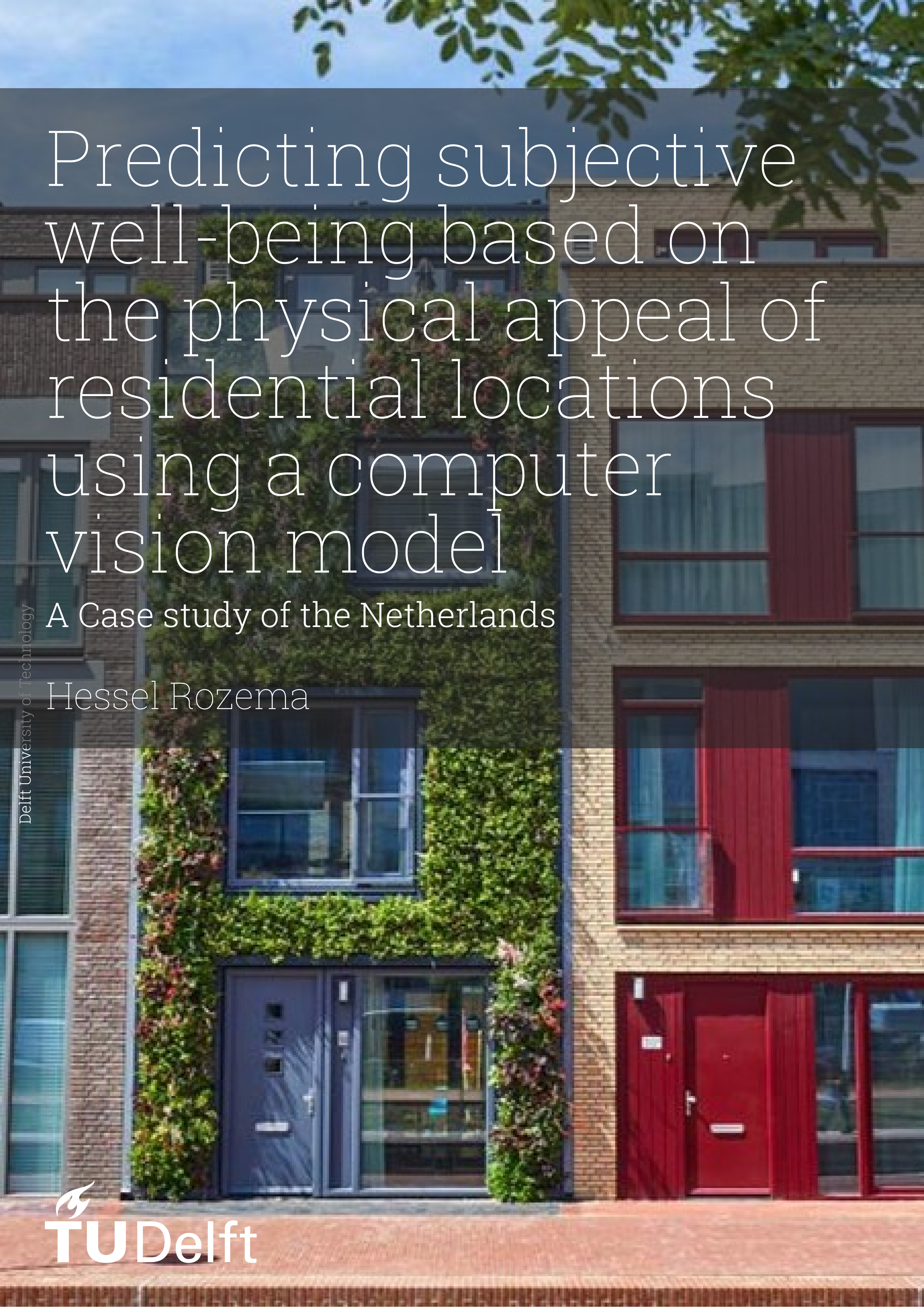

Predicting subjective well-being based on the physical appeal of residential locations using a computer vision model

A Case study of the Netherlands

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Delft University of Technology

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by

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Preface

About six months ago, I started looking for a thesis topic. At first, the whole process felt a bit overwhelming, there were so many directions I could go, and I really wanted to pick something I found interesting. My initial idea ended up not working out because the data I needed just wasn't available and I wasn't comfortable going out to collect it myself.

After a meeting with my supervisors, Maarten and Kees, Maarten suggested a topic he had in mind: validating a computer vision model. I'd actually seen this model before in one of my courses, and it had caught my interest, so this seemed like a good fit. That's how I ended up choosing to be validating this computer vision model for my thesis.

In the beginning, I was unsure about what was feasible in the time I had. But as I got further into the project, things started to fall into place and I got a much better sense of what I could realistically achieve. Looking back now, I'm happy with how things turned out. The writing part took a lot more time and effort than I expected, and the programming tested my patience more than once, but pushing through those challenges helped me learn and grow a lot. All in all, I'm really glad to have had this experience, not just for what I learned academically, but also for how much I've grown personally and professionally.

I want to say thanks to Francisco for helping me set up the supercomputer and assisting with the model, and to Sander for always being approachable and answering my extra questions, even though he wasn't my supervisor. Especially thanks to Maarten and Kees for helping me choose my topic, and for their feedback throughout the process. Joslyn, thank you for your valuable input during the midterm and greenlight meetings. And finally, an extra thank you to Maarten for all the bi-weekly meetings and for steering me in the right direction every time I needed it.

Hessel Rozema
Delft, August 2025

Summary

Over the years, subjective well-being has emerged as a central goal in urban planning. Research has consistently shown that city design can significantly improve residents' subjective well-being. This thesis explores the specific contribution of aesthetic quality to effect subjective well-being.

Traditional studies have shown that factors such as green spaces and clean streets contribute to higher subjective well-being. However, these researches often use segmentation based approaches, which are good in measuring the existence of such features, but fail to capture the more subjective nature and nuanced ways people experience and interpret their surrounding.

The computer vision model developed by Van Cranenburgh and Garrido-Valenzuela (2025) fills this gap, as instead of analyzing predefined segmentation's, this model uses a feature extractor to holistically analyze street-level images and extract relevant visual features without prior specification. This approach allows the model to learn features that can't be learned with segmentation data alone, such as trade-offs between well-maintained and neglected green spaces. However, before such computer vision model can be used in urban practices, it should be validated, to see if it really measures the same things as previous studies have shown.

This thesis aims to analyze how effective this new computer vision model is in predicting subjective well-being. The main research question therefore, is phrased as:

To what extent does the utility derived from computer vision model influences subjective well-being, controlling for socio-demographics characteristics and built environment variables?

To answer this, Structural Equation Modeling (SEM) is used to examine the relationships between the computer vision-derived utility score, socio-demographic variables, built environment characteristics, and two components of subjective well-being: life satisfaction and hedonic well-being. Data on subjective well-being are obtained from the Netherlands Mobility Panel (MPN), using the Satisfaction With Life Scale (SWLS) for life satisfaction (2020–2022) and the Mental Health Index-5 (MHI-5) for hedonic well-being (2020 only). Utility scores are generated for each residential location based on Google Street View images and calculated at both the five-digit (PC5) and six-digit (PC6) postal code levels.

The model does not reveal which visual features contribute to higher or lower utility, as it operates as a black box. Nevertheless, based on visual comparison of images with high and low utility scores, it is assumed that features such as well maintained greenery, aesthetically pleasing architecture, and spacious streetscapes positively influence utility. In contrast, little greenery, a dense concentration of parked cars, and a visual constrained layout lead to lower utility scores.

The results show that utility scores aggregated at the PC5 level perform better in explaining variance of subjective well-being than those at the PC6 level, suggesting that people are more influenced by their neighborhood rather than just their street. In addition, population density, income, and age are found to be the most important factors in shaping visual utility. While income and population density show linear relationships, age exhibits a non-linear effect, where younger residents tend to live in areas with lower utility scores, and middle-aged and older residents prefer similar locations which are on average of higher utility scores.

Controlling for the non-linear effect of age reveals a small but significant path between utility and life satisfaction. However, this effect remains largely driven by socio-demographic variables, where people with higher incomes and older age are more likely to live in visually appealing neighborhoods and also report higher life satisfaction. No significant relationship is found between utility and hedonic well-being, which may be more strongly influenced by short-term fluctuations rather than by stable factor such as neighborhood characteristics.

Overall, this thesis shows that predicting subjective well-being using a continuous, perception-based utility score remains challenging and currently has limited explanatory power. Although the model was

not trained for this purpose, it demonstrates promising results by capturing the expected relationships, however of smaller magnitude. Future research should focus on training the model specifically on subjective well-being and incorporating segmentation data to better understand which visual features drive subjective well-being.

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1 Introduction

1.1. Background

In recent years, subjective well-being (SWB) has more often become the central goal of urban planning, rather than a secondary objective. SWB is measured in three key components: hedonic well-being, which refers to emotional states such as happiness and distress; eudaimonic well-being, which involves having a sense of purpose and meaning in life; and life satisfaction, a cognitive evaluation of one's overall quality of life (OECD, 2013).

Increasingly, urban planners acknowledge that enhancing SWB is fundamental to creating thriving cities. Rather than solely emphasizing economic growth or infrastructural development, the success of urban planning is now often measured by how well it improves the well-being of residents, which is frequently seen as the ultimate goal (WHO, 2023; Nicolás-Martínez et al., 2024). As Mouratidis (2021) points out, with urban populations continuing to grow, ensuring a high standard of living through well-being-focused design is a critical challenge. This perspective is reinforced by the WHO (2025), who state that "cities will be used in the way we design them," emphasizing that well-planned urban environments can actively promote subjective well-being and lead to happier, healthier populations.

Urban planning can shape SWB through multiple interrelated pathways. Mouratidis (2021) developed a framework identifying seven pathways linking the built environment to SWB, including travel, leisure, social relationships, and emotional responses. Emotional responses explain how people perceive and experience their surroundings. Elements such as the aesthetic quality, maintenance, and design of urban spaces influence emotional states and can significantly impact SWB. This thesis focuses explicitly on this pathway, exploring how the aesthetics of the built environment contribute to enhancing subjective well-being.

1.2. Insights from the Literature and Knowledge Gaps

A growing body of research highlights how various visual aspects of the urban environment, such as green and blue spaces, architectural design, and street cleanliness, contribute to SWB. Green spaces near residential areas have been consistently linked to higher life satisfaction and lower distress, especially when they are of high-quality and well-maintained (Bertram and Rehdanz, 2015; Zhang et al., 2017). Blue spaces like rivers and lakes as well as visually appealing built environments also positively affect happiness and lower mental distress (Seresinhe et al., 2015). At the same time, factors such as poor cleanliness, noise, or monotonous architecture tend to reduce neighborhood satisfaction (Wu et al., 2024; Mouratidis, 2020). These findings reveal that various spatial and aesthetic variables influence SWB. However, capturing and systematically analyzing the full range of visual characteristics in urban environments remains methodologically challenging. Traditional studies rely on subjective assessments, making it difficult to measure urban environmental quality objectively and to capture the complex interactions among multiple environmental factors within one framework.

To overcome these limitations, recent advances in computer vision (CV) offer a solution by providing objective and scalable methods that can simultaneously quantify multiple features of the built environment. CV has enabled the systematic extraction of visual features from street-level imagery and linking them to SWB. By applying deep learning models to images, researchers can quantify greenness, visual complexity, walkability, and other environmental qualities across urban areas (Wu et al., 2022; Fan et al., 2023). These visual indicators are increasingly used to predict SWB, typically by assessing them on survey data. Unlike satellite-based metrics, street-level CV approaches offer a more accurate representation of what people see in their surroundings, capturing elements that influence how individuals experience their neighborhoods (Helbich et al., 2019). While CV methods offer a scalable way to quantify the environment, they often don't capture how residents perceive these features, missing nuances like greenery quality and the trade-offs people make between different visual aspects.

Research by Van Cranenburgh and Garrido-Valenzuela (2025) offers a promising solution in addressing these shortcomings. Van Cranenburgh and Garrido-Valenzuela (2025) developed a computer vision-based discrete choice model (CV-DCM) to estimate a perception-based utility score of the urban environments. By combining visual features extracted from images using a vision transformer and contextual factors, such as housing cost and commute time, the model captures real trade-offs people make when choosing residential environments. Through a stated choice experiment, participants selected preferred residential options based on images and numerical data, enabling the model to learn how various visual characteristics influence individual residential preferences. This research resulted in a trained model that generates a continuous utility score from image data, reflecting perceived visual quality in an objective and scalable way. However, the CV-DCM's image-based utility scores must be validated to ensure they reflect residents' SWB and not other environmental factors before it can be used as an urban policy tool. This thesis will evaluate whether the visual utility scores, derived from the CV-DCM, show the same relationship with SWB as earlier urban CV studies have demonstrated.

However, to accurately assess the relationship between visual utility scores and SWB, it is necessary to control for socio-demographic factors. Without this, it remains challenging to determine whether associations with SWB are driven by visual aesthetics alone or by the characteristics of the people who live in those areas. Variables such as age, income, education, and population density are known to influence both residential location and subjective well-being (Wu et al., 2022; Ma et al., 2024; Nguyen et al., 2021). Controlling for these socio-demographic factors is therefore essential to explain the specific effect of visual aesthetics on SWB and to validate the CV-DCM as a reliable tool for urban analysis.

1.3. Research Objective and Research Questions

This thesis aims to contribute to the existing literature regarding the relationship between the built environment and subjective well-being by evaluating the effectiveness of a newly developed perception-based CV model in predicting SWB. Specifically, this thesis researches whether the utility scores predicted by this CV model of Van Cranenburgh and Garrido-Valenzuela (2025) can explain residents' SWB. To achieve this, it controls for socio-demographic characteristics and built environment variables. The main question is phrased as follows:

To what extent does the utility derived from a computer vision model influence subjective well-being, controlling for socio-demographic characteristics and built environment variables?

To fully answer the research question, the following sub-questions have been formulated:

1. **SQ1 How is utility derived from the built environment of one's residential location?**

   This sub-question focuses on explaining how the computer vision model estimates utility scores. It aims to clarify how visual features are processed by the model and translated into utility scores for residential locations.

2. **SQ2 How does the built environment and socio-demographics explain the utility derived from the CV-model?**

   This question examines how much of the variation in utility scores can be explained by the built environment and differences in socio-demographic characteristics. For example, it explores whether older individuals or higher-income groups tend to live in visually different areas, and how that is reflected in the model's utility scores.

3. **SQ3 To what extent does the relationship between utility and subjective well-being vary between one's immediate environment and the wider neighborhood?**

   Next, this question examines whether the immediate surroundings (one's street) or the wider neighborhood area substantially affects the link between visual utility and subjective well-being.

4. **SQ4 How do built environment and socio-demographic variables affect the relationship between utility and subjective well-being?**

   Finally, this question investigates how controlling for built environment and socio-demographic variables influences the relationship between utility and subjective well-being. It examines the extent to which the relation between utility and SWB changes in strength when these factors are considered.

1.4. Scope

A structural equation method is used to analyze the relation between the socio-demographics, computer vision-derived utility score, and the subjective well-being components. This method allows for systematic analysis of the paths between each of the variables and explains the explanatory power of those.

This thesis focuses on two components of subjective well-being, life satisfaction and hedonic well-being, as these are the only subjective well-being variables available in the dataset. To get information about these variables, this thesis uses data provided by the Netherlands Mobility Panel (MPN), which measures life satisfaction with the Satisfaction With Life Scale (SWLS) and hedonic well-being with the Mental Health Index-5 (Diener et al., 1985; Hoogendoorn-Lanser et al., 2015; Veit and Ware, 1983). The Life Satisfaction data is available for 2020 to 2022, whilst the hedonic well-being data is only available in 2020. Therefore, this thesis uses two separate datasets to individually analyze life satisfaction and hedonic well-being. The analysis consists of respondents from across the Netherlands and uses each individual's most recent life satisfaction and hedonic well-being score.

1.5. Reading Guide

This thesis is structured into seven chapters. Chapter 1 introduces the research topic, objectives, questions, and scope. Chapter 2 reviews the literature on subjective well-being, the built environment, and computer vision applications in urban research. Chapter 3 outlines the methodology, covering data sources, the computer vision model, and the structural equation model. Chapter 4 presents the computer vision model's results, showing variation in visual utility across residential areas. Chapter 5 shows the findings from the structural equation model, highlighting the roles of visual utility, socio-demographics, and neighborhood characteristics. Next, Chapter 6 discusses the structural equation method results and connects them to the literature. Finally, Chapter 7 summarizes the key insights and offers conclusions.

2

Literature Review

2.1. How to determine subjective well-being

OECD (2013) introduced a clear framework for measuring subjective well-being (SWB), which focuses on how people evaluate their own lives. This framework includes three main dimensions:

- **Hedonic well-being** - refers to an individual's emotional states, including the experience of positive emotions and the absence of negative ones. It is typically assessed at a specific point in time and reflects short-term affective experiences.
- **Eudaimonic well-being** - relates to a sense of purpose and meaning in life. It includes aspects such as personal growth, independence, and psychological health, highlighting the importance of long-term fulfillment and self-realization.
- **Life Satisfaction** - refers to a thoughtful evaluation of an individual's overall life or particular areas, including health, employment, or interpersonal relationships. It represents a more stable and evaluative dimension of well-being, distinct from momentary emotional states.

These dimensions are usually measured through self-reported surveys, using standardized questions that make comparing results across different studies and contexts easier. The OECD (2013) highlights the importance of using a combination of indicators to fully reflect the complexity of SWB, since no single measure can capture it completely.

This approach to SWB is now widely used in urban planning research, in which it helps to understand better how people experience life in different urban environments (Mouratidis, 2021; Patino et al., 2023).

2.2. How urban aesthetics influence well-being

Research has consistently shown that green spaces positively affect subjective well-being. A study from Ambrey and Fleming (2014) reports a positive relationship between the percentage of public green space in one's local area and self-reported life satisfaction in Australian cities. Similar results were found in Germany, where Krekel et al. (2016) found that living closer to urban green areas correlates with higher life satisfaction, whereas living near wasteland correlates with lower satisfaction. Additional research in Germany acknowledged these results, showing that greener neighborhoods tend to have happier residents (Bertram and Rehdanz, 2015). Furthermore, Patino et al. (2023) found a strong correlation between greenness and self-reported happiness, noting that the quality of green spaces in densely populated urban areas significantly impacts well-being.

In a related study, Zhang et al. (2017) demonstrated that beyond the mere quantity of green space, its quality plays a crucial role in shaping residents' perceptions of their living environment. Their study showed that neighborhoods with accessible and well-maintained green spaces report higher resident satisfaction levels. Likewise, Douglas et al. (2019) found that the overall characteristics and aesthetics of green spaces contribute to neighborhood satisfaction, emphasizing that well-designed and visually appealing green spaces enhance the perceived life satisfaction.

Further research by Feng et al. (2022) highlights that the perceived benefits of green spaces vary depending on their type. Their study revealed that tree canopy coverage was associated with lower levels of psychological distress. In contrast, open grass areas did not always provide similar mental health benefits and, in some cases, were linked to increased distress.

Beyond green spaces, blue spaces, such as rivers, lakes, and coastal areas, also significantly influence health and well-being. Smith et al. (2021) identified positive health outcomes associated with urban blue spaces, contributing to improved mental health and overall well-being. Additionally, Seresinhe et al. (2015) demonstrated the importance of scenic beauty, including blue and brown landscapes, in positively influencing health. A different study indicates that proximity to water bodies is associated with increased momentary happiness and overall life satisfaction (Krekel and Mackerron, 2020).

The aesthetic characteristics of the built environment, in addition to natural landscapes, play a crucial role in influencing human well-being. Liang et al. (2024) used machine learning to assess public perceptions of building exteriors in cities like Singapore, San Francisco, and Amsterdam. They found that historical and visually complex architectural façades generate positive responses, whereas monotonous modern designs were considered boring or depressing. Seresinhe et al. (2019) similarly found that aesthetically pleasing built environments significantly contribute to everyday happiness, independent of the presence of green spaces.

