could be applied.
'Discrete choice model' **'Multinomial logit model'** **'Experimental design'**	All terms possible with the AND operator in pairs of two.

'Deep learning' **'Image processing'** **'Machine learning'** **'Urbanisation'** **'Urban planning'**	
'Perceived safety' **'Perceived beauty'** **'Urbanisation'** **'Built environment'** **'Urban design'**	All terms possible with the AND operator in pairs of two.

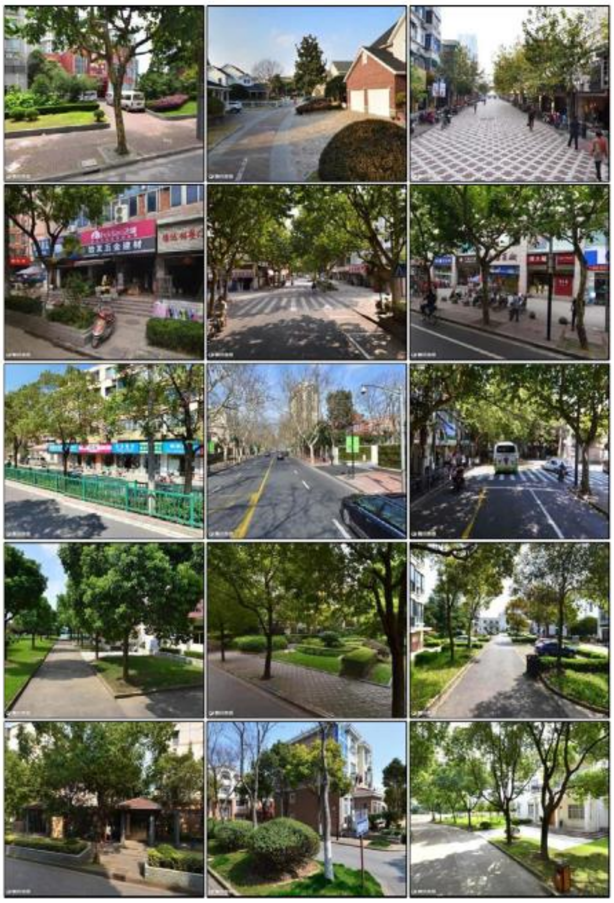
Appendix B

Pictures of urban scenes that people rather perceive as …

B1) … beautiful.

From Quercia et al. (2014)

B2) … safe.



From Zhang et al. (2018)

Appendix C

An overview of ecosystem (ES) goods and services and their functions used in the study of (Costanza et al., 1997) in order to emphasize the importance of ecosystem valuation. All formulations are copied from the study at stake.

ES goods and services	ES functions
Gas regulation	Regulation of atmospheric chemical composition.
Climate regulation	Regulation of global temperature, precipitation, and other biologically mediated climatic processes at global or local level.
Disturbance regulation	Capacitance, damping, and integrity of ecosystem response to environmental fluctuations.
Water regulation	Regulation of hydrological flows.
Water supply	Storage and retention of water.
Erosion control and sediment retention	Retention of soil within an ecosystem.
Soil formation	Soil formation processes.
Nutrient cycling	Storage, internal cycling, processing, and acquisition of nutrients.
Waste treatment	Recovery of mobile nutrients and removal of breakdown of excess or xenic nutrients and compounds.
Pollination	Movement of floral gametes.
Biological control	Trophic-dynamic regulations of populations.
Refugia	Habitat for resident and transient populations.
Food production	That portion of gross primary production extractable as food.
Raw materials	That portion of gross primary production extractable as raw materials.
Genetic resources	Sources of unique biological materials and products.
Recreation	Providing opportunities for recreational activities.
Cultural	Providing opportunities for non-commercial uses.

Appendix D

Both theory-driven choice modelling and data-driven deep learning are grounded in statistical theory. Therefore, they have many concepts in common, but they come under different names, as shown by the table below (source: Cranenburgh et al. (2021)).