Furthermore, architectural features in built environments can enhance social well-being and psychological health. In their study, Brown et al. (2009) examined design features like porches and windows, which encourage ”eyes on the street” interactions. These interactions increase social connections, improve perceived social support, and reduce psychological distress, especially among elderly urban residents.

The cleanliness and street quality are essential elements that significantly influence residents' perceptions and neighborhood satisfaction. Mouratidis (2020) highlighted that deprived neighborhoods, despite adequate physical amenities like green spaces and transport access, often suffer from lower perceived cleanliness, increased noise, reduced safety, and lower aesthetic quality. Wu et al. (2024) further emphasizes that neighborhood appearance and basic features, such as cleanliness and design, strongly influence neighborhood satisfaction. These negative perceptions notably decrease neighborhood satisfaction and emotional responses, further impacting residents' overall well-being.

The findings from these various studies highlight the significance of the visual aesthetics of the built environment with SWB, indicating that multiple factors contribute to the overall visual appeal.

2.3. Computer Vision in urban studies

Computer vision (CV) models have been integrated in urban planning to capture the complexity of the large number of variables described in the previous section. This section highlights the implementation of those CV models and how they explain SWB.

Helbich et al. (2019) used Tencent Street View (Chinese equivalent of Google Street View) images and deep learning semantic segmentation to quantify street-level green and blue spaces across neighborhoods in Beijing. They compared these measures with traditional remote sensing metrics, including Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and GlobeLand30 land cover data. Using a fully convolutional neural network (FCN), they extracted the proportion of visible greenery (e.g., trees, grass) and blue features from over 130,000 street view images. These exposure measures were linked to depressive symptoms, assessed via the GDS-15 scale. Multilevel regression models showed that higher exposure to street-level green and blue spaces was significantly associated with lower depression scores, whereas satellite-based metrics showed no significant association. Highlighting that satellite images may not capture what people see on the streets. These results align with prior findings on the positive psychological impacts of green and blue spaces in urban environments (Ambrey and Fleming, 2014; Krekel et al., 2016; Smith et al., 2021).

Similarly, Wu et al. (2021) used Tencent Street View images and semantic segmentation techniques to examine how street-level visible greenness affects life satisfaction among working adults in Beijing. Using an FCN, the study quantified visible greenery at residential and workplace locations within 500-meter buffers. Greenness exposure was also measured using the NDVI for comparison purposes.

These spatial variables were linked to individual life satisfaction responses from the Chinese Livable Survey. Multilevel logistic regression results showed that residential greenness positively influenced life satisfaction, while workplace greenness showed no significant association. This supports previous research emphasizing the importance of green spaces near living areas for life satisfaction (Bertram and Rehdanz, 2015; Patino et al., 2023). The study further explored interactions and subgroup differences, identifying stronger associations among males, younger adults, and individuals with lower income or educational attainment.

Expanding on this work, Wu et al. (2022) integrated street-level remote sensing data, deep learning techniques, and detailed land-use entropy metrics to examine the relationship between urban greenness, mixed land-use, and life satisfaction. Like the previous study, Tencent Street View images and semantic segmentation methods were used to measure greenness near residential and workplace areas (Wu et al., 2021; Helbich et al., 2019). The study confirmed the previous finding that residential greenness positively correlates with life satisfaction but further revealed a negative correlation with workplace greenness, which was previously found to be insignificant (Wu et al., 2021). Additionally, mixed land-use was quantified using point-of-interest entropy from online mapping tools and revealed beneficial effects in both residential and workplace contexts. Notably, significant interaction effects between greenery and mixed land-use were observed, highlighting the complex relationships between urban design and individual well-being.

Whilst the research of Helbich et al. (2019) found no significant correlation between satellite images and depression scores. Research of Bahr (2024) still used satellite images to predict life satisfaction. The study used satellite images and deep learning semantic segmentation to quantify nine distinct types of urban green space across Switzerland. This method enabled detailed spatial measurement of green elements, such as trees and grass in gardens, parks, forests, and recreational areas, within a 1260-meter neighborhood. These green space components were combined with land-use data from OpenStreetMap to assess their association with individual life satisfaction scores from the Swiss Household Panel. The analysis included age-specific interactions using linear regression and random forest models. The findings showed that only older adults (65+) benefited from greener neighborhoods, particularly trees and grass in gardens and parks. Additionally, mixed land-use, measured via land-use entropy, was positively linked with life satisfaction among younger individuals, with effects diminishing with age.

Shifting focus to broader urban aesthetics, Nguyen et al. (2021) analyzed more than 31 million Google Street View images from 2,916 U.S. counties to study how built environment characteristics relate to health outcomes. Using image classification, they extracted features such as crosswalks, non-single-family buildings, single-lane roads, utility wires, proxies for walkability, mixed land-use, urban development, and physical disorder. These indicators were linked to public health metrics, including obesity, diabetes, physical inactivity, mental distress, and premature death. Results showed that the presence of crosswalks and mixed land-use was associated with better physical and mental health. In contrast, single-lane roads and visible utility wires were linked to negative health indicators, including mental distress. These associations reflect earlier research emphasizing the importance of cleanliness, infrastructure, and visual quality for neighborhood satisfaction and emotional well-being (Mouratidis, 2020; Wu et al., 2024).

Similarly to the research of Feng et al. (2022), Fan et al. (2023) focused more on urban features of the built environment, whilst also taking into account the greenery as mentioned by Helbich et al. (2019); Wu et al. (2022). Using a deep learning segmentation model, they applied computer vision to 27 million Google Street View images across seven major U.S. metropolitan areas to extract semantic features of the built environment, such as trees, sidewalks, façades, and greenery. These street view features (SVF) were then used to predict neighborhood-level socio-economic indicators, including health outcomes, poverty, crime, and travel behavior. Mental health was one of the health variables assessed, alongside physical inactivity, obesity, and chronic disease prevalence. Using LASSO regression, the models based on SVF explained up to 62% of the variance in mental health outcomes, outperforming models using points of interest or population data alone. However, this paper also noted that mental health is less explainable by image data alone, compared to the other variables assessed, since this is mainly explained by socio-demographic variables.

Like the research of Fan et al. (2023), Ma et al. (2024) used urban features to determine street quality. Using multi-source data and machine learning, they examined the mismatch between street space quality and residents' SWB in central Qingdao. They applied an FCN to Tencent Street View images to measure street quality across four dimensions, safety, comfort, attractiveness, and interactivity, based on features such as greenness, walkability, and visual diversity. SWB was estimated through sentiment analysis of geotagged Weibo posts (Chinese equivalent of Twitter). The study found that only about 21% of areas clearly matched high-quality street environments and high SWB. Residents often reported high well-being despite lower street quality, and vice versa. Through ordered logistic regression and restricted cubic spline models, the study identified several key factors linked to this mismatch: road network accessibility, green space agglomeration, housing prices, and living convenience were positively associated with higher SWB relative to street quality, while population density, mixed land-use, and night-time light levels were negatively associated.

To summarize, these recent computer vision studies focus on hedonic well-being and life satisfaction, often using street-level images. Table 2.1 provides an overview of these studies, highlighting which component of the subjective well-being was studied and what types of data were used. While both hedonic well-being and life satisfaction have been studied multiple times, the effect on eudaimonic well-being has yet to be studied with computer vision. Notably, researchers tend to favor street view images over satellite imagery, likely due to their closer alignment with the visual experience of urban residents.

Table 2.1: Overview of Computer Vision studies and their impact on subjective well-being

Study	Hedonic	Eudaimonic	Life Satisfaction	Data
Helbich et al. (2019)	x	-	-	street view and satellite images
Wu et al. (2021)	-	-	x	street view
Wu et al. (2022)	-	-	x	street view
Bahr (2024)	-	-	x	satellite images
Nguyen et al. (2021)	x	-	-	street view
Fan et al. (2023)	x	-	-	street view
Ma et al. (2024)	x	-	-	street view

Computer vision model to derive utility

Traditional CV methods used in urban studies primarily rely on segmentation-based models, which quantify the presence or extent of specific urban features such as greenery, sidewalks, or water bodies from street-level images. While these approaches provide objective, scalable measures of visual characteristics, they focus solely on quantifying the physical presence of these elements rather than capturing subjective preferences or perceptions of how people interpret these. As a result, they may overlook important nuances, such as individual preferences for qualities like the maintenance of parks, the difference between aesthetically pleasing vegetation and overgrown spaces, or trade-offs between multiple features.

To address this gap, the Computer Vision-enriched Discrete Choice Model (CV-DCM) developed by Van Cranenburgh and Garrido-Valenzuela (2025) takes a different approach. Instead of relying on pre-defined segmentations, the CV-DCM uses a modern vision transformer model that learns relevant patterns and features from images holistically, without prior specification. More importantly, the CV-DCM directly links these visual features to actual human choices within a random utility maximization framework. This means the model learns how the presence, quality, and combination of features in an image influence individuals' decisions, capturing the subjective and perception-driven aspects of urban environments.

Trained on stated choice data, where respondents weigh trade-offs between housing costs, commute times, and different street-level images, the CV-DCM produces a continuous, perception-based utility score for any image. Unlike traditional models that only quantify physical characteristics, this approach provides more insights into how people subjectively experience and value urban environments, making it possible to understand real-world trade-offs and preferences.

2.4. Covariates for determining subjective well-being

While visual aesthetics are known to influence subjective well-being, research also highlights the important roles of socio-demographic and built environment factors. Variables such as age, gender, education, income, employment status, and population density affect both how individuals perceive their surroundings and how they report subjective well-being. These covariates are essential for explaining variation in subjective well-being across urban contexts and were selected because they were consistently studied over several studies. Controlling for these factors helps understand the individual effect of visual aesthetics on subjective well-being. Research has shown these variables shape subjective well-being by:

- **Population density** — Several studies report that SWB tends to drop in highly dense urban areas. Ma et al. (2024) show that once population density exceeds around 1700 people per km^2, life satisfaction decreases noticeably. In contrast, Nguyen et al. (2021) found that people experience less distress in denser areas. Whereas research of Wu et al. (2022) found no significant correlation.
- **Age** — Age shows a clear positive relationship with SWB. Older people generally report being more satisfied with their lives than younger people, a pattern that holds across several contexts (Wu et al., 2022; Bahr, 2024; Helbich et al., 2019; Nguyen et al., 2021). However, these researches all used linear coding, while a research that did not use linear coding found a U-shaped relation with age (Graham and Ruiz Pozuelo, 2017).
- **Gender** — The role of gender is a bit mixed. In some cases, men seem to benefit more from green spaces and walkable environments (Wu et al., 2022; Nguyen et al., 2021). Helbich et al. (2019), on the other hand, found no major differences. While Kaiser et al. (2025) found a paradox in women's subjective well-being, where women tend to report higher life satisfaction but lower hedonic well-being.
- **Education** — Higher education is usually linked with better SWB. People with higher education tend to have better access to information, health care, and job opportunities, which can contribute to higher SWB (Wu et al., 2022). However Helbich et al. (2019) found no significant correlation.
- **Employment** — Being employed is another strong covariate of well-being. It not only provides income but also structure, purpose, and social contact (Wu et al., 2022).
- **Income** — Wu et al. (2022) found that income tends to increase life satisfaction. Bennedsen (2024) found similar results, however after a certain income this effect diminishes.

2.5. Conclusion and Discussion

This literature review has outlined the findings relevant to understanding the relationship between the built environment and SWB. The first section introduced the concept of SWB, as proposed by international guidelines, which defines it in three dimensions: hedonic well-being, eudaimonic well-being, and life satisfaction.

Urban studies have examined these three aspects of SWB and found that many features of the built environment, such as greenness, cleanliness, visual appeal, and safety, can significantly influence how people feel about their surroundings. These findings highlight the importance of visual qualities in shaping residents' experiences of their neighborhoods.

Recent research has turned to CV techniques using street-level and satellite imagery to better understand what people see in their environment. These methods often rely on segmentation models to process large datasets and identify elements like greenery, building façades, and road conditions. Compared to earlier approaches that relied on surveys or general neighborhood data, CV methods offer a more direct and scalable way to measure urban characteristics.

However, many CV-based studies still use segmentation-based metrics that measure the existence of features, such as the amount of visible greenery or whether a sidewalk is present. Although these methods provide objective and scalable measurements, they do not capture the more subjective and nuanced ways people experience and interpret their surroundings. For example, they may miss distinctions between well-maintained and neglected green spaces or fail to account for how individuals weigh multiple features when seeing urban environments.

To address these limitations, the CV-DCM model developed by Van Cranenburgh and Garrido-Valenzuela (2025) uses a different approach. Instead of analyzing predefined segmentation's, this model uses a vision transformer to holistically analyze street-level images and extract relevant visual features without prior specification. These visual features are incorporated into a discrete choice framework where people make real trade-offs. This allows the model to estimate utility scores that reflect how people subjectively value different urban areas, as learned from stated choice experiments where respondents make trade-offs between housing costs, commute times, and street-view images. These scores offer a continuous and scalable way to represent urban quality as humans perceive it.

While the CV-DCM offers a richer and more nuanced representation of urban visual environments, it remains to be validated whether the utility scores it produces capture to the visual qualities that explain SWB. This highlights the need for further validation before such tools can be used in urban planning.

Conceptual model

To validate the CV-DCM model proposed by Van Cranenburgh and Garrido-Valenzuela (2025), this study created a conceptual framework that aligns with existing research on the built environment and SWB. The model, illustrated in Figure 2.1, explores the relationship between perceived physical aesthetics, measured in utility, and individuals' SWB.

The main idea is that the physical aesthetics of a neighborhood, how visually appealing it is, can explain people's SWB. These physical aesthetics are measured by utility scores generated using the CV-DCM. This score reflects how much people value certain features of the built environment, and it is used as an measure of how good the aesthetic quality of a neighborhood is perceived.

The utility score is then linked to SWB to see if people report higher SWB when they live in more aesthetically pleasing neighborhoods. Socio-demographic factors such as age, gender, income, education, employment status, and population density are also included in the model. These factors can directly affect SWB as shown in the literature, but may also shape how people perceive their environment. In particular, residential self-selection is considered, people with higher incomes might choose to live in more attractive neighborhoods, which could then lead to higher SWB scores partly driven by living in a better aesthetically neighborhood, instead of income alone. Including these variables helps separate the effect of neighborhood aesthetics from the influence of who lives where.

In this thesis, subjective well-being is measured as life satisfaction and hedonic well-being, as these are the only available components of SWB in the dataset. At the same time, a complete assessment of SWB would ideally include eudaimonic dimensions as well.

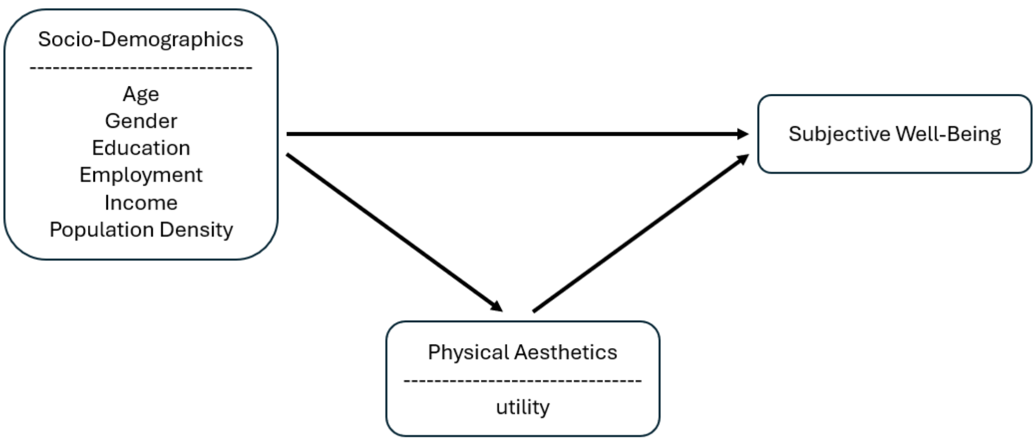


Figure 2.1: Conceptual model as derived from the literature

3 Methodology

This Chapter first explains how data is collected using a Dutch survey containing socio-demographic variables and information about subjective well-being. Subsequently, the computer vision model is described, showcasing how the model derives a utility score based on the residential location. Lastly, the structural equation method is discussed, illustrating how the models examine the relationships between the variables.

3.1. MPN data collection

This Section highlights how data is collected using the Netherlands Mobility Panel (MPN). First, some background information about the MPN is given to provide context. Next, the data collection is discussed, explaining which variables and waves are selected, how the data is cleaned, and the descriptive statistics of the research group.

3.1.1. Background

The Netherlands Mobility Panel (MPN) is a web-based longitudinal survey administered by the Netherlands Institute for Transport Policy Analysis (KiM) (Hoogendoorn-Lanser et al., 2015). Approximately 2,000 complete households participate in the MPN, with all household members aged 12 and over keeping a three-day travel diary once per year. Each respondent is assigned three consecutive days in September-November; those same weekdays recur in every subsequent wave. Besides a travel diary, respondents also fill in a background questionnaire which contains information about themselves, their environment, and their opinion about certain aspects, such as how they feel about trains and how they rate their subjective well-being.

3.1.2. Variables

This research is only interested in the background questionnaire of the MPN, which contains information about the socio-demographics. Focusing on the variables as described by the conceptual model, leading to the following socio-demographic variables being captured:

- **Age (years).** Categorized in ten categories.
- **Gender.** Man / woman.
- **Education.** Highest completed level, categorized in primary, secondary, or tertiary.
- **Employment status.** Employed / not employed.
- **Household income.** Gross monthly household income in six categories.
- **Population density.** Residents per km^2 in five categories.

Besides socio-demographic variables, the background questionnaire also contains information about the respondents' subjective well-being. This research is interested in life satisfaction and hedonic well-being.

In the MPN, life satisfaction is captured with the satisfaction with life scale (SWLS) developed by Diener et al. (1985). This scale consists of five statements assessing global cognitive judgments of one's life (e.g., "In most cases my life is almost ideal"). Respondents indicated how much they agree on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). The five questions and scale can be found in Appendix A.

Hedonic well-being is captured similarly, through five statements and a Likert scale. Veit and Ware (1983) initially created 38 items to assess hedonic well-being, which was later reduced by Berwick et al. (1991) to 5 items, the Mental Health Inventory-5 (MHI-5). This MHI-5 is included in the MPN and used to capture the hedonic well-being. Respondents rate each of the five statements on a 6-point Likert scale (Never to Always). Three items (1, 2, and 4) assess psychological distress (e.g., "The last couple of months I was very nervous"), while two items (3 and 5) evaluate positive well-being (e.g., "The last couple of months I felt calm and relaxed"). The full scale and questions can be found in Appendix B.

To summarize, subjective well-being is captured in the following two variables:

- **Satisfaction With Life Scale (SWLS).** Captures life satisfaction through five items from Diener et al. (1985), each on a 7-point Likert scale.
- **Mental Health Index-5 (MHI-5).** Captures hedonic well-being though five items from Berwick et al. (1991), each on a 6-point Likert scale.

3.1.3. Wave selection

Research has shown that individual life evaluation may vary from year to year (World Happiness Report, 2025). Since MPN is a longitudinal survey in which respondents appear in multiple waves, this thesis uses each respondent's most recent subjective well-being evaluation to be the most up-to-date. The latest data available is from the year 2022.

Life satisfaction, measured through the SWLS has only been included in the MPN from 2020 onward. This leads to the waves 2020-2022 being selected for assessing life satisfaction.

Hedonic well-being is measured through the MHI-5, which was only included in 2020. Therefore, only the year 2020 is used as a dataset to assess the impact on hedonic well-being, leading to a different dataset than the one used for life satisfaction.

It should be noted that the 2020–2022 waves took place during the COVID-19 pandemic, which research shows lowers life satisfaction (Delgado-Rodríguez et al., 2024). Still, since everyone in this study experienced the same event, the pandemic's effect is equal across the sample. By focusing only on individuals who shared this challenge, it is expected that comparisons of life-satisfaction scores remain free from bias. Therefore, even though average well-being may be lower than before the pandemic, comparing respondents' scores is still meaningful.

3.1.4. Data cleaning

To asses the impact on life satisfaction and hedonic well-being a complete and adequate dataset is needed, therefore some cleaning needs to be done. Starting with all background-questionnaire respondents across 2020–2022 for life satisfaction and 2020 for hedonic well-being, several cleaning steps were performed, which are:

1. **Age restriction.** Remove respondents under the age of 18.
2. **Most recent record.** For panel members who completed multiple waves, use only their most recent complete response, yielding a cross-section reflecting each individual's "latest" available data.
3. **Incomplete cases.** Remove respondents who did not fill in each of the questions.
4. **Residential images available.** Removes respondents who do not have images available of the residential location.

After cleaning, the final sample size for life satisfaction is $N = 2\,235$ respondents, whereas for hedonic well-being this is $N = 1\,986$ respondents. Table 3.1 summarizes the cleaned wave sizes and the new unique respondents per wave.

Table 3.1: Respondent counts by wave

	Life Satisfaction		Hedonic Well-Being
Wave	Total respondents	Unique respondents	Total respondents
2022	2 000	2 000	-
2021	2 079	145	-
2020	2 047	90	1986
Final sample	-	**2 235**	**1986**

3.1.5. Descriptive analysis

A descriptive analysis is performed to analyze how the sample size is distributed, which can be found in Table 3.2. This Table shows a similar distribution for both life satisfaction and hedonic well-being over all variables.

Table 3.2: Demographic distribution of both the sample sizes

		Life Satisfaction		Hedonic Well-Being	
Category	**Subcategory**	**Frequency**	**Percent (%)**	**Frequency**	**Percent (%)**
Household income					
	minimum (<€14,100)	130	5.8	119	6.0
	below benchmark (€14,100–<€29,500)	435	19.5	394	19.8
	benchmark (€29,500–<€43,500)	522	23.4	496	25.0
	1–2× benchmark (€43,500–<€73,000)	686	30.7	611	30.8
	2× benchmark (€73,000–<€87,100)	150	6.7	129	6.5
	>2× benchmark (≥€85,100)	312	14.0	237	11.9
Population density					
	Non-urban (<500)	150	6.7	174	8.8
	Sparsely urban (500–1000)	432	19.3	392	19.7
	Moderately urban (1000–1500)	343	15.3	334	16.8
	Highly urban (1500–2500)	755	33.8	677	34.1
	Very strongly urban (>2500)	555	24.8	409	20.6
Gender					
	Man	1004	44.9	903	45.5
	Woman	1231	55.1	1083	54.5
Education Level					
	Tertiary II (Master's/Doctorate)	304	13.6	253	12.7
	Tertiary I (Bachelor's)	631	28.2	568	28.6
	Upper secondary general	256	11.5	239	12.0
	Upper secondary vocational	593	26.5	523	26.3
	Lower secondary general	226	10.1	200	10.1
	Lower secondary vocational	188	8.4	173	8.7
	Primary/No education	37	1.7	30	1.5
Employment Status					
	Active	1630	72.9	1447	72.9
	Not working	605	27.1	539	27.1
Age Group					
	18–24 years	60	2.7	66	3.3
	25–29 years	107	4.8	105	5.3
	30–39 years	402	18.0	372	18.7
	40–49 years	408	18.3	320	16.1
	50–59 years	431	19.3	393	19.8
	60–69 years	392	17.5	378	19.0
	70–79 years	326	14.6	271	13.6
	80+ years	109	3.9	81	4.1
Total		2235	100.0	1986	100

Overall, the MPN sample closely reflects the Dutch adult population but with a few notable deviations. Young adults under 30 are underrepresented. The gender distribution, 55% female and 45% male, closely mirrors the national 50/50 balance. In terms of education, higher educational levels are somewhat overrepresented, while lower levels are underrepresented. The employment rate in the sample aligns well with national figures. (CBS, 2025)

The sample contains a higher proportion of individuals in upper income brackets compared to national averages, suggesting an over-representation of wealthier respondents. Regarding residential context, most participants live in urban or semi-urban areas. Although the most densely populated areas are slightly underrepresented, the urban-rural distribution remains broadly consistent with national patterns. (CBS, 2025)

Despite these imbalances, the sample displays sufficient diversity to support meaningful insights into subjective well-being across the different demographic groups.

3.1.6. Factor analysis on subjective well-being

Subjective well-being is not as straightforwardly measured as the variables in Table 3.2. Life satisfaction and hedonic well-being are measured through five statements that need to be aggregated into one variable to assess them.

Life satisfaction is measured through the SWLS, and responses are typically summed to yield a total life satisfaction score ranging 5–35, with higher scores indicating greater life satisfaction.

For hedonic well-being, this is a bit more complicated. Since not all items are positively measured within the MHI-5, simply summing these would lead to a wrong score. That's why items 1, 2, and 4 are reversed to measure a positive impact instead of a negative one, similar to items 3 and 5. This leads to a total score ranging from 5 (worst hedonic well-being) to 30 (best hedonic well-being).

However, before summing the results of the five statements to one variable, it should be verified that they indeed reflect a single underlying construct. This is done through a factor analysis; this technique is used to uncover the latent structure of a set of observed variables.

Table 3.3 shows the correlation between the different SWLS questions, which show an inter-item correlation ranging from 0.468 to 0.772, demonstrating consistently high correlations among all five SWLS items, which all exceed the threshold of 0.3. These results support a single-factor variable, justifying the combination of all five items into one overall life satisfaction score.

Table 3.3: Correlation Matrix Satisfaction With Life Scale

	SWLS_S1	SWLS_S2	SWLS_S3	SWLS_S4	SWLS_S5
SWLS_S1	1.000	-	-	-	-
SWLS_S2	.765	1.000	-	-	-
SWLS_S3	.772	.761	1.000	-	-
SWLS_S4	.634	.629	.688	1.000	-
SWLS_S5	.523	.468	.540	.546	1.000

Besides the correlation matrix, the Kaiser–Meyer–Olkin measure of sampling adequacy yields 0.871, being above the 0.60 threshold and indicating that the item correlations were strong enough for factor analysis. Another test, Bartlett's test of sphericity, was significant, χ^2 = 7011, p < .001, confirming that the correlation matrix was not an identity matrix and thus appropriate for factor extraction. All these tests support that the SWLS in this thesis can be summed to one total life satisfaction score, which can be found in Figure 3.1.

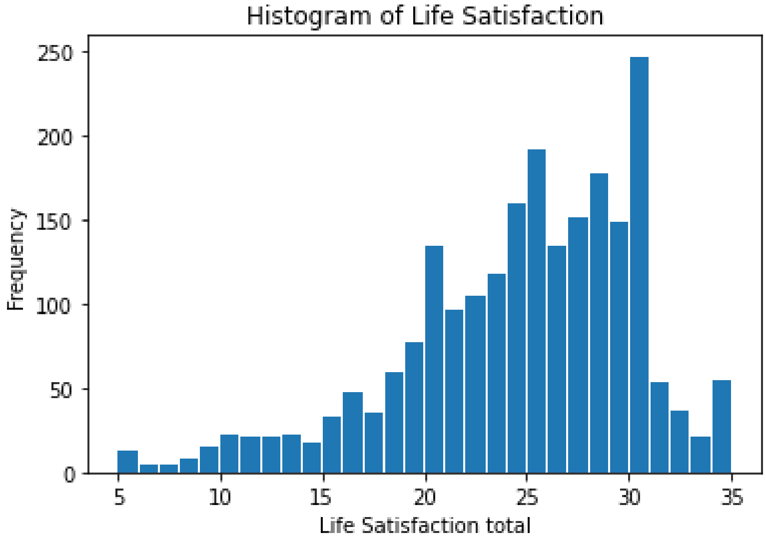


Figure 3.1: Distribution of Life Satisfaction scores

Similarly, the correlation between the different MHI-5 statements, as shown in Table 3.4, all show a correlation that exceeds the threshold of 0.3. Besides that, it shows that items 1, 2, and 4 are indeed reverse-ordered. The Kaiser-Meyer-Olkin measure shows an adequacy of 0.821, above the 0.60 threshold. And the Bartlett's test of sphericity was significant, χ^2 = 5004, p < .001. Indicating that the MHI-5 indeed can be summed to one cumulative variable of hedonic well-being, which can be seen in Figure 3.2.

Table 3.4: Correlation Matrix Mental Health Index-5

	MHI_Q1	MHI_Q2	MHI_Q3	MHI_Q4	MHI_Q5
MHI_Q1	1.000	-	-	-	-
MHI_Q2	.624	1.000	-	-	-
MHI_Q3	-.514	-.520	1.000	-	-
MHI_Q4	.604	.759	-.533	1.000	-
MHI_Q5	-.423	-.544	.636	-.566	1.000

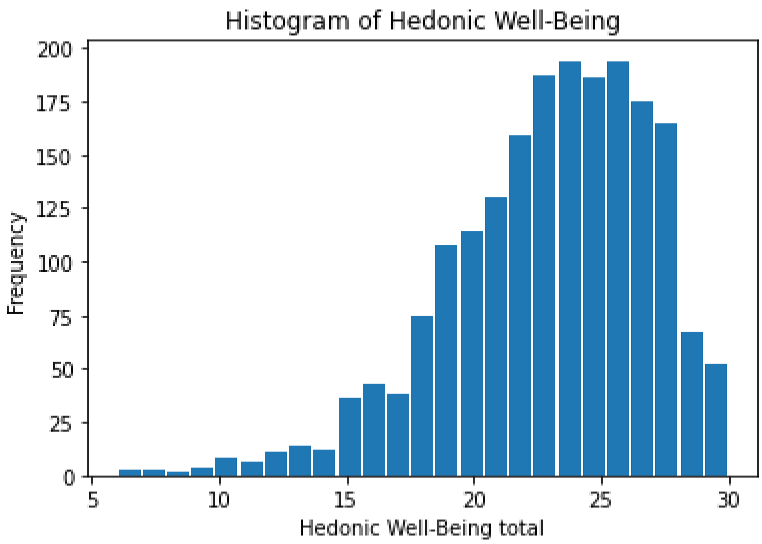


Figure 3.2: Distribution of Hedonic Well-Being scores

3.2. Computer vision model

This section explains the Computer Vision (CV) model, the method used to extract useful information from images. This method was developed by Van Cranenburgh and Garrido-Valenzuela (2025) specifically for analyzing residential location choices using visual data. This section shows a summary of this method; for a full explanation, see the research of Van Cranenburgh and Garrido-Valenzuela (2025). Initially, the method for collecting residential-level images is described, followed by an explanation of how the model generates a utility score from these images. Lastly, it discusses how these utility scores were linked to the MPN.

3.2.1. Residential-level image retrieval

Before the model can calculate a utility score for a residential location, images need to be collected. This thesis uses data provided by the research of Garrido-Valenzuela et al. (2023), which has a dataset containing google street-view images (streetscapes) for different postal code areas in the Netherlands. In total, streetscapes are available for 344.000 of the 460.000 six-digit postal code areas (PC6), roughly 75 %.

The streetscapes are stored as panoramic photos; however, the computer vision model only works with images of size 224 x 224 pixels; therefore, these streetscapes need to be transformed. This is done by sampling a left and right orientation per streetscape and transforming both orientations to the desired size. As not all PC6 regions have the same number of streetscapes available, a random sample of five streetscapes per PC6 region is selected to have good coverage. If a PC6 region had fewer than five streetscapes, all were selected for this region. Using this method, a maximum of 10 images per PC6 were collected to analyze.

3.2.2. Utility estimation

The collected images are transformed into a utility score using the CV model. CV is a new technology that automatically identifies and interprets visual information from images. Images are composed of pixels, each pixel containing three colours: red, green, and blue (RGB). These pixels are arranged in two dimensions, height and width. Mathematically, images are represented as three-dimensional arrays (tensors). For example, an image of 100×50 pixels is represented as an array with dimensions $100 \times 50 \times 3$, where the last dimension corresponds to the RGB colour channels. Processing images directly at the pixel level is computationally challenging because images contain extensive data, yet each pixel individually offers limited information. To overcome this, the CV model uses a feature extractor and a classifier, transforming raw images into meaningful data.

The CV model uses feature extraction to simplify images into structured numeric data called feature maps. It specifically uses a Vision Transformer (ViT), a deep neural network. The ViT extracts important visual features from images, turning them into compact numerical arrays known as feature maps. These feature maps usually have a size of 1×1000, significantly reducing the data complexity. The classifier then assigns weights to each of these features, indicating their relative importance for determining the utility score. The CV model can be seen in Figure 3.3. The model started with a pre-trained DeiT (Data-efficient image Transformer) base model, consisting of a relatively modest 86 million weights, known for its efficiency and accuracy, especially on large datasets like ImageNet (Deng et al., 2009; Touvron et al., 2021). It was then trained to predict residential location choices using data from a stated choice experiment, which led to a fully trained CV-DCM. This thesis uses this fully trained CV-DCM model, designed by Van Cranenburgh and Garrido-Valenzuela (2025), containing the trained ViT and classifier to generate utility scores for a new set of street-level images provided by Garrido-Valenzuela et al. (2023).

While the feature extractor effectively changes images into meaningful numerical representations, precisely identifying which particular visual elements contribute to higher or lower utility scores remains a black box. Consequently, the model does not reveal why certain features lead to specific utility levels. Nevertheless, it is possible to visually compare images alongside their utility scores to make assumptions about which visual features might influence perceived utility.

The model designed by Van Cranenburgh and Garrido-Valenzuela (2025) is age-dependent, as different age groups prioritize different aesthetic aspects of their surroundings. Mathematically, the utility of features derived from an image for an alternative i is represented by:

$$U_i = \sum_{\text{age}} \sum_{k} \beta_k^{\text{age}} \times age \times z_{ik} + \varepsilon_i \tag{3.1}$$

Where:

- Z_{ik} are elements from the image's feature map for alternative i and feature map element k,
- β_k^{age} are coefficients indicating the influence strength of each visual feature k for age group age,
- ϵ_i is an error term representing unknown or unmeasured factors.

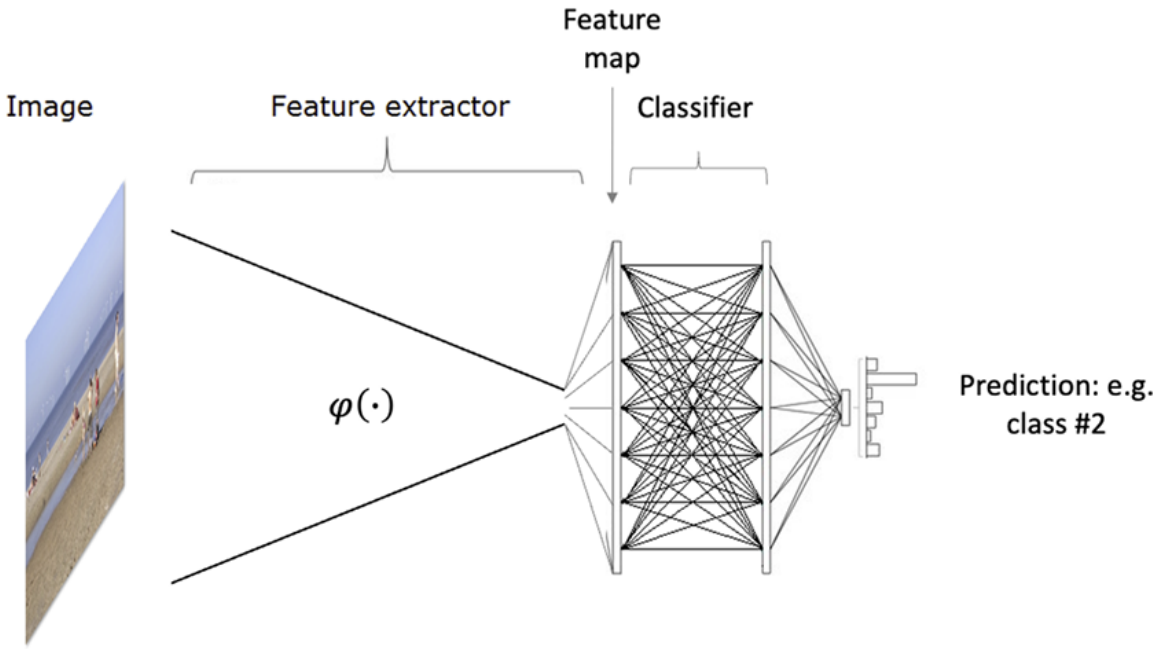


Figure 3.3: Feature extraction and classifier as developed by Van Cranenburgh and Garrido-Valenzuela (2025)

Using this model, an age-dependent utility score is calculated per image. This thesis, however, uses one utility score per residential location; therefore, this age dependency has to be overcome. This is done by aggregating the age-dependent utility by multiplying it by the population density for that specific age group to derive one utility score. As a postal code region contains multiple images, an average utility needs to be calculated. Since the utility is linearly dependent, this is done by averaging the utility score over all images in that region, leading to one non-age-dependent utility score per postal code. This is done for postal code areas with five (PC5) and with six digits (PC6).

3.2.3. Linking utility to MPN

Since the MPN is an anonymous survey and the utility scores contain information about the residential location, directly linking these could infringe anonymity. Therefore, all utility scores are rounded to one decimal, and outliers were rounded to the closest non-unique value to ensure no unique utility score exists. These PC-level utility scores were sent directly to KiM, the MPN administrator, who is aware of the respondents' residential location. They linked the utility scores generated by the CV model with the unique ID of each respondent. At no time did the research team have access to the specific PC codes or addresses of the respondents; only the utility scores per unique respondents' ID were made available for further analysis. This approach preserved participant privacy by ensuring that researchers worked solely with the derived utility scores, without knowledge of the residential location of the participants.

3.3. Structural Equation Method

The conceptual model presented in Figure 2.1 illustrates both direct and indirect relationships. To explore these relationships, this study uses Structural Equation Modeling (SEM), which is well-suited for analyzing complex systems with multiple variables. SEM enables the simultaneous testing of the relationship between aesthetic quality (measured as utility) and subjective well-being, while also accounting for the influence of socio-demographic factors on this relationship.

Through SEM, the analysis tests whether aesthetic quality mediates the relationship between the socio-demographic variables and subjective well-being. This is especially important in addressing residential self-selection: individuals with certain characteristics may be more likely to live in visually appealing neighborhoods and report higher well-being, which may be partly driven by neighborhood quality. By modeling both direct and indirect effects within a single framework, SEM helps to uncover such complex relationships.

Because the datasets for life satisfaction and hedonic well-being differ, the SEM analyses are conducted separately for each variable.

3.3.1. Top-Down

The first approach is the more traditional a top-down strategy. This approach starts with a fully saturated model that includes all paths as described by the conceptual model in Figure 2.1. Iteratively, the least significant path is removed and the model is re-estimated, until all path coefficients are significant $p < 0.05$, with the exception of the path between utility and subjective well-being (Arbuckle, 2019). This approach shows the importance and explanatory power of the different paths, giving general information about how the interplay between variables works.

3.3.2. Bottom-Up

In contrast, the bottom-up approach starts with a minimal model, containing only the utility to subjective well-being path. Then, adding covariates based on the importance found in the top-down approach. This method is useful, since it enables a transparent assessment of how each added variable influences the explanatory power of the model. Secondly, it allows to measure the changes in the strength or direction of the utility to subjective well-being relationship as covariates are introduced. This step-by-step process gives a more detailed understanding of how variables interact with each other.

3.3.3. Non-linearization

Finally, a non-linear model is developed to address known non-linear relationships observed in the literature, particularly with respect to age and income with the relation to subjective well-being. Research has found age to have an U-shaped relationship with life satisfaction, while income shows diminishing effects on subjective well-being once a certain threshold is met (Graham and Ruiz Pozuelo, 2017; Bennedsen, 2024).

These patterns mean that a standard linear approach would not show the true impact of these variables. To solve this, the model includes age and income as non-linear variables, by using dummy coding. This helps to better understand how these factors affect both utility and subjective well-being in a non-linear way. It allows the model to reflect differences between age or income groups more accurately.