Table 1: Shared concepts

Terminology in …	
Choice modelling	***Machine learning***
Attribute, covariate	*Feature, input*
Alternative	*Class*
ASC	*Intercept*
Observation	*Example, instance*
Log-likelihood	*Cross-entropy*
Model parameter	*Weight*
Hit rate	*Accuracy*
Binary Logit function	*Sigmoid function*
Multinomial Logit function	*Softmax function*
Estimation	*Training*
Efficient experimental design	*Active learning*
Full information maximum likelihood estimation	*Batch gradient descent training*

Appendix E

Below is the code that was written in R to analyzethe dataset on perceived beauty. The R-code for the analysis of perceived safety is exactly the same except for

database = subset(database, database$category_x == "beautiful"),

which should be

database = subset(database, database$category_x == "safe").

```
 ###########################
### INITIALISE THE CODE ###
###########################
rm(list = ls())
library(apollo)
library(miscTools)
library(maxLik)
apollo_initialise()
apollo_control = list(
  modelName = "Beauty choice model",
  modelDescr = "MNL model to predict perceived beauty",
  indivID = "id"
)
#####################
### READ THE DATA ###
#####################
database =
read.csv("E:/_SCHOOL/_MASTERTHESIS/_RECENT/RStudio/final_merged_choice_model_SD_LOGS
.csv",header=TRUE)
###########################
### PREPROCESS THE DATA ###
###########################
 ##############################################################
All variables used in the utility functions should be numerical
##############################################################
  database$chnr <- as.character(database$chnr)
```

```
database$chnr[which(database$chnr=="left")] <- "1"

database$chnr[which(database$chnr=="right")] <- "2"

database$chnr <- as.numeric(database$chnr)

################################################################
Use only data that is related to the variable "beautiful"
################################################################

database = subset(database, database$category_x == "beautiful")

###################################

Drop unnecessary variables

###################################

database = subset(database, select = -c(category_x,
                                  category_beautiful,
                                  category_boring,
                                  category_depressing,
                                  category_lively,
                                  category_safety,
                                  category_wealthy,
                                  left_id,
                                  right_id,
                                  left_lat,
                                  left_long,
                                  right_lat,
                                  right_long,
                                  winner_x))

################################################################
Just to make the model easier to interpret: Talk of "alt1" and "alt2"
################################################################

names(database)[names(database) == "orange_left"] <- "orange_alt1"

names(database)[names(database) == "green_left"] <- "green_alt1"

names(database)[names(database) == "grey_left"] <- "grey_alt1"

names(database)[names(database) == "blue_left"] <- "blue_alt1"
```

```
  names(database)[names(database) == "yellow_left"] <- "yellow_alt1"
  names(database)[names(database) == "red_left"] <- "red_alt1"
  names(database)[names(database) == "orange_right"] <- "orange_alt2"
  names(database)[names(database) == "green_right"] <- "green_alt2"
  names(database)[names(database) == "grey_right"] <- "grey_alt2"
  names(database)[names(database) == "blue_right"] <- "blue_alt2"
  names(database)[names(database) == "yellow_right"] <- "yellow_alt2"
  names(database)[names(database) == "red_right"] <- "red_alt2"
########################
### MODEL PARAMETERS ###
########################
apollo_beta = c(asc_alt1 = 0,
                asc_alt2 = 0,
                b_orange = 0,
                b_green = 0,
                b_grey = 0,
                b_blue = 0,
                b_yellow = 0,
                b_red = 0)
apollo_fixed = c("asc_alt1")
##################
### VALIDATION ###
##################
apollo_inputs = apollo_validateInputs()
############################
### LIKELYHOOD COMPONENT ###
############################
apollo_probabilities = function(apollo_beta, apollo_inputs, functionality = "estimate"){
  ####################################################
  Attach inputs and detach after function exit
  ####################################################
```

```
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
   #######################################
  Create list of probabilities P
  #######################################
  P = list()
  #########################
  List of utilities
  #########################
  V = list()
  V[['alt1']] = asc_alt1  + b_orange * orange_alt1 + b_green * green_alt1 + b_grey * grey_alt1 +
b_blue * blue_alt1 + b_yellow * yellow_alt1 + b_red * red_alt1
  V[['alt2']] = asc_alt2  + b_orange * orange_alt2 + b_green * green_alt2 + b_grey * grey_alt2 +
b_blue * blue_alt2 + b_yellow * yellow_alt2 + b_red * red_alt2
  ################################################
  Define settings for MNL model component
  ################################################
  mnl_settings = list(
    alternatives = c(alt1 = 1, alt2 = 2),
    avail = list(alt1 = av1, alt2 = av2),
    choiceVar = chnr,
    V = V
  )
  ##############################################
  Compute probabilities using MNL model
  ##############################################
  P[["model"]] = apollo_mnl(mnl_settings, functionality)

##############################################################
 Prepare and return outputs of function
##############################################################
  P = apollo_prepareProb(P, apollo_inputs, functionality)
```

```
  return(P)
}
##################
### ESTIMATION ###
##################
model = apollo_estimate(apollo_beta,
                        apollo_fixed,
                        apollo_probabilities,
                        apollo_inputs)
######################
### REPORT RESULTS ###
######################
apollo_modelOutput(model)
```