4

Computer vision model results

This Chapter presents the results of the computer vision model used to quantify the utility of residential locations across the Netherlands. First, the model is visualized to better explain what the model sees as high and low utility. Subsequently, a descriptive analysis shows the differences in utility scores across the Netherlands.

4.1. CV model visualization

Three samples from the dataset are provided to better understand what the CV model sees as high and low utility scores. Showcasing the PC6 with ten images with the highest, lowest, and median utility scores.

Starting with the PC6 with the highest utility score, 7875BP, which is visualized in Figure 4.1. This Figure shows that spacious layouts, well-maintained green spaces, and limited visual clutter characterize the residential areas.

Figure 4.1: Highest utility. 7875BP

Figure 4.2: Lowest utility, 6822BK

Subsequently, Figure 4.2 shows the PC6 with the lowest utility scores, 6822BK. This environment has little greenery, a dense concentration of parked cars, and a generally cluttered and constrained visual layout.

Finally, the average utility PC6 is shown in 4.3, 7425BT. This area balances the previous two PC6, with moderate greenery, typical suburban housing, and reasonable upkeep.

Figure 4.3: Median utility, 7425BT

These findings align with the research presented by Van Cranenburgh and Garrido-Valenzuela (2025), which mentioned that spacious, leafy, and water-abundant areas tend to show high utility scores. Meanwhile, cramped, urbanized, and grayish areas lead to lower utility scores.

4.2. Descriptive Analysis

Not all PC6 had the same number of images, which led to a total of 344.000 of the 460.000 PC6 being analyzed, accumulating a total of 2.7 million images. As mentioned in Section 3.2, the CV-model derives utility per different age groups, which are then aggregated to one utility score by multiplying them by the population of the Netherlands as given by CBS (2025).

Figure 4.4 shows the distribution of utility scores for the three different age groups. It is important to recognize that the absolute utility values themselves are not directly comparable between age groups, as the scale is arbitrary. What matters are the differences in utility within each age group. This thesis is interested in one utility score for an image; therefore, this is only assessed after aggregation and has been shown in Section 4.1.

There could, however, be seen in Figure 4.4 that younger people derive less value from the residential images as it has a sharper curve, indicating less influence by a change in residential scenery. This influence increases with age, as the curve gets wider for middle-aged people and even wider for older people. This is consistent with previous research, which indicates that older adults tend to place greater importance on their residential environment and perceive changes in residential settings more strongly compared to younger individuals (Mu et al., 2024).

Table 4.1: Age distribution (CBS, 2025)

Age group	Category	Percent (%)
18 - 39 year	”Young”	35.0
40 - 59 year	”Middle”	31.7
60+ year	”Old”	33.3
Total	-	100.0

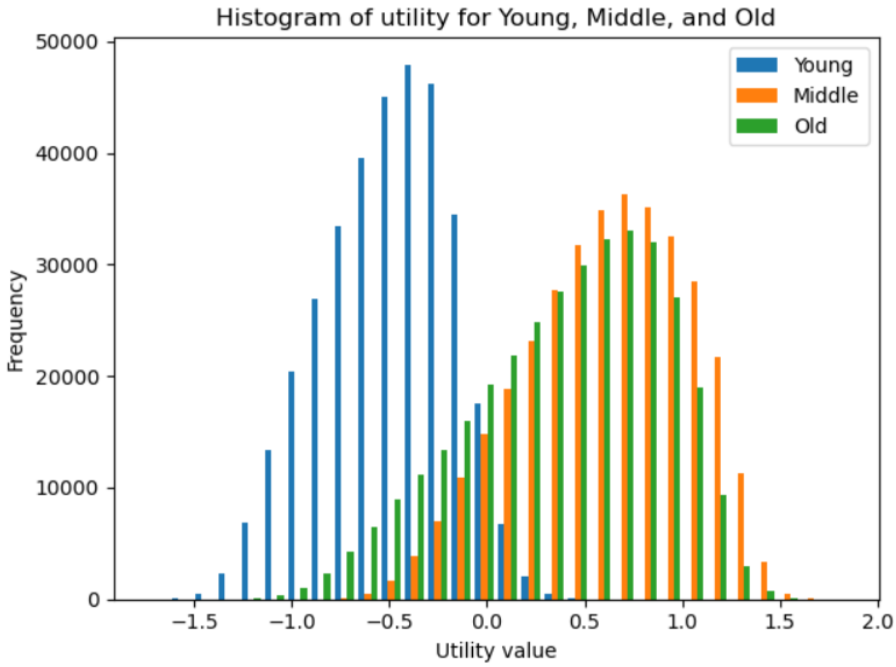


Figure 4.4: Distribution of utility per age group

The aggregated utility scores given the population of The Netherlands can be found in Figure 4.5, which shows the distribution of utility scores at PC6 and PC5 levels for all evaluated PC6 scores in The Netherlands. This Figure shows that the PC5 score removes the outliers and shows a sharper curve than the PC6 scores and range between -1 and 1.

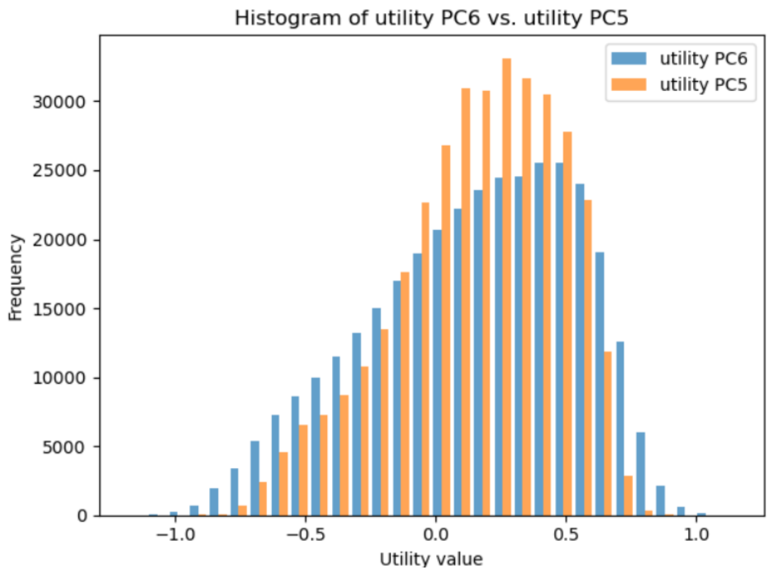


Figure 4.5: Distribution of utility per PC6 and PC5

Figure 4.6 shows the utility of the Life Satisfaction and Hedonic Well-Being dataset. In this Figure can be seen that it shows a similar curve as can be found in 4.5, which shows the utility of the entire Netherlands. Highlighting that the sample size is representative of the population size.

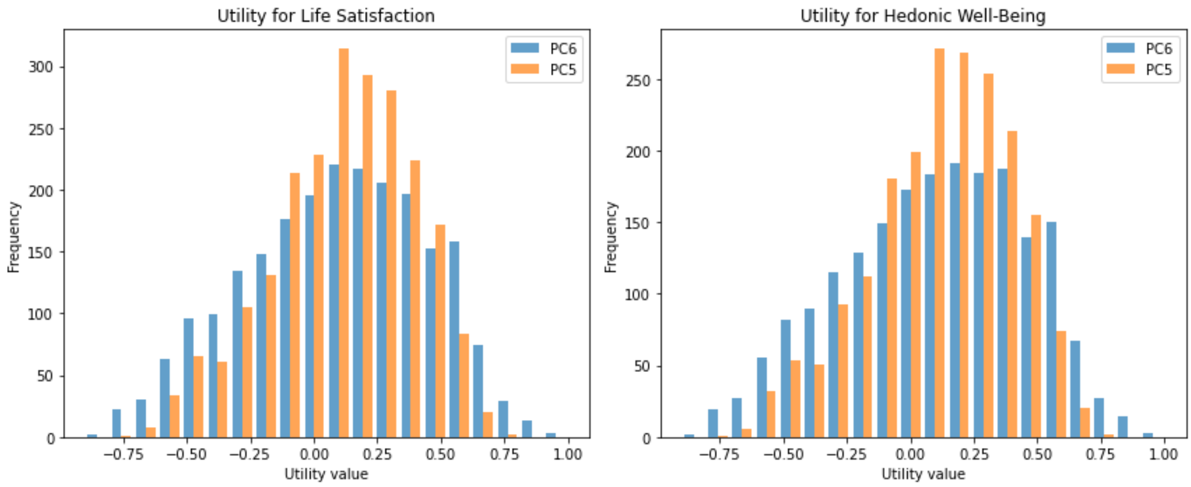


Figure 4.6: Utility distribution for Life Satisfaction and Hedonic Well-Being

The research of Van Cranenburgh and Garrido-Valenzuela (2025) showed that utility scores correlate with population density. Figure 4.7 visualizes this utility distribution over the Netherlands. Higher utility clusters are found in suburban or peri-urban areas with more green space and lower building density. In contrast, lower utility areas tend to align with dense inner-city zones or industrial districts, similar to the research of Van Cranenburgh and Garrido-Valenzuela (2025). In this Figure can be seen that some PC5 do not have an utility score (e.g. the island Vlieland) since no images were available.

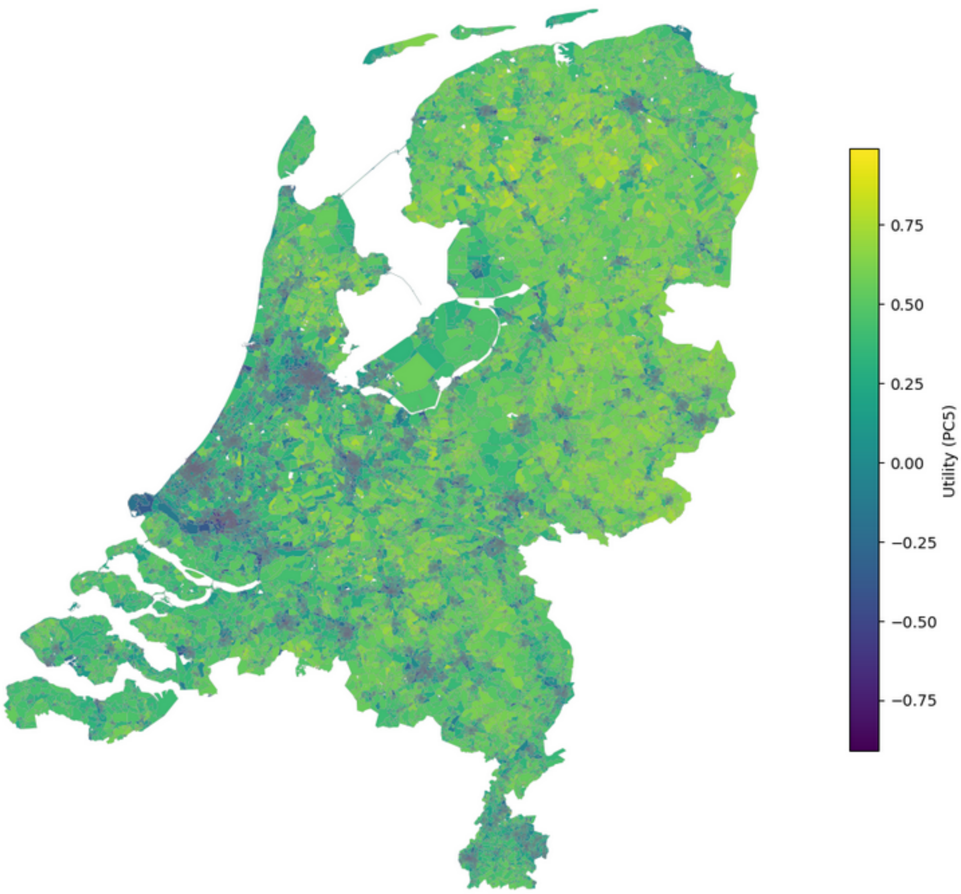


Figure 4.7: Utility of the Netherlands per PC5

5

Results SEM

This Chapter shows the results for the Structural Equation Method. First, the base model is presented, which additionally shows the correlation matrix of the entire dataset. Since both life satisfaction and hedonic well-being have different datasets, these are individually modeled. Starting with the results for life satisfaction and finishing with those for hedonic well-being.

5.1. Base model and correlation matrix

For both life satisfaction and hedonic well-being, the same base model is used, which can be seen in Figure 5.1. This model shows the correlation between all exogenous socio-demographic variables, paths defined between the variables as described by the conceptual model in Figure 2.1, and error terms for both endogenous variables. The subjective well-being component represents either life satisfaction or hedonic well-being, given the dataset selected.

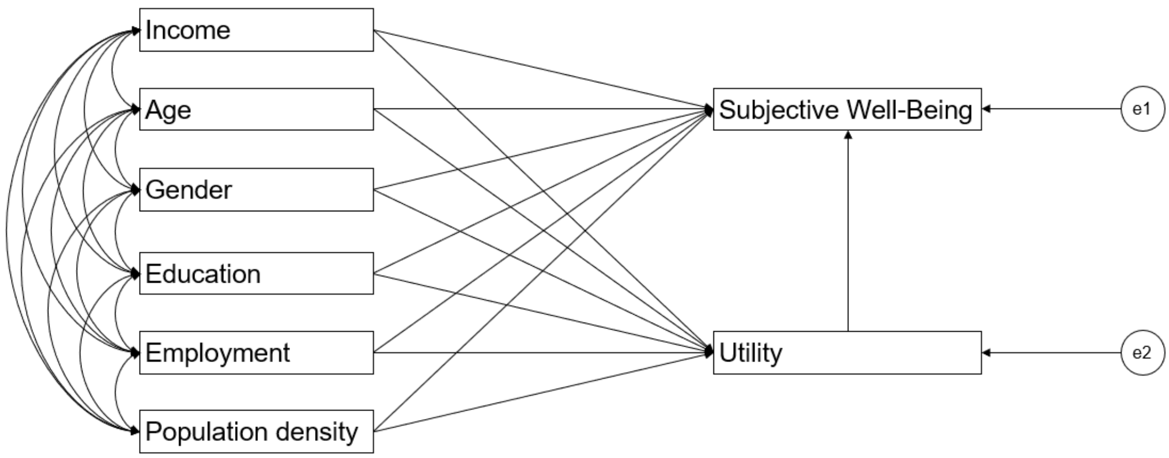


Figure 5.1: Base model of SEM

To show the correlation between all variables, a correlation matrix is computed, which can be found in Table 5.1. This correlation matrix is derived through a pairwise comparison, which leads to a total of 1937 respondents, which is close to the full dataset of both variables. The most interesting results are that the PC5 and PC6 scores are highly correlated (.765), hedonic well-being (HWB) and life satisfaction (LS) do also show a high correlation (.532), and the correlation between PC6 to life satisfaction and hedonic well-being (.061 & .071) is larger than that of PC5 (.051 & .062).

Table 5.1: Correlation matrix for all study variables ($N = 1{,}937$) (* = $p < .05$; ** = $p < .01$)

	HWB	Gender	Employ	Income	Age	Education	Pop dens	PC5	PC6	LS
HWB	1.00	–	–	–	–	–	–	–	–	–
Gender	–0.16**	1.00	–	–	–	–	–	–	–	–
Employ	–0.03	0.04	1.00	–	–	–	–	–	–	–
Income	0.18**	–0.20**	0.22**	1.00	–	–	–	–	–	–
Age	0.27**	–0.19**	–0.41**	0.00	1.00	–	–	–	–	–
Education	0.04	–0.01	0.26**	0.35**	–0.29**	1.00	–	–	–	–
Pop dens	–0.03	0.03	0.02	0.00	–0.10**	0.07**	1.00	–	–	–
PC5	0.06**	–0.03	–0.01	0.11**	0.12**	–0.02	–0.59**	1.00	–	–
PC6	0.07**	–0.04	0.01	0.15**	0.12**	0.04	–0.45**	0.77**	1.00	–
LS	0.53**	–0.03	0.09**	0.28**	0.06**	0.16**	0.00	0.05*	0.06**	1.00

5.2. Life Satisfaction

This section highlights the results of the life satisfaction analysis. Starting with the Top-Down approach to see the direction and importance of the paths. Next, the Bottom-Up approach is used to highlight the explanatory power of the different variables. Finally, age and income are modeled as non-linear in the Top-Down approach to see how these interact with the endogenous variables.

5.2.1. Top-Down

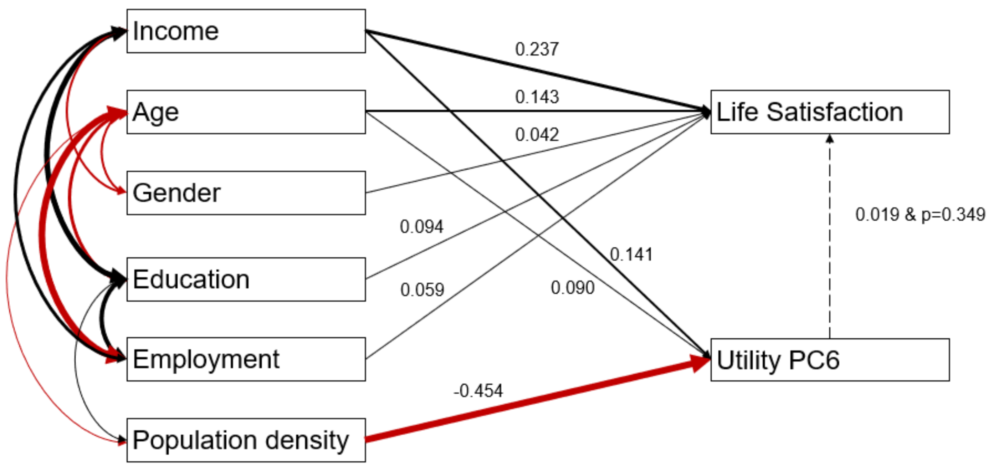
The first analysis is a Top-Down approach, starting with the base model as shown in Figure 5.1, where the subjective well-being component is life satisfaction. Paths are removed as they are deemed insignificant $(p > 0.05)$. The variables gender, education, and employment have been shown to have insignificant paths to utility scores. Whereas, population density to life satisfaction is also proven to be insignificant. These paths were removed, leading to the model as visualized in Figure 5.2 and summarized in Table 5.2.

From Figure 5.2 and Table 5.2, it can be seen that both the PC5 and PC6 analyses converge to the same model, in which every path has the same sign, though the standardized coefficients differ in magnitude. Income and age each have effects on utility scores and life satisfaction, with income consistently showing the larger effects. Higher educated people, women, and people who are employed show to have a positive effect on life satisfaction, while higher population density reduces the utility scores. This reduction in utility scores was expected as Figure 4.7 shows that denser areas show lower utility scores. The direct path from utility to life satisfaction proves to be insignificant in both models.

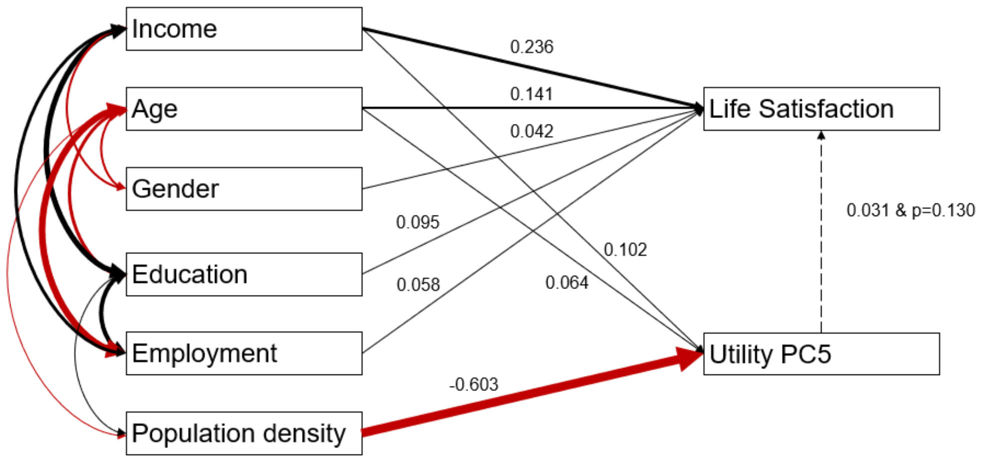
Finally, the PC5-based analysis explains 38.6% of the variance in utility scores and 9.7% of the variance in life satisfaction, whereas the PC6 analysis accounts for 24.1% and 9.7%, respectively. This indicates that the PC5-based analysis does explain more of the variance of utility scores and similarly for the life satisfaction, which is also supported by the overall fit statistics as shown in Table 5.3, in which the PC5 outperforms the PC6 analysis.

Table 5.2: Standardized effects of variables for PC6 and PC5

	PC6		**PC5**	
Independent variable	Utility	LS	Utility	LS
Income	0.141	0.237	0.102	0.236
Age	0.090	0.143	0.064	0.141
Gender		0.042		0.042
Education		0.094		0.095
Employment		0.059		0.058
Population density	-0.454		-0.603	
Utility		*		*
Explained variance (%)	24.1	9.7	38.6	9.7



(a) Final model for PC6 using Top-Down approach



(b) Final model for PC5 using Top-Down approach

Figure 5.2: Final models of Top-Down approach: A visual representation. Line thickness represents the strength of a relation. A straight line with one arrow is a causal path; a curved line with two arrows shows a correlation. A red line represents a negative relation, a black line a positive one, and a dashed line means an insignificant one.

Table 5.3: Fit indices for PC6 and PC5

	χ^2	df	χ^2/df	RMSEA	Probability level
PC6	6.580	4	1.645	0	0.160
PC5	2.547	4	0.637	0	0.636

Since the PC5-based analysis explains a larger share of the utility score variance and shows a better fit, only this model is used in further analysis.

5.2.2. Bottom-Up

The second analysis is the Bottom-Up approach, which starts with solely the path from utility score to life satisfaction and then adds paths in order of importance. The order is determined by total magnitude of effect as shown in Table 5.2, which is first population density, then income, age, education, employment and finally gender. Table 5.4 shows the results of the standardized effects, in which each of the variables is stepwise added. However, this Table does not show the gender variable addition, since this is the full model and can be found in Table 5.2.

Table 5.4: Loadings of independent variables on dependent factors

	Saturated		Pop. dens.		Income		Age		Education		Employment	
IV	U	LS	U	LS	U	LS	U	LS	U	LS	U	LS
Income					0.101	0.272	0.102	0.276	0.102	0.238	0.102	0.228
Age							0.064	0.084	0.064	0.110	0.064	0.133
Gender												
Education										0.102		0.096
Employment												0.057
Pop. density			-0.609		-0.609		-0.603		-0.603		-0.603	
Life Satisfaction		0.068		0.068		0.041		*		*		*
Expl. var. (%)	0	0.5	37.1	0.5	38.1	7.8	38.6	8.5	38.6	9.3	38.6	9.6

Table 5.4 shows the results of the Bottom-Up approach. In the saturated model, the path utility to life satisfaction is significant with a coefficient of $\beta = 0.068$; however, this explains little variance of life satisfaction, namely 0.5%.

When population density is introduced in the second step, the coefficient remains unchanged, but the explained variance of the utility score increases substantially to 37.1%. The addition of income in the third step reduces the utility to life satisfaction coefficient to $\beta = 0.041$, while the variance explained in life satisfaction rises to 7.8%, marking a notable increase of 7.3%. Utility variance also experiences a modest increase to 38.1%. With the inclusion of age in the fourth step, life satisfaction variance further increases to 8.5%, and utility variance to 38.6%. At this stage, the path from utility to life satisfaction becomes statistically insignificant (denoted "*"). Subsequent additions of education, employment, and gender each contribute marginally to the variance in life satisfaction, adding between 0.8% and 0.1%.

5.2.3. Non-linear variables Age and Income

The final analysis for life satisfaction is controlling the model for the non-linear variables, age and income.

First age is tested for non-linearity, which can be found in Table 5.5. As a reference category, the youngest group was chosen, which is the 18-24 category. In this Table, the unstandardized estimate, the p-value, and the standard error are given. If a variable showed a significant path, this was standardized; if a path was insignificant, the standardized component was noted with an asterisk (*).

Table 5.5: Non-linear model for age, with age group 18-24 as reference category

	Utility				Life satisfaction			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Income	0.02	0.00	0.00	0.09	1.19	0.00	0.09	0.29
Gender					0.58	0.02	0.24	0.05
Education					0.26	0.00	0.08	0.07
Employment					1.37	0.00	0.31	0.11
Population density	–0.14	0.00	0.00	–0.60				
Utility					0.85	0.03	0.40	0.04
Age (25–29)	0.02	0.67	0.04	*	–0.56	0.52	0.88	*
Age (30–39)	0.09	0.01	0.03	0.12	–1.62	0.04	0.77	–0.11
Age (40–49)	0.08	0.01	0.03	0.11	–2.20	0.01	0.77	–0.15
Age (50–59)	0.11	0.00	0.03	0.14	–1.97	0.01	0.78	–0.14
Age (60–69)	0.10	0.00	0.03	0.13	–0.28	0.72	0.78	*
Age (70–79)	0.12	0.00	0.03	0.14	1.65	0.04	0.79	0.06
Age (80 +)	0.10	0.01	0.04	0.07	1.52	0.09	0.91	*
Expl. var. (%)	38.9				12.6			

Table 5.5 shows the results of the non-linearity check for the variable age. The standardized values for the linear variables are comparable to those in the Top-Down approach as discussed in section 5.2.1. Interestingly, the path from utility to life satisfaction now becomes significant; however, it is of small magnitude.

The results show that for all age categories, except (25-29), utility is significantly different from the reference category. In contrast, for life satisfaction only the middle-aged columns show significant differences, which are negatively correlated. These β estimates are visualized in Figure 5.3, which shows a clear increase in utility as people get older, especially for the younger age groups. However, as people move beyond the age of 34, this increase in utility seems to stagnate. Besides that, a clear U-shaped relation between age and life satisfaction is shown.

Finally, with the age codes as non-linear, the explained variance of the utility slightly increases by 0.3% whilst for the life satisfaction, this increases by 2.9%.

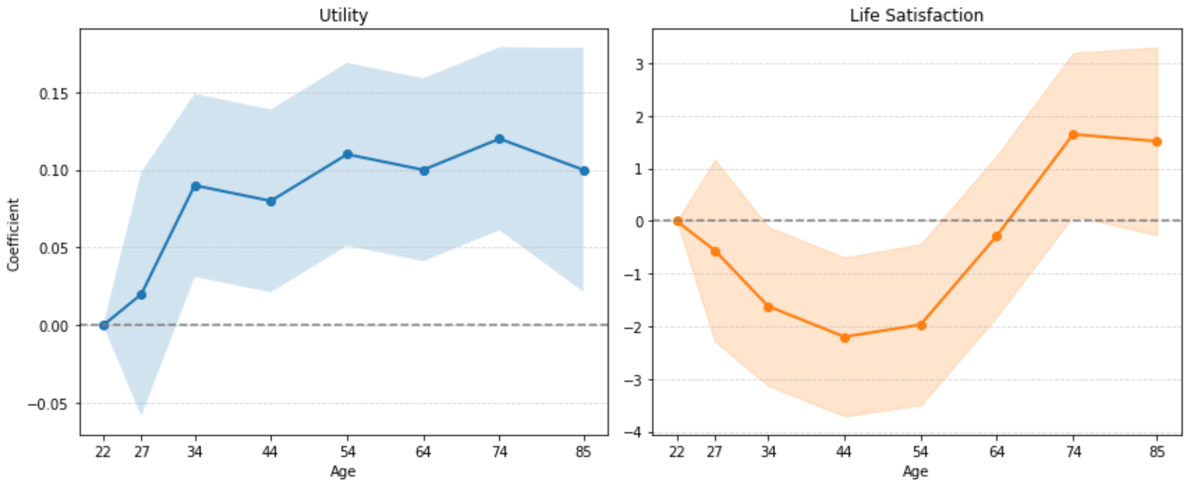


Figure 5.3: Estimated β visualized for non-linear variable Age

Next, the variable income is tested for non-linearity, which can be found in Table 5.6. Again, the reference category was set to the lowest category, in this case, the minimum income.

Table 5.6: Non-linear model for Income, with minimum income as reference category

	Utility				**Life satisfaction**			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Age	0.01	0.00	0.00	0.06	0.47	0.00	0.08	0.14
Gender					0.56	0.02	0.24	0.05
Education					0.33	0.00	0.08	0.09
Employment					0.70	0.02	0.30	0.05
Population density	–0.14	0.00	0.00	–0.60				
Utility					0.64	0.11	0.40	*
Income (below benchmark)	0.04	0.08	0.02	*	–0.20	0.72	0.56	*
Income (benchmark)	0.07	0.00	0.02	0.10	2.00	0.00	0.56	0.14
Income (1–2× benchmark)	0.08	0.00	0.02	0.13	2.78	0.00	0.55	0.22
Income (2× benchmark)	0.08	0.00	0.03	0.07	4.03	0.00	0.68	0.18
Income (>2× benchmark)	0.13	0.00	0.02	0.15	3.96	0.00	0.60	0.24
Expl. var. (%)	38.6				10.5			

The results for income are similar to age, with every standardized value of the linear variables being comparable to the Top-Down approach. However, in this, the relationship between utility and life satisfaction remains insignificant. Utility and life satisfaction seem to increase with age, and all categories are significant except the below benchmark category.

The estimated β are visualized in Figure 5.4. This Figure shows a linear relationship for the utility score. This is also the case for life satisfaction for the first categories of income. However, after earning 2x the benchmark, no further increase in life satisfaction is found. The explained variance for utility remains the same as with linear variables, since income and utility show a linear relationship. However, life satisfaction is explained with an additional 0.8%.

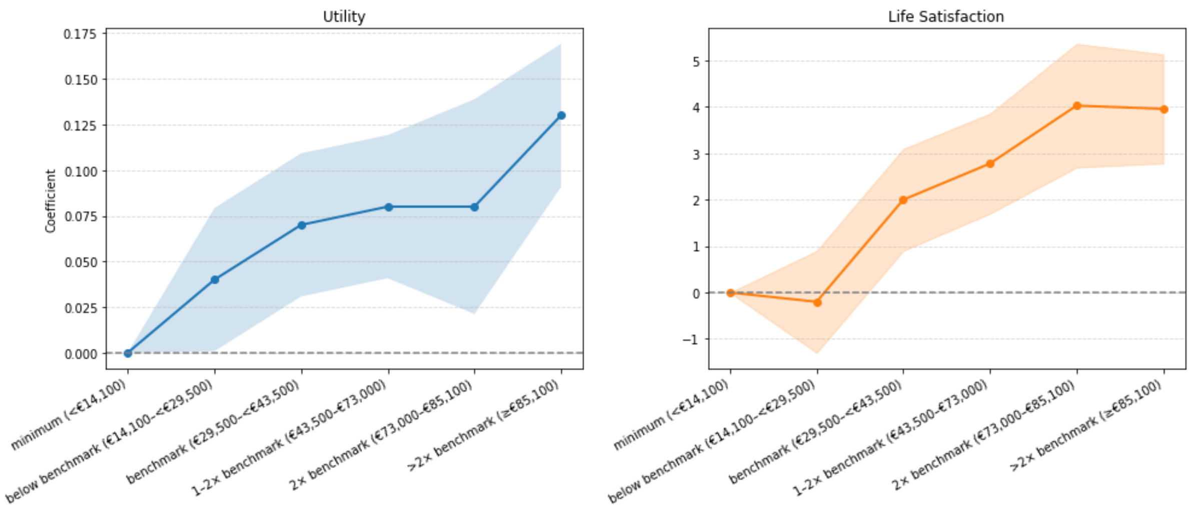


Figure 5.4: Estimated β visualized for non-linear variable Income

The non-linear age model shows a great improvement in model fit as can be seen in Table 5.7, whilst income only shows a small increase in model fit. This Table also shows a combination of both non-linear variables in a model; however, this did not increase the model-fit any further and therefore is not shown. The results for this model can be found in Appendix C.

Table 5.7: Fit indices for models with non-linear variables

	χ^2	df	χ^2/df	RMSEA	Probability level
Age	0.966	4	0.242	0	0.915
Income	2.434	4	0.609	0	0.657
Income & Age	0.996	4	0.249	0	0.910

5.3. Hedonic Well-Being

Similarly to the life satisfaction, the same three approaches are conducted to understand the relationships between each of the variables and hedonic well-being. These approaches are all based on the PC-5 approach, since Section 5.2.1 showed this had more explanatory power.

5.3.1. Top-Down

First, the Top-Down approach is modeled, which almost converged to the same relevant paths as for life satisfaction. The magnitudes and signs of some paths differed, whilst the variable employment showed no significant paths. The results of this analysis are visualized in Figure 5.5 and summarized in Table 5.8. Hedonic well-being is computed as a positive variable, in which higher scores indicate better hedonic well-being.

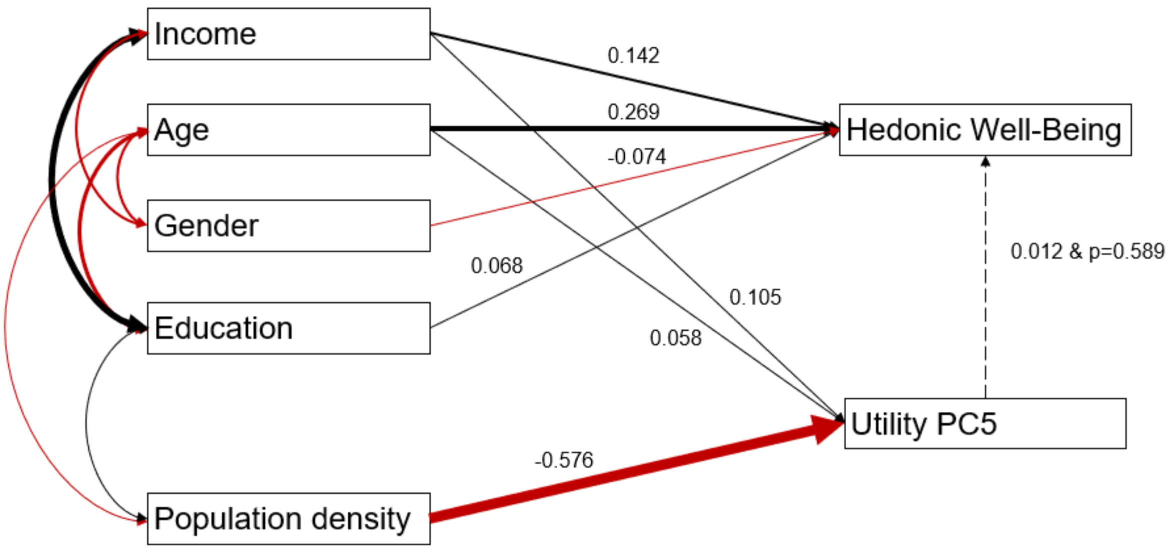


Figure 5.5: Final model of Top-Down approach for Hedonic Well-Being: A visual representation. Line thickness represents the strength of a relation. A straight line with one arrow is a causal path; a curved line with two arrows shows a correlation. A red line represents a negative relation, a black line a positive one, and a dashed line means an insignificant one.

Table 5.8: Standardized effects of variables for PC5

	PC5	
Independent variable	Utility	HWB
Income	0.105	0.142
Age	0.058	0.269
Gender		-0.074
Education		0.068
Population density	-0.576	
Utility		*
Explained variance (%)	35.3	11.3

In contrast to the life satisfaction analysis, the significance of age and income has reversed, with age now playing a more important role in explaining hedonic well-being, whereas income held that position previously. Furthermore, while being a woman had a positive impact on life satisfaction, it now shows a negative correlation with hedonic well-being.

Some correlations do remain the same; the relationship between employment and education to hedonic well-being remains little, and the population density still largely explains the utility scores. Additionally, the link from utility to hedonic well-being continues to be insignificant, this time being much further from significant.

5.3.2. Bottom-Up

Next, the Bottom-Up approach is conducted for the hedonic well-being. The order in which the variables are added has slightly changed. First, the population density is added, subsequently age, income, gender, and finally education. The results can be found in Table 5.9. Again, the results of the addition of the final variable are not accounted for in this Table, since this is the full model and can be found in Table 5.8.

Table 5.9: Loadings of independent variables on dependent factors

	Saturated		Pop. dens.		Age		Income		Gender	
IV	U	HWB	U	HWB	U	HWB	U	HWB	U	HWB
Income							0.105	0.179	0.105	0.166
Age					0.059	0.263	0.058	0.264	0.058	0.249
Gender										-0.074
Education										
Employment										
Pop. density			-0.582		-0.576		-0.576		-0.576	
Utility		0.059		0.059		*		*		*
Expl. var. (%)	0	0.3	33.9	0.3	34.2	7.1	35.3	10.3	35.3	10.8

Table 5.9 further explains the switch in importance of the variables as found in Figure 5.5, since age has more explanatory power over hedonic well-being than income. In contrast to the life satisfaction analysis, the path from utility to hedonic well-being became insignificant after the addition of only the first mediating variable, age.

Population density largely explains the utility variables, while age and income contribute to both utility and hedonic well-being. Similarly, gender and education both contribute little to the explained variance of hedonic well-being, both 0.5%.

5.3.3. Non linearity

The final analysis for hedonic well-being is testing the model for the non-linear variables age and income. First age is tested, of which the results can be found in Table 5.10.

Table 5.10: Non-linear model for age, with 18-24 as reference category

	Utility				Hedonic Well-Being			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Income	0.02	0.00	0.00	0.09	0.53	0.00	0.08	0.17
Gender					-0.58	0.00	0.18	-0.07
Education					0.17	0.01	0.06	0.06
Population Density	-0.13	0.00	0.00	-0.57				
Utility					0.25	0.41	0.31	*
Age (25–29)	0.06	0.14	0.04	*	-1.24	0.05	0.39	-0.07
Age (30–39)	0.09	0.01	0.03	0.12	-0.20	0.71	0.34	*
Age (40–49)	0.09	0.01	0.03	0.11	-0.48	0.30	0.34	*
Age (50–59)	0.11	0.00	0.03	0.15	1.02	0.07	0.34	8
Age (60–69)	0.11	0.00	0.03	0.15	1.60	0.00	0.34	*
Age (70–79)	0.12	0.00	0.03	0.14	2.69	0.00	0.35	0.22
Age (80 +)	0.08	0.05	0.04	*	2.63	0.00	0.42	0.13
Expl. var. (%)	35.6				12.6			

Table 5.10 shows similar results for the linear variables as found in the Top-Down analysis, where all standardized effects show similar magnitudes. The different age categories do not linearly interact with both utility and hedonic well-being, as can be seen in the visualization of Table 5.10 in Figure 5.6.

For utility, the youngest age group scores noticeably lower, followed by a sharp increase in the next age group. After that, scores remain relatively stable until a decline occurs among those aged 80 and above. The effect of age on hedonic well-being mirrors the pattern observed for life satisfaction but is more linear: after a slight dip in the younger age groups, hedonic well-being increases more steadily rather than forming a U-shaped curve.

Non-linearizing age increased the explained variance of utility with an additional 0.3% whilst the hedonic well-being was better explained by 1.3%.

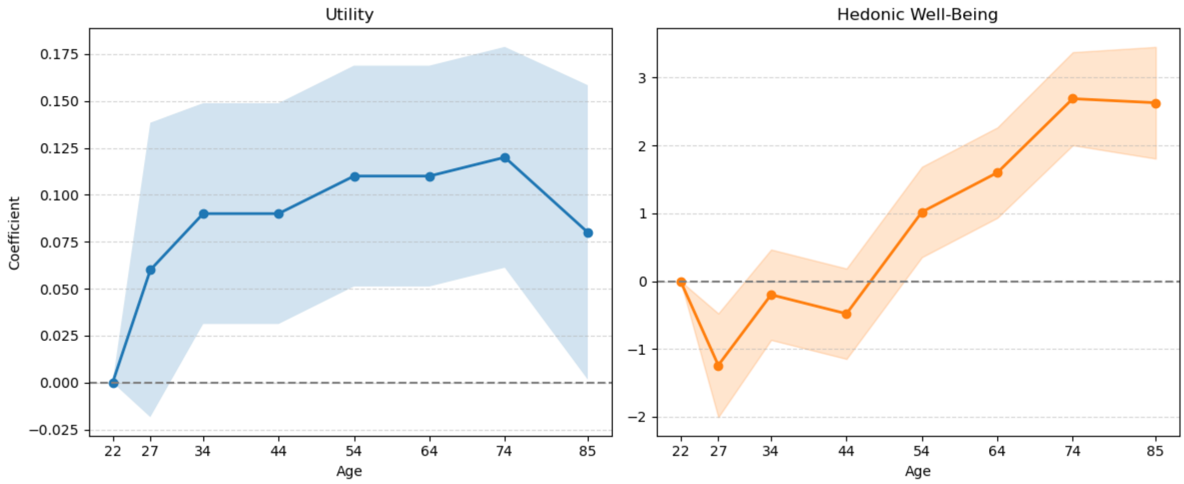


Figure 5.6: Estimated β visualized for non-linear variable Age

Next, income is modeled as non-linear variable. The results of this analysis can be found in Table 5.11.

Table 5.11: Non-linear model for Income, with minimum income as reference category

	Utility				Hedonic Well-Being			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Age	0.01	0.01	0.00	0.05	0.66	0.00	0.06	0.27
Gender					-0.63	0.00	0.18	-0.08
Education					0.18	0.01	0.06	0.07
Population Density	-0.13	0.00	0.00	-0.57				
Utility					0.16	0.60	0.31	*
Income (below benchmark)	0.07	0.01	0.03	0.09	0.43	0.31	0.42	*
Income (benchmark)	0.07	0.01	0.03	0.10	0.68	0.10	0.42	*
Income (1–2× benchmark)	0.10	0.00	0.02	0.14	1.26	0.00	0.41	0.14
Income (2× benchmark)	0.11	0.00	0.03	0.14	2.35	0.00	0.52	0.14
Income (>2× benchmark)	0.14	0.00	0.03	0.15	1.92	0.00	0.46	0.15
Expl. var. (%)	35.4				11.4			

Similar to the previous findings, the linear variables show similar magnitudes as found in the Top-Down analysis. In the visualization of the income estimated β as can be found in Figure 5.7, can be seen that income is linearly dependent on utility, which is also found in life satisfaction. Whereas the hedonic well-being also has a linear increase over income, however, when it reaches >2x benchmark, it reduces again.

Since both utility and hedonic well-being show predominantly linear relationships with income, introducing non-linear income categories results in only a minimal improvement in explained variance, an increase of just 0.1% for both variables.

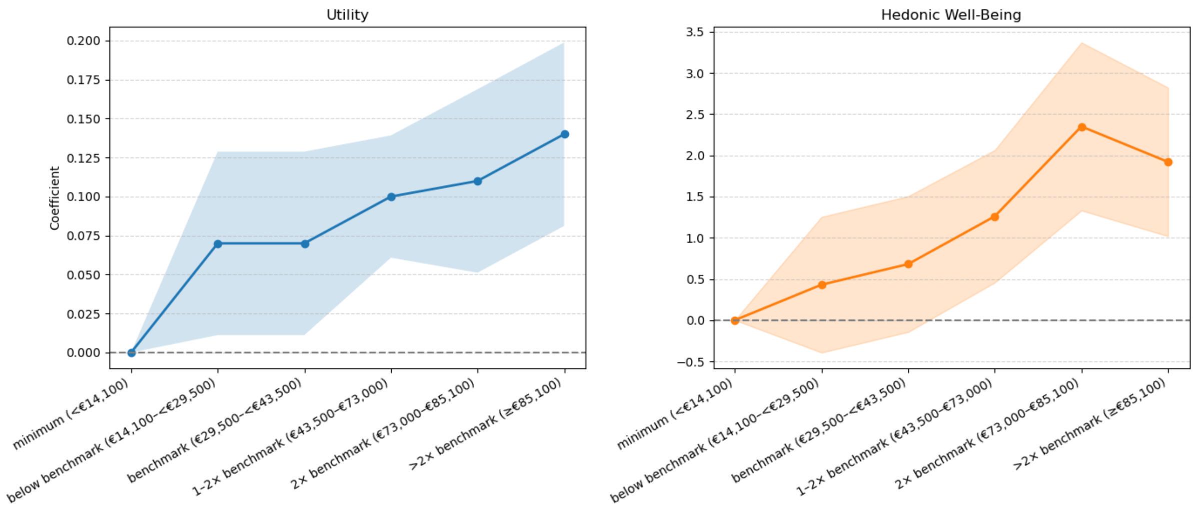


Figure 5.7: Estimated β visualized for non-linear variable Income

6 Discussion

This chapter discusses the findings from the structural equation modeling and relates them to the existing literature. It interprets the limited direct influence of visual utility on subjective well-being, the results of how utility is shaped, the non-linear effects of age and income, the control of the socio-demographic variables, and the difference in explanatory power of PC5 versus PC6 levels.

6.1. Little explanatory power of utility to subjective well-being

The correlation matrix in Table 5.1 shows a small correlation between the utility scores of both PC5 and PC6 with subjective well-being, which is slightly larger for PC6. However, the structural equation method revealed that these utility scores have a limited direct impact on subjective well-being once socio-demographic variables are taken into account. In the bottom-up approach, the models show a positive relation between neighborhood utility scores and both life satisfaction and hedonic well-being, but this effect became insignificant after controlling for the variables, age, and income.

This supports the larger correlation with PC6 as the Top-Down approach showed that income and age have a larger effect on the utility score compared to PC5, which was also found in the correlation matrix shown in Table 5.1. This observed effect suggests that the positive relation between urban aesthetics and SWB is largely explained by who lives in which neighborhoods, rather than the neighborhoods' aesthetics measured through utility scores. Older and wealthier people may both live in more spacious and prettier neighborhoods and report better subjective well-being.

This is supported by the research of (Van Cranenburgh and Garrido-Valenzuela, 2025), which found that older people indeed tend to favor greener and more spacious locations, which corresponds to higher utility scores. Additionally, researches have consistently shown that older people tend to report higher subjective well-being (Wu et al., 2022; Bahr, 2024; Helbich et al., 2019; Nguyen et al., 2021). Besides that, Wu et al. (2022) showed that higher income leads to higher subjective well-being, whereas more spacious and more attractive neighborhoods, which lead to higher utility scores, often cost more.

The structural equation model, therefore, captures a correlation that is driven more by the characteristics of the residents rather than by a direct causal effect of the aesthetics on subjective well-being.

6.2. Age, Income, and Population density shape utility

The results clearly show that utility scores are shaped by age, income and population density, with population density having the largest influence, explaining between $33.9\% - 37.1\%$ of the variance. This aligns with findings from Van Cranenburgh and Garrido-Valenzuela (2025), who found that higher population density correlates with lower utility scores, as also can be seen in Figure 4.7.

Income explains slightly more of the variance than Age when measured linearly ($1.0 - 1.3\%$ vs $0.3\% - 0.5\%$). However, it seems that age does not linearly affect utility. Younger people tend to favor more urbanized environments with lower utility scores, while middle-aged and older individuals prefer more spacious and greener areas, typically associated with higher utility scores. This aligns with research from Dökmeci and Berköz (2000); Andersson et al. (2018), who found that different age groups live in different urban areas, reflecting their distinct needs and preferences.

The non-linearization of age seemed to increase the explained variance of utility by an additional 0.3%. Income, in contrast, did not or only improve the explained variance by 0.1%, indicating a more linear relation.

6.3. Non-linear effect on subjective well-being

Previous research has demonstrated that both age and income have non-linear relationship with subjective well-being (Graham and Ruiz Pozuelo, 2017; Bennedsen, 2024). This research confirms those findings. Age shows a U-shaped relationship with life satisfaction, while for hedonic well-being, it first shows a small dip and then linearly increases. Similar to previous research, income increases subjective well-being linearly, which effect diminishe after a certain income.

This non-linear relationship of age was also relevant in explaining utility scores, as previously mentioned. Younger individuals tend to select lower-utility neighborhoods, while the middle-aged and older individuals showed similar higher-utility neighborhoods, which can be seen in Figures 5.3 & 5.6. Interestingly, accounting for this non-linearity in age improved the explained variance of the utility scores, which lead to the path from utility to life satisfaction becoming statically significant, while being of small magnitude. This supports earlier studies, that found a correlation between neighborhood aesthetics and life satisfaction (Wu et al., 2021, 2022; Bahr, 2024).

However, this path was not significant for hedonic well-being ($p = 0.41$). Reasoning for this could be that life satisfaction is a more constant subjective well-being evaluation method and, therefore, more influenced by stable factors such as the aesthetics of the residential location. This is in line with the research from Fan et al. (2023), as they noted that hedonic well-being is less explainable by image data alone and more by socio-demographic characteristics. This difference is further supported by the comparative analysis of explained variance for both subjective well-being components. Socio-demographic factors accounted for a greater proportion of explained variance in hedonic well-being than in life satisfaction (Table 5.4 vs 5.9).

6.4. Control for socio-demographic variables

Besides the non-linear effects of age and income, other socio-demographic variables also played a role in shaping subjective well-being. In line with findings from Wu et al. (2022), both education and employment were positively associated with well-being. The gender-related paradox identified by Kaiser et al. (2025) was also observed: women reported higher life satisfaction but, conversely, lower hedonic well-being. No strong direct effect of population density on subjective well-being was found; however, a small indirect effect emerged. Higher population density was associated with lower utility, which in turn slightly reduced life satisfaction, though this effect was minimal in magnitude.

6.5. PC5 versus PC6

The analysis demonstrated that the explained variance of the utility scores are better explained at the PC5 level compared to the PC6 level. Reasoning for this is that PC5 averages over multiple PC6 areas, thereby reducing the influence of outlier streets. One very beautiful street can be next to several less appealing ones. PC6 captures only one street, which may not reflect the broader neighborhood experience.

In contrast, PC5 combines multiple PC6 areas, therefore averaging these variations and providing a more representative view of neighborhood aesthetics as experienced by residents. This likely explains why the path from utility to subjective well-being was closer to significance in PC5 models. People experience and evaluate their broader environment, not just a single street, and PC5 better captures this holistic perception.

7 Conclusion

This Chapter summarizes the conclusion of this thesis, starting with the key findings. Subsequently the policy recommendations are given. Following this, the limitations and future research opportunities are mentioned.

7.1. Key Findings

This thesis aimed to research whether the utility scores generated by the computer vision model developed by Van Cranenburgh and Garrido-Valenzuela (2025) could effectively explain subjective well-being, while controlling for socio-demographic and built environment variables. The main question was stated as:

To what extent does the utility derived from computer vision model influences subjective well-being, controlling for socio-demographics characteristics and built environment variables?

To answer this, four sub-questions were addressed.

Sub-question 1 focuses on understanding how utility is visually derived from the residential location, focusing more on the visual aspects. This sub-question stated: *How is utility derived from the built environment of one's residential location?* Chapter 4 demonstrated that the CV-model assigns higher utility scores to areas with spacious layouts, well-maintained green spaces and limited visual clutter. Conversely, little greenery, a dense concentration of parked cars, and a generally cluttered and constrained visual layout led to lower utility scores.

The second sub-question examined the factors that shape the utility scores, phrased as: *How does the built environment and socio-demographics explain the utility derived from the CV-model?* Results showed that the utility scores are mostly shaped by the population density, where higher density means lower utility scores. Income also has a linear effect, with higher income associated with higher utility scores. Age, however, showed a non-linear relationship: younger people tend to prefer lower-utility areas, while middle-aged and older individuals favored similar, higher-utility environments.

Sub-question three explored whether immediate surroundings or broader neighborhood play a different role in shaping subjective well-being. This was phrased as: *To what extent does the relationship between utility and subjective well-being vary between one's immediate environment and the wider neighborhood?* Findings revealed that utility scores measured at PC5 level has greater explanatory power than PC6 level. This is likely because PC5 averages over larger spatial areas, reducing outlier streets and better reflecting how individuals experience their neighborhood as a whole.

The final sub-question investigated how the built environment and socio-demographic characteristics affect the relation between utility and subjective well-being and is phrased as: *How do built environment and socio-demographic variables affect the relationship between utility and subjective well-being?* Results show that there is a correlation between the utility scores and subjective well-being as predicted, but this relationship is mostly explained by income and age. In other words, individuals with higher incomes and older age tend to live in areas that the model sees as more aesthetically pleasing, while these groups also reported higher subjective well-being. As such, no significant direct effect is found between utility scores and subjective well-being once these socio-demographic factors were controlled for. However, when controlling for the non-linear effects of age, a weak but statistically significant path exists between utility and life satisfaction. This suggests that urban aesthetics may have a direct effect on life satisfaction consistent with findings from previous research, though of smaller magnitude. This effect is not found for hedonic well-being, since this component is less explained by stable factors such as the aesthetic quality.

Ultimately this thesis concludes that the trained computer vision model created by Van Cranenburgh and Garrido-Valenzuela (2025) is currently not effective in predicting subjective well-being as it shows much smaller predictive results than previous research has shown. The SEM model showed that subjective well-being appears to be influenced more by the socio-demographic characteristics of residents, than by the visual aesthetics of the built environment generated by the CV-model.

Nevertheless, the findings offer promising results for using perception driven computer vision models in this domain. Despite this computer vision model was not designed to predict subjective well-being, it was capable of measuring a small relation between the derived utility score and life satisfaction. Highlighting that with potentially a improvement of this model or a different training approach, it could be more effective in predicting subjective well-being and ultimately be used as a tool in urban planning.

7.2. Policy recommendations

This research highlights the potential of using perception based computer vision models as tools in urban planning policies. Although the current predictive capability of these models is limited, their demonstrated correlation between visual aesthetics and subjective well-being suggests significant potential for future applications once predictive power increases.

Moreover, the findings indicate that residents perceive their neighborhoods beyond just their immediate streets. Policymakers should therefore adopt a holistic approach to urban improvements, focusing on enhancing overall neighborhoods rather than isolated streets or blocks. This broader neighborhood approach ensures improvements that benefit residents' subjective well-being.

Additionally, recognizing that different socio-demographic groups prefer distinct neighborhood characteristics is essential. Policymakers must tailor neighborhood characteristics to align with the demographic profiles and preferences of residents. For instance, neighborhoods predominantly inhabited by younger people might require different types of aesthetic and functional improvements compared to areas with older residents. By adopting demographic-sensitive urban planning, policymakers can effectively increase residents' subjective well-being through targeted and relevant improvements.

7.3. Limitations and Future Research

While this thesis provides new insights into the relationship between computer vision-derived utility scores and subjective well-being, several limitations must be acknowledged. At the same time, these limitations offer opportunities for future research to strengthen the analysis. This Section will explain the limitations, how these can be overcome, and future research opportunities that can be taken to improve the analysis.

7.3.1. Data collection

The data collection part shows several limitations. First, not all PC6 postal codes had Google Street View images available, approximately 25% of all PC6 units lacked any imagery. This missing data introduces a source of bias, as it may disproportionately affect certain areas and result in their underrepresentation in the SEM model. Among the PC6 areas that did have imagery, the number of available streetscape images varied considerably. In some cases, only a single image was retrieved, while in others, more than five streetscapes were accessible. This thesis attempted to reduce data variance by randomly sampling five streetscapes in locations with more than five images. However, the dataset still suffers from uneven representation, as some postal code areas have limited or no imagery at all. This uneven distribution can skew the SEM analysis, giving more weight to areas with richer visual data.

Furthermore, the use of postal codes as spatial units (PC5 and PC6) introduced additional variance, as these regions differ greatly in size and may not accurately reflect the area that residents perceive as their "neighborhood." For example, the smallest PC5 area measured just $45m^2$, while the largest spanned $117,676,092m^2$. This spatial difference introduces bias since some postal code areas cover large, diverse environments, while others are very small and specific. This makes it more difficult to compare neighborhoods fairly across the dataset.

Finally, there was a temporal mismatch between the image and survey data. The subjective well-being measures were collected between 2020 and 2022, while the available Google Street View images span from 2015 to 2022. This mismatch introduces further bias, as neighborhood conditions, as well as subjective well-being, can evolve over time. World Happiness Report (2025) highlights that subjective well-being fluctuates over time, and likewise, street-level conditions can change due to neighborhood upgrades, construction, or decline. Using outdated imagery to represent current living conditions can therefore increase variance in the data and weaken the explanatory power of the model.

To address these data collection limitations, future research should aim for a standardized data collection approach. Residential images should be collected subsequently with the subjective well-being evaluations. Furthermore, instead of using postal code areas, fixed-radius buffers around each respondent's residential location (e.g., 500 meters or 1 km) should be used to more accurately capture the perceived neighborhood and reduce spatial bias. Finally, efforts should be made to ensure an equal number of images are collected per residential location to increase uniform representation and comparability across spatial units.

7.3.2. Interaction Effects in SEM

The SEM results suggest that the effect of neighborhood aesthetics on subjective well-being is not the same for everyone. Once age and income are included in the model, the previously significant path from utility to subjective well-being becomes insignificant. This suggests that socio-demographic characteristics may influence the effect of neighborhood aesthetics. For instance, older and higher-income individuals are more likely to live in visually appealing areas and report higher well-being, whereas younger or lower-income individuals tend to live in less attractive neighborhoods and report lower well-being. Additionally, age showed a non-linear relationship with utility scores, and accounting for this pattern slightly improved the explanatory power of aesthetics on life satisfaction. These findings indicate potential interaction effects between socio-demographics and neighborhood characteristics that were not captured in the current SEM model. Future research should incorporate such interaction terms to better understand how aesthetic quality affects well-being across different groups.

7.3.3. Computer vision model changes

The computer vision model developed by Van Cranenburgh and Garrido-Valenzuela (2025) was originally trained to predict residential choice based on street-level images, it was not trained for predicting subjective well-being. It could be that residential choice and subjective well-being rely on different visual and contextual features. As a result, a model trained specifically to predict residential choice selection may not capture the visual features that are most relevant to individuals' subjective well-being.

To improve predictive power, future work should consider retraining the model with the goal of predicting subjective well-being. This involves collecting a new dataset that directly links street-level images to subjective well-being scores, while also including socio-demographics as control variables. With such data, the model can be trained to learn the specific visual features that matter for subjective well-being. Instead of giving a utility score, the model would then provide an expected subjective well-being score given an image.

Unlike segmentation-based approaches, which detect and quantify predefined visual elements before putting them into a separate regression model, end-to-end architectures using a feature extractor and classifier, like the model of Van Cranenburgh and Garrido-Valenzuela (2025), learn directly from raw image data. This enables the model to identify more complex or abstract visual patterns, such as cleanliness, maintenance, or aesthetic quality, that are hard to define in advance or capture through segmentation alone. The classifier can then evaluate which features most influence subjective well-being, even when those features are too subtle or complex to be captured by predefined categories. This approach allows the model to learn more complex features than can't be obtained through segmentation-based approaches.

However, the interpretability of this approach remains a challenge, as it is not know which visual elements contribute to better subjective well-being. To address this, future studies should incorporate an additional segmentation method. This approach can help identify which elements of an image contribute most when predicting subjective well-being, for example, the role of greenery, architectural variation, or street cleanliness. Although such tools could theoretically be applied to the existing model, their usefulness is limited due to the current model's small predictive accuracy in estimating subjective well-being. Therefore, these techniques are best introduced once the models outcome achieves better predictive power.

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A

Satisfaction with life scale statements

This Chapter shows the statements asked to measure the satisfaction with life scale. In total five statements are asked, where respondents ranked based on a Likert scale how much they agreed with the statement. The statements are in line with the original scale of Diener et al. (1985), and are phrased as:

1. In most cases my life is almost ideal
2. My living conditions are excellent
3. I am satisfied with life
4. So far I have achieved the most important things in my life
5. If I could start my life all over again, I wouldn't change almost anything

Respondents could choose out of these seven scale points:

1. Strongly disagree
2. Disagree
3. Slightly disagree
4. Neither disagree or agree
5. Slightly agree
6. Agree
7. Strongly agree

B

Mental health statements

This Chapter shows the MHI-5 statements respondents ranked their mental health. These statements are in line with the research of Berwick et al. (1991) and answered on a 6-point Likert scale. The statements are phrased as:

1. The last couple of months I was very nervous
2. The last couple of months I was depressed and nothing could cheer me up
3. The last couple of months I felt calm and relaxed
4. The last couple of months I felt down and sad
5. The last couple of months I felt happy

And respondents answered by a 6-point Likert scale phrased as:

1. Never
2. Rarely
3. Sometimes
4. Often
5. Mostly
6. Always

C

Full non-linear model

Table C.1: Non-linear Model: Age and Income

	Utility				**Life satisfaction**			
Variable	est	p-val	s.e.	std	est	p-val	s.e.	std
Gender					0.64	0.01	0.24	0.06
Education					0.28	0.00	0.08	0.08
Employment					1.29	0.00	0.31	0.10
Population Density	-0.14	0.00	0.00	-0.60				
Utility					0.87	0.03	0.40	0.04
Age (25–29)	0.01	0.77	0.04	*	-0.73	0.41	0.89	*
Age (30–39)	0.09	0.01	0.03	0.11	-1.74	0.03	0.80	-0.12
Age (40–49)	0.08	0.02	0.03	0.10	-2.35	0.00	0.80	-0.16
Age (50–59)	0.10	0.00	0.03	0.14	-2.08	0.01	0.80	-0.14
Age (60–69)	0.10	0.01	0.03	0.12	-0.40	0.62	0.81	*
Age (70–79)	0.11	0.00	0.03	0.13	1.45	0.10	0.83	*
Age (80+)	0.09	0.03	0.04	0.06	1.31	0.17	0.94	*
Income (below benchmark)	0.03	0.23	0.02	*	0.38	0.50	0.57	*
Income (benchmark)	0.05	0.03	0.02	0.08	2.61	0.00	0.57	0.19
Income (1–2× benchmark)	0.07	0.01	0.02	0.10	3.75	0.00	0.57	0.30
Income (2× benchmark)	0.06	0.03	0.03	0.05	4.96	0.00	0.69	0.22
Income (>2× benchmark)	0.11	0.00	0.03	0.13	5.14	0.00	0.62	0.31
Variance (% explained)	38.9				13.3			

Predicting subjective well-being based on the physical appeal of residential locations using a computer vision model

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Abstract. Over recent years, subjective well-being (SWB) has become a primary goal in urban planning, with research showing that the built environment can significantly influence residents' well-being. This study focuses on the role of the subjective nature of aesthetic quality, which traditional segmentation-based computer vision approaches often fail to capture. To address this, we evaluate the Computer Vision-enriched Discrete Choice Model (CV-DCM) developed by Van Cranenburgh and Garrido-Valenzuela (2025), which uses a vision transformer and classifier to extract holistic visual features from Google Street View images and estimate continuous utility scores that reflect perceived visual quality, trained on stated trade-offs that people make between visual environments. We link these scores to life satisfaction and hedonic well-being measures from the Netherlands Mobility Panel (SWLS, 2020–2022; MHI-5, 2020) and analyze their relationships using Structural Equation Modeling (SEM), controlling for socio-demographic and built environment variables. Results show that PC5-level utility aligns more closely with life satisfaction than PC6, indicating that broader neighborhood context matters more than immediate street conditions. When non-linear age effects are modeled, a small but significant direct path from utility to life satisfaction emerges, whereas no significant association is found for hedonic well-being. Overall, the current explanatory power for SWB is modest and appears mainly driven by who lives where. Nevertheless, a perception-based computer vision model provides a scalable way that can quantify subjective visual quality, which could gain relevance when improved model fit is achieved by reducing variance in data collection or retraining the model on SWB-specific objectives.

Keywords: Subjective well-being, Computer vision, Structural equation modeling, Residential aesthetics.

1 Introduction

In recent years, subjective well-being (SWB) has more often become the central goal of urban planning, rather than a secondary objective. SWB is measured in three key components: hedonic well-being, which refers to emotional states such as happiness and distress; eudaimonic well-being, which involves having a sense of purpose and meaning in life; and life satisfaction, a cognitive evaluation of one's overall quality of life (OECD, 2013).

Increasingly, urban planners acknowledge that enhancing SWB is fundamental to creating thriving cities. Rather than solely emphasizing economic growth or infrastructural development, the success of urban planning is now often measured by how well it improves the well-being of residents (Nicolás-Martínez et al., 2024; WHO, 2025). Within this perspective, the built environment influences SWB through multiple pathways, including travel, leisure, social relationships, and emotional response (Mouratidis, 2021). This paper is interested in the emotional response pathway, explaining how elements such as the aesthetic quality and design of streets and buildings influence SWB.

A growing body of literature links visual characteristics of urban environments, green and blue spaces' presence and quality, architectural form, and cleanliness, to higher life satisfaction and lower distress, while poor cleanliness, noise, and monotonous architecture reduce satisfaction

(Bertram and Rehdanz, 2015; Mouratidis, 2020; Wu et al., 2024; Zhang et al., 2017). Yet systematically capturing the full range of such visual features remains challenging: traditional studies rely on subjective assessments and struggle to objectively capture multiple urban factors within one framework.

Recent advances in computer vision (CV) provide scalable, more objective measures by extracting features from street-level imagery using segmentation, enabling the capture of features such as greenness, visual complexity, and walkability to be quantified and linked to SWB, typically via survey data (Fan et al., 2023; Helbich et al., 2019; Nguyen et al., 2021; Wu et al., 2022). Although segmentation CV offers an objective and scalable way to quantify the urban environment, it still falls short in capturing how residents perceive feature quality and make trade-offs among them, which traditional studies have shown to matter as well (Zhang et al., 2017)

Research by Van Cranenburgh and Garrido-Valenzuela (2025) offers a promising solution in addressing these shortcomings. Van Cranenburgh and Garrido-Valenzuela (2025) developed a computer vision-based discrete choice model (CV-DCM) to estimate a perception-based utility score of the urban environments. By combining visual features extracted from images using a vision transformer and contextual factors, such as housing cost and commute time, the model captures real trade-offs people make when choosing residential environments. Through a stated choice experiment, participants selected preferred residential options based on images and numerical data, enabling the model to learn how various visual characteristics influence individual residential preferences. This research resulted in a trained model that generates a continuous utility score from image data, reflecting perceived visual quality in an objective and scalable way. Nevertheless, the CV-DCM's image-based utility scores must be validated to ensure they reflect residents' SWB and not other urban factors before they can be used as an urban policy tool.

To accurately assess the relationship between visual utility scores and SWB, it is necessary to control for socio-demographic factors. Without this, it remains challenging to determine whether associations with SWB are driven by visual aesthetics alone or by the characteristics of the people who live in those areas. Variables such as age, income, education, and population density are known to influence both residential location and subjective well-being (Ma et al., 2024; Nguyen et al., 2021; Wu et al., 2022).

This paper, therefore, evaluates whether this perception-based visual utility score can effectively predict subjective well-being, even when controlling for socio-demographic characteristics. The main research question is phrased as:

To what extent does the utility derived from a computer vision model influence subjective well-being, controlling for socio-demographic characteristics and built environment variables?

The structure is as follows: Section 2 outlines the conceptual model and methodology, including the CV-DCM and the structural equation modelling approach. Section 3 presents the results. Section 4 discusses these results. Section 5 concludes the main findings and states the future research opportunities.

2 Methodology

This Section first introduces the conceptual model that links the visual aesthetics of the residential location (measured as a utility score) to subjective well-being (SWB), while controlling for socio-demographics. Next, it details the data from the Netherlands Mobility Panel (MPN), followed by the approach to obtain street-level images and analyse these using the CV-DCM. Finally, it outlines the Structural Equation Method (SEM) used to estimate the relationships between variables as described by the conceptual model.

2.1 Conceptual model

The conceptual model, as shown in Figure 1, links the visual aesthetics of the residential environment, captured by a perception-based utility score, to subjective well-being (SWB). SWB is operationalized in two components available in the data: life satisfaction and hedonic well-being. The utility score is derived from a computer-vision-based discrete choice model (CV-DCM) that combines visual features from street-level images with contextual attributes (Van Cranenburgh and Garrido-Valenzuela, 2025).

To better explain this relation, six covariates are included as controls as derived from the literature (Ma et al., 2024; Nguyen et al., 2021; Wu et al., 2022): age, household income, gender, education, employment status, and population density. These variables are specified with direct effects on both SWB and the utility score to account for residential self-selection; for example, older or higher-income residents may live in visually more appealing neighbourhoods and also report higher SWB due to that. Modelling these paths separates the contribution of visual aesthetics from who lives where.

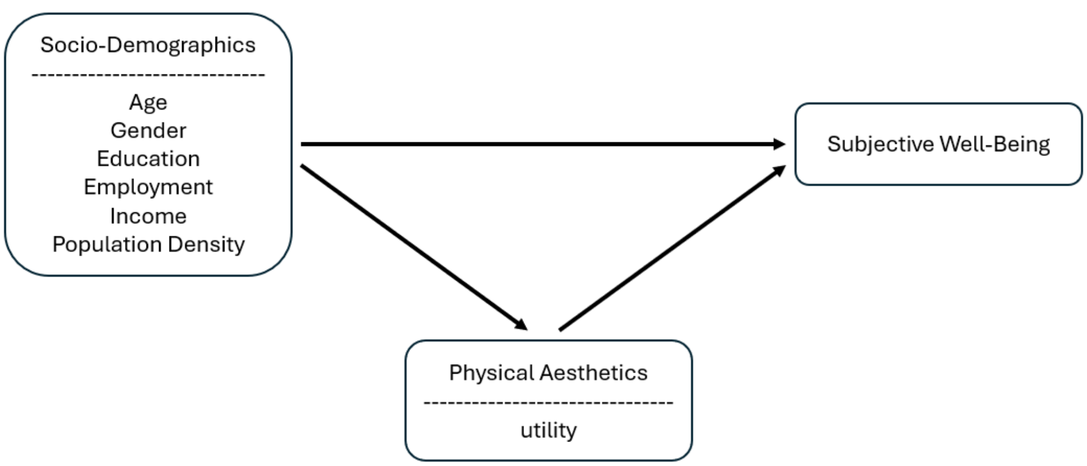

Fig 1 Conceptual model as derived from the literature

2.2 Data collection

2.2.1 MPN

Data is obtained from the Netherlands Mobility Panel (MPN), a longitudinal household survey that collects detailed information on travel behaviour, socio-demographics, and subjective well-being across the Netherlands (Hoogendoorn-Lanser et al., 2015). In the MPN, life satisfaction is measured using the Satisfaction With Life Scale (SWLS), while hedonic well-being is measured using the Mental Health Index-5 (MHI-5) (Berwick et al., 1991; Diener et al., 1985). This study uses three MPN waves (2020–2022) for life satisfaction and only the 2020 wave for hedonic well-being, as these are the only years in which these variables are available. Both subjective well-being components are measured through five statements and are aggregated to one score, where a higher score indicates a better subjective well-being. Factor analyses confirmed the validity of these aggregations, with all item correlations above 0.3, KMO values exceeding 0.8, and Bartlett's tests significant at $p < 0.001$. In addition to subjective well-being indicators, the MPN contains socio-demographic variables, where this study is interested in the age, household income, gender, population density, employment status, and education level.

2.2.2 Images of residential location

Since the MPN is an anonymous survey, the research team may not know the residential location of respondents. Therefore, a postal code approach is chosen, where the entire Netherlands is analyzed based on postal codes. These PC-level utility scores were sent directly to KiM, the MPN administrator, who is aware of the respondents' residential location. They linked the utility scores generated by the CV model with the unique ID of each respondent. This approach allows the research team to assess the generated utility scores with subjective well-being variables without knowing the residential location of the respondents of the MPN.

Street-level images were provided by Garrido-Valenzuela et al. (2023) and covered approximately 344.000 of the 460.000 six-digit postal codes (PC6) of The Netherlands, amounting to around 2.7 million images. For each PC6, up to five panoramic streetscapes were retrieved, split into left- and right-facing perspectives, cropped, and resized to 224 × 224 pixels to match the CV-DCM input format.

2.3 CV-model

The CV-DCM, developed by Van Cranenburgh and Garrido-Valenzuela (2025), integrates computer vision with discrete choice modelling to estimate a perception-based utility score for residential environments. A vision transformer is used as a feature extractor to capture holistic visual characteristics from street-level images, which are then combined with contextual variables such as housing cost and commute time in a classifier. The model was trained on a stated choice experiment in which respondents selected preferred residential alternatives based on combinations of images and numerical attributes. This design allowed the model to learn which visual characteristics contribute positively or negatively to residential preferences without relying on predefined segmentation categories, leading to a fully trained feature extractor and classifier. Figure 2 shows the model, where as input an image is given, which is then transformed using the feature extractor and classifier to a utility score.

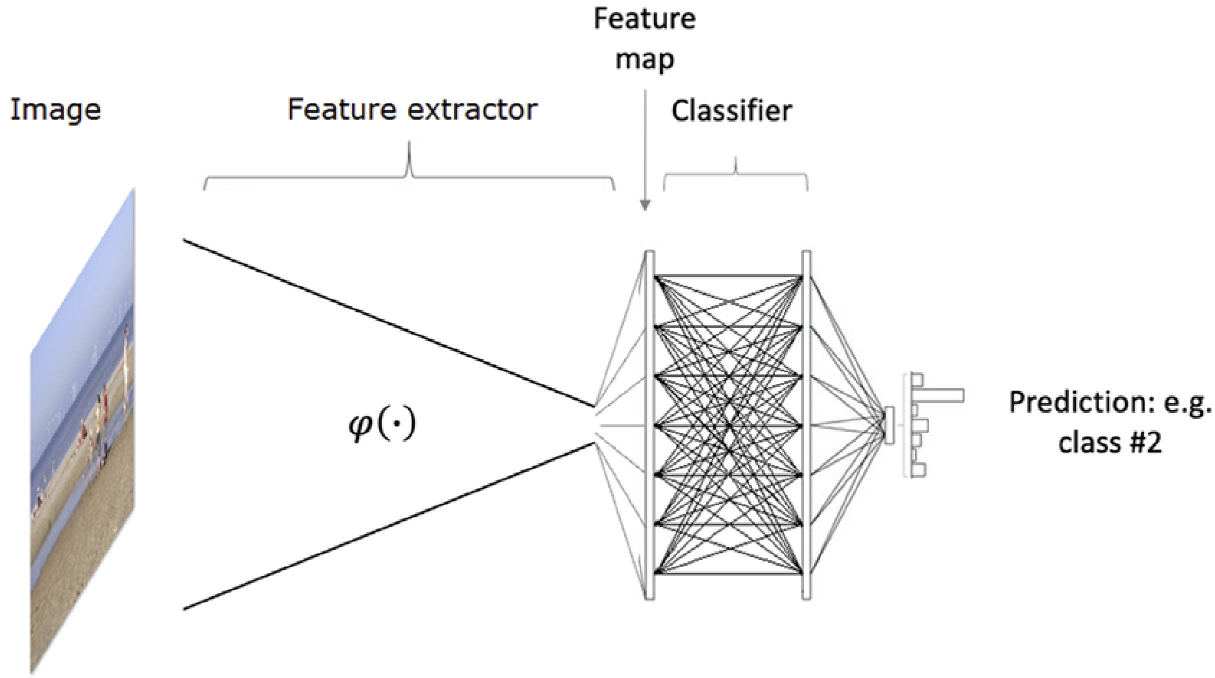

Fig 2 Feature extraction and classifier as developed by Van Cranenburgh and Garrido-Valenzuela (2025)

The mathematical representation of the model is given as:

$$U_i = \sum_{\text{age}} \sum_{k} \beta_k^{\text{age}} \times age \times z_{ik} + \varepsilon_i \tag{1}$$

Where:

- Z_{ik} are elements from the image's feature map for alternative i and feature map element k,
- β_k^{age} are coefficients indicating the influence strength of each visual feature k for age group age,
- ϵ_i is an error term representing unknown or unmeasured factors.

For this study, the trained CV-DCM, including feature extractor and classifier, was applied to all residential images collected in the research of Garrido-Valenzuela et al. (2023), to generate a continuous utility score for each residential location. Since the model is age dependent and one utility score is assessed per residential location, utility scores were generated for each image separately for each age category and then using the national population distributions from the CBS (2025), weighted averaged to one score per image.

These scores were then transformed in two ways to represent a residential location score. At the PC6 level, the utility was averaged across all available images for that postal code. At the PC5 level, the utility was averaged across all PC6s within the same PC5, weighted by the images available of each PC6. This dual aggregation allows a comparison between street-level and neighbourhood-level visual quality.

2.4 *Structural Equation Modeling (SEM)*

To analyse the relationships as described in the conceptual model (Figure 1), Structural Equation Modeling (SEM) is applied. This method allows for the simultaneous estimation of direct and indirect paths. This is modeled through two approaches: in the top-down approach, the full hypothesised model is estimated first and then simplified by removing non-significant paths, while in the bottom-up approach, the model is built step by step, starting with the path between utility and SWB and adding variables based on the importance derived in the top-down approach. Finally, age and income are modelled non-linearly, as research has shown these do not interact linearly. Age has shown to have a U-shaped pattern on life satisfaction (Graham and Ruiz Pozuelo, 2017), and income has diminishing returns after a certain level on subjective well-being (Bennedsen, 2024).

3 Results

This Section starts with the CV-DCM output: examples of high and low utility and a map of utility across the Netherlands. The SEM analysis then follows. Life satisfaction is presented first, comparing PC6 and PC5 and reporting both the Top-Down and Bottom-Up strategies, after which age and income are tested for non-linearity. Hedonic well-being is analysed with the same approach; since the extra checks do not affect the outcome, only the Top-Down model is shown.

3.1 *CV-visualization*

The CV-DCM produces a continuous perception-based utility score for each residential location, reflecting its visual quality. Figure 3 - 4 illustrates the postal codes with the highest and lowest utility scores in the dataset. The highest-scoring location (PC6: 7875BP) features a spacious street layout, well-maintained greenery, and clean façades. The lowest-scoring location (PC6: 6822BK) contains little greenery, a dense concentration of parked cars, and a visually constrained street profile. This is in line with the research of Van Cranenburgh and Garrido-Valenzuela (2025)

Fig 3 Highest utility. 7875BP

Fig 4 Lowest utility, 6822BK

When aggregated to the PC5 level, a clear spatial pattern emerges (Figure 5). Higher utility scores are concentrated in suburban and rural areas, while lower scores are generally found in dense urban neighbourhoods. These differences align with visible contrasts in greenery, openness, and architectural orderliness.

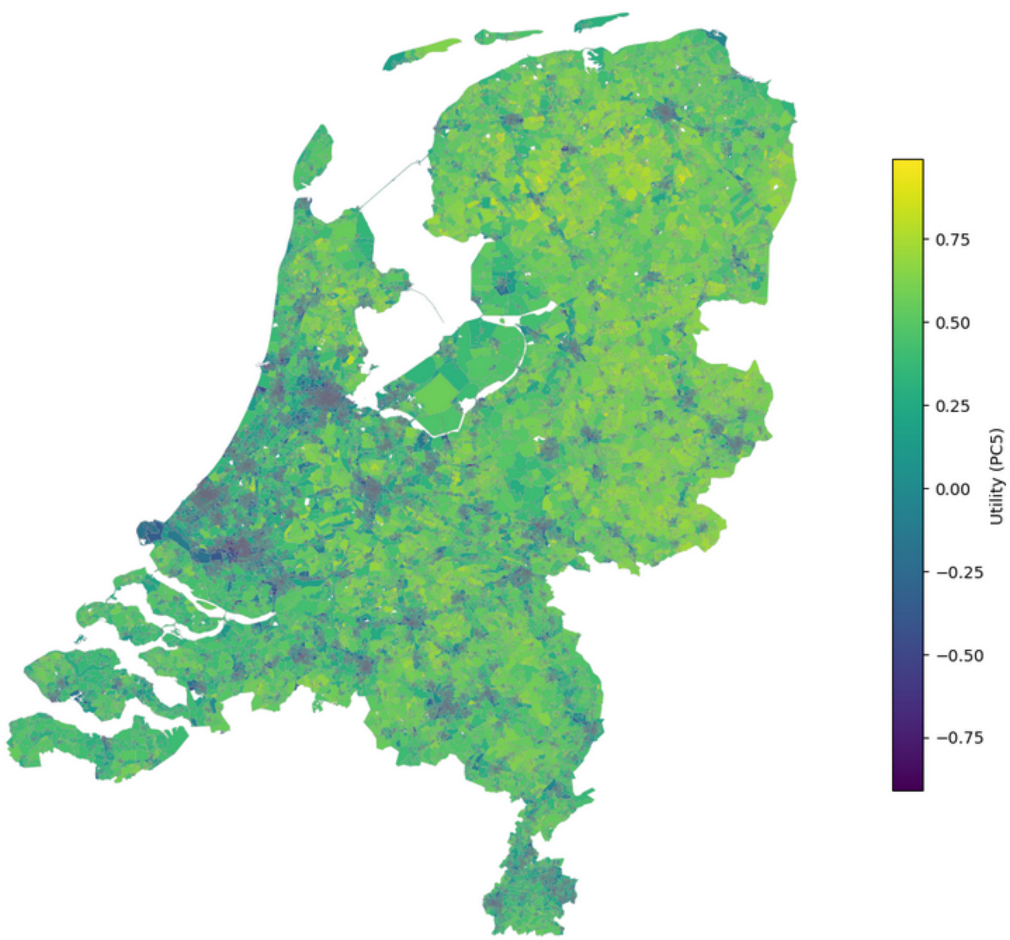

Fig 5 Utility of the Netherlands per PC5

3.2 *Results SEM*

3.2.1 *Life Satisfaction*

In the top-down model, shown in Figure 6, income, age, and population density show significant paths to utility, with population density being the strongest negative predictor ($\beta = -0.60$). Income and age both have positive paths to utility. The direct path from utility to life satisfaction is not significant. All control variables show a significant effect on life satisfaction, excluding population density.

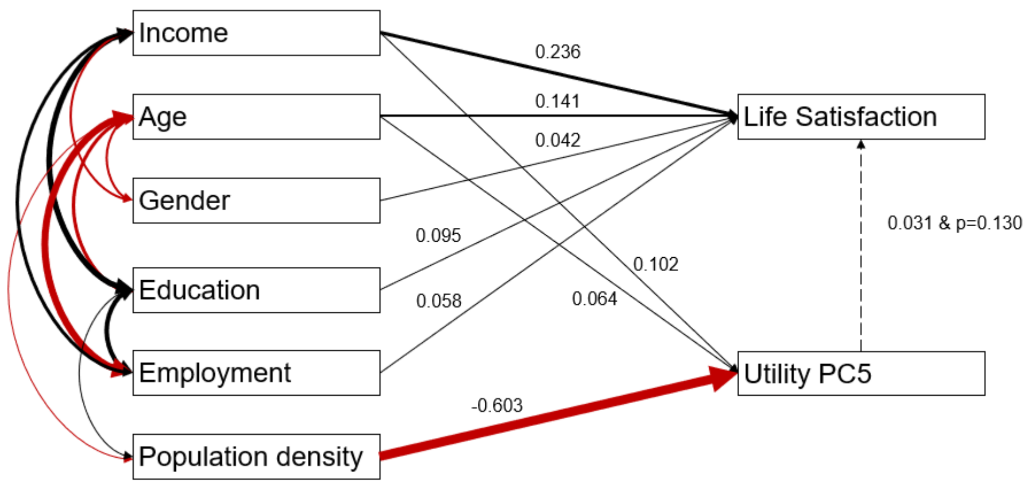

Fig 6 Final model of Top-Down approach: A visual representation. Line thickness represents the strength of a relation. A straight line with one arrow is a causal path; a curved line with two arrows shows a correlation. A red line represents a negative relation, a black line a positive one, and a dashed line means an insignificant one.

The same analysis was conducted for PC6 and showed similar results; however, model fit comparisons between PC5- and PC6-level utility indicate that the PC5 score provides a better overall fit to the data (Table 1). This suggests that neighbourhood-scale visual quality (PC5) is more closely aligned with life satisfaction than street-level measures (PC6). Consequently, subsequent analyses focus exclusively on the PC5-level utility.

Table 1 Fit indices for PC6 and PC5

	χ^2	*df*	χ^2/df	RMSEA	Probability level
PC6	6.580	4	1.645	0	0.160
PC5	2.547	4	0.637	0	0.636

The bottom-up approach starts with utility as the only predictor of life satisfaction and is shown in Table 2. In this first step, the path from utility to life satisfaction is significant. Adding population density in the next step significantly explains the utility scores, approximately 37%. When income is added, the explained variance in life satisfaction increases considerably, while the effect of utility becomes smaller. Adding age alongside income results in the path from utility to life satisfaction becoming insignificant, indicating that much of the relationship is explained by socio-demographic differences in residential location. Throughout all steps, population density remains the main explanatory variable for utility, and income explains the largest share of variance in life satisfaction. Adding the remaining variables, education, employment, and gender, only slightly increases the explained variance of life satisfaction.

Table 2 Loadings of independent variables on dependent factors

	Saturated		**Pop. dens.**		**Income**		**Age**		**Education**		**Employment**	
IV	U	LS	U	LS	U	LS	U	LS	U	LS	U	LS
Income					0.101	0.272	0.102	0.276	0.102	0.238	0.102	0.228
Age							0.064	0.084	0.064	0.110	0.064	0.133
Gender												
Education										0.102		0.096
Employment												0.057
Pop. density			-0.609		-0.609		-0.603		-0.603		-0.603	
Life Satisfaction		0.068		0.068		0.041		*		*		*
Expl. var. (%)	0	0.5	37.1	0.5	38.1	7.8	38.6	8.5	38.6	9.3	38.6	9.6

Research has indicated that age does not linearly shape life satisfaction, but more in a U-shaped way (Graham and Ruiz Pozuelo, 2017). This non-linearity is modelled and shown in Table 3 and Figure 7. Similar to previous research, a similar U-shaped relation was found. But more importantly, a non-linear relation between age and utility became evident. Middle-aged and older people have higher utility scores compared to the younger 18–24 reference group. This non-linearity leads to the path from utility to life satisfaction becoming small but significant ($\beta = 0.04$, $p = 0.03$), indicating that the visual aesthetics do have a small but significant path to life satisfaction.

Table 3 Non-linear model for age, with age group 18-24 as reference category

	Utility				**Life satisfaction**			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Income	0.02	0.00	0.00	0.09	1.19	0.00	0.09	0.29
Gender					0.58	0.02	0.24	0.05
Education					0.26	0.00	0.08	0.07
Employment					1.37	0.00	0.31	0.11
Population density	–0.14	0.00	0.00	–0.60				
Utility					0.85	0.03	0.40	0.04
Age (25–29)	0.02	0.67	0.04	*	–0.56	0.52	0.88	*
Age (30–39)	0.09	0.01	0.03	0.12	–1.62	0.04	0.77	–0.11
Age (40–49)	0.08	0.01	0.03	0.11	–2.20	0.01	0.77	–0.15
Age (50–59)	0.11	0.00	0.03	0.14	–1.97	0.01	0.78	–0.14
Age (60–69)	0.10	0.00	0.03	0.13	–0.28	0.72	0.78	*
Age (70–79)	0.12	0.00	0.03	0.14	1.65	0.04	0.79	0.06
Age (80 +)	0.10	0.01	0.04	0.07	1.52	0.09	0.91	*
Expl. var. (%)	38.9				12.6			

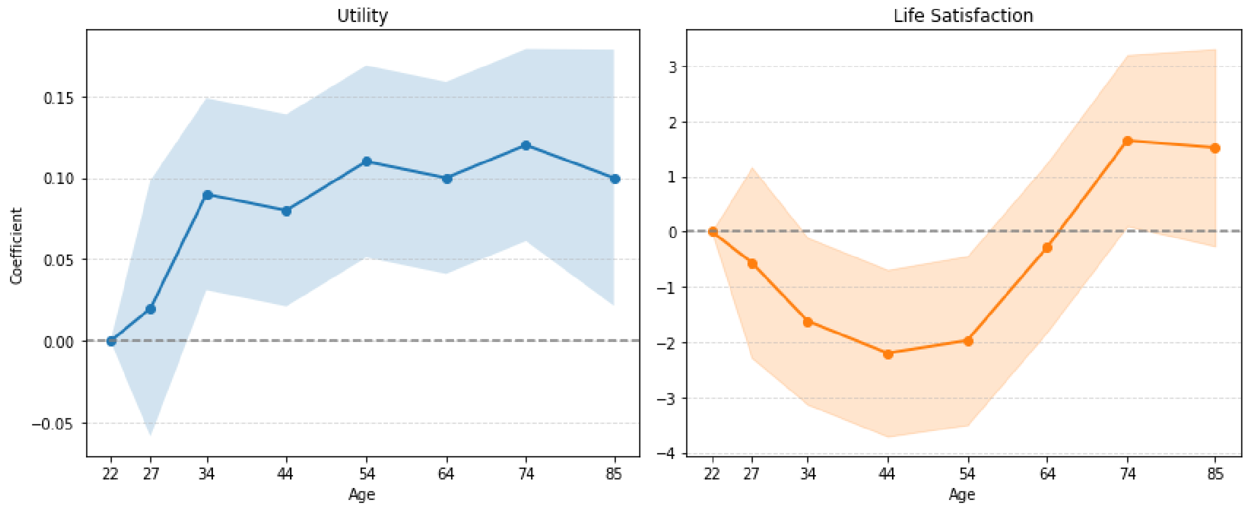

Fig 7 Estimated β visualized for non-linear variable Age

Besides a non-linear age variable, previous research has also shown that income shows a non-linear effect on life satisfaction (Bennedsen, 2024). This non-linear effect is modelled and shown in Table 4 and Figure 8. The results show a more linear relation with utility, but the increases in life satisfaction show diminishing returns at the top income levels, similar to what research has shown (Bennedsen, 2024). With this non-linearization, the path between utility and life satisfaction remains insignificant.

Table 4 Non-linear model for Income, with minimum income as reference category

	Utility				**Life satisfaction**			
Variable	Est.	p-val	s.e.	Std.	Est.	p-val	s.e.	Std.
Age	0.01	0.00	0.00	0.06	0.47	0.00	0.08	0.14
Gender					0.56	0.02	0.24	0.05
Education					0.33	0.00	0.08	0.09
Employment					0.70	0.02	0.30	0.05
Population density	–0.14	0.00	0.00	–0.60				
Utility					0.64	0.11	0.40	*
Income (below benchmark)	0.04	0.08	0.02	*	–0.20	0.72	0.56	*
Income (benchmark)	0.07	0.00	0.02	0.10	2.00	0.00	0.56	0.14
Income (1–2× benchmark)	0.08	0.00	0.02	0.13	2.78	0.00	0.55	0.22
Income (2× benchmark)	0.08	0.00	0.03	0.07	4.03	0.00	0.68	0.18
Income (¿2× benchmark)	0.13	0.00	0.02	0.15	3.96	0.00	0.60	0.24
Expl. var. (%)		38.6				10.5		

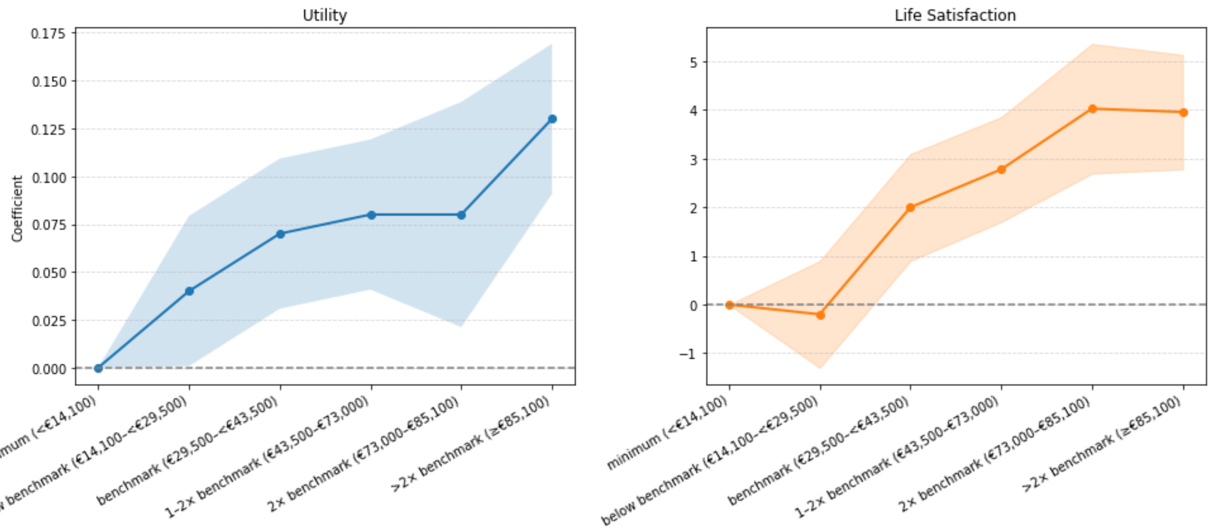

Fig 8 Estimated β visualized for non-linear variable Income

Finally, both variables are modelled together; however, this did not show to improve the model fit compared to age being solely modelled as non-linear (Table 5).

Table 5 Fit indices for models with non-linear variables

	χ^2	df	χ^2/df	RMSEA	Probability level
Age	0.966	4	0.242	0	0.915
Income	2.434	4	0.609	0	0.657
Income & Age	0.996	4	0.249	0	0.910

3.2.2 Hedonic well-being

Hedonic well-being is analysed in a similar way to life satisfaction. The Top-Down model converges to a structure comparable to the life-satisfaction model, with differences in magnitudes and signs for several control paths: gender becomes negative, and the relative magnitudes of income and age are reversed. Employment shows no significant association with hedonic well-being. Crucially, the direct path from residential visual aesthetics (utility) to hedonic well-being is far from significant.

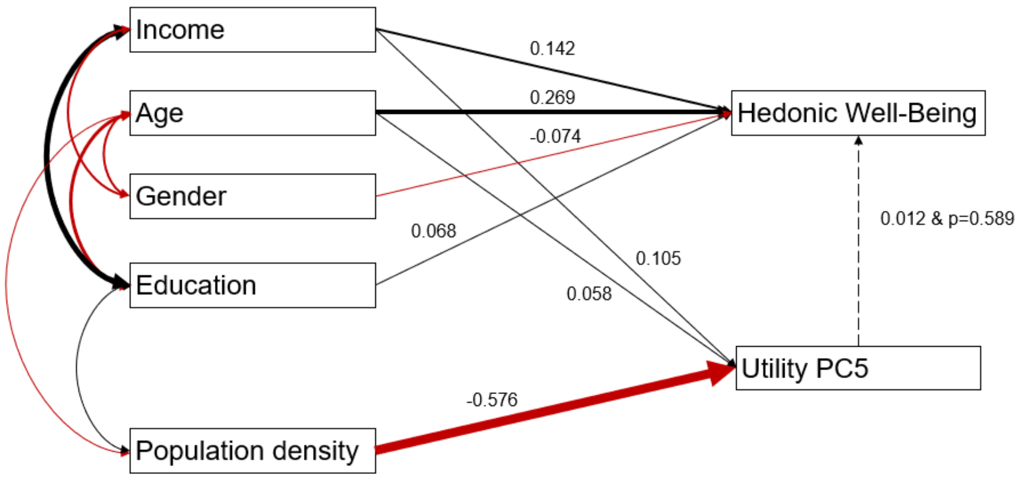

Fig 9 Final model of Top-Down approach for Hedonic Well-Being: A visual representation. Line thickness represents the strength of a relation. A straight line with one arrow is a causal path; a curved line with two arrows shows a correlation. A red line represents a negative relation, a black line a positive one, and a dashed line means an insignificant one.

Finally, bottom-up and non-linear analyses were conducted for the hedonic well-being as well. However, these did not yield any significant changes nor meaningfully improved model fit; therefore, these are not shown in this paper.

4 Discussion

The most important result of this research is that the explanatory power of the utility score for subjective well-being is limited. For life satisfaction, the results suggest that this relationship is more strongly explained by who lives in a certain location than by the visual utility of that location itself. People with higher incomes and older age are more likely to live in neighbourhoods which the model sees as having higher utility scores, and also tend to report higher life satisfaction, independent of each other. However, when controlling for the non-linear effect of age, a small but significant direct effect between utility and life satisfaction is found, which is smaller than previous research has found. For hedonic well-being, no significant relationship is found, which is consistent with the view that it is a short-term evaluation that is less influenced by stable factors such as neighbourhood characteristics.

Utility is strongly shaped by socio-demographic characteristics, in particular income, age, and population density. Income and age have a positive relationship with utility, while population density has a strong negative association. The positive relationship between income and utility is consistent with the expectation that higher-income households can afford more visually appealing environments. Age shows a non-linear effect: younger residents more often live in visually less appealing neighbourhoods, whereas middle-aged and older residents live in areas with higher utility scores. This non-linear relationship has an important influence on the link between utility and life satisfaction. Without controlling for it, the relationship is not significant; when it is taken into account, a small positive effect emerges.

A comparison between the two aggregation levels shows that PC5-level utility scores better explain subjective well-being than PC6-level scores. This suggests that people's life evaluations are shaped more by the broader characteristics of their neighbourhood than by the immediate surroundings of their street. The spatial scale at which visual quality is measured, therefore, plays an important role in understanding its relationship with well-being.

5 Conclusion

This study assessed whether a perception-based utility score, derived from a computer vision–enriched discrete choice model, can explain life satisfaction and hedonic well-being in the Netherlands while controlling for socio-demographic and built environment characteristics. The results indicate that the explanatory power of the utility score is limited. For life satisfaction, the observed association is largely explained by who lives where rather than by the visual utility of the location itself, as older and higher-income residents both tend to live in neighbourhoods with higher utility scores and report higher life satisfaction. Nevertheless, when the non-linear pattern of age is taken into account, a small but statistically significant direct path from utility to life satisfaction becomes visible, whereas no such effect is found for hedonic well-being. Neighbourhood-level (PC5) utility performs better than street-level (PC6), suggesting that broader spatial context is more relevant for subjective well-being than immediate street conditions.

Taken together, the trained model is, in its current form, not effective for predicting subjective well-being, as the predictive power is smaller than earlier work suggests; subjective well-being appears to be influenced more by socio-demographic characteristics than by the visual aesthetics captured by the model. Even so, the findings are promising for perception-driven computer vision in this domain: despite not being designed for predicting subjective well-being, the model still captures a small relationship with life satisfaction when age non-linearity is controlled.

To strengthen this result, data collection should be standardised so that visual inputs better match the outcomes they are intended to explain. In practical terms, images should be collected in the same time window as the surveys; residential context should be defined using fixed-radius buffers around home locations rather than postal codes to reduce spatial bias; and the number of images per residential area should be balanced to address incomplete PC6 coverage and heterogeneous unit sizes. These steps directly target the variance introduced by missing or uneven images and temporal mismatch.

In parallel, the model should be retrained with the explicit objective of predicting subjective well-being rather than residential choice, using a dataset that links street-level images to well-being scores while controlling for socio-demographics. Such training allows the network to learn visual patterns that are predictive of well-being and, once predictive power improves, can be complemented with an interpretable component, such as segmentation, to clarify which features drive the predictions. By combining neighbourhood-scale measurement, standardised data collection, and specific subjective well-being retraining, perception-based utility can move from a weak predictive power to a practically useful tool that supports targeted, neighbourhood-level policies aimed at improving residents' subjective well-being.

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