Navigating the Trade-off Between Green Spaces and Convenient Parking through Computer Vision-Enriched Discrete Choice Model

Insights from the Residential Areas in the Netherlands

Thesis

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Navigating the Trade-off Between Green Spaces and Convenient Parking through Computer Vision-Enriched Discrete Choice Model

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by

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Preface

Almost two years ago, I started my journey as master's student transitioning from urban planning to core transportation sciences. The courses imparted in the first year, particularly Transport Modelling and Quantitative Methods for Logistics were challenging yet interesting. One such course which enthused me was Statistical Analysis of Choice Behaviour, where the research conducted at the CITY AI Lab on the advancements in choice modelling instantly caught my attention. One year down the line, when I was searching my thesis topic, I came across the opportunity at Advier. The challenge of finding solution to an urban problem using spatial analysis, choice modelling and computer vision perfectly aligned with my interests.

In the beginning, shaping my research was a challenge although with a few discussions with my supervisors, I was able to solve it. I worked at the Advier office where the environment was always cheerful and lively, proximal to my room and with very supportive supervisors. In addition, the opportunity to participate in team barbecues, present my work in Broodje Case, and cook for Thursday lunches made a cohesive and vibrant setting. At the university, it was insightful to interact with all the peers in the CITY AI lab group working on innovative topics related to city. All in all it was a great journey with its crests and troughs.

This was never possible without the invaluable support of the supervisors from Delft University of Technology, Dr. Sander van Cranenburgh, my Chair and Dr. Kees Maat and supervisors from company Arne Brugman and Jarco Vianen. Their readiness to navigate me into the unknown waters with patience, kindness and enthusiasm not only increased my curiosity into the topic but also kept me motivated all along my thesis. On the same thought, I would also like to express my sincere gratitude to Francisco, Gabriel, Niels and Roos for helping me throughout my journey. From clearing my doubts till helping me see a clearer overall picture, their assistance has been really helpful.

Finally, I would like to thank my parents, brother for their unwavering support and conviction on my efforts and hard work. This achievement is as much their as it is mine. Love of my dog, Jaadu who brought smile on my stressful face several times just by existing. A special thanks to the wonderful set of friends I have and was able to make during my master's journey whose constant understanding, encouragement and help during times of confusion has been a source of strength.

With this thesis marking the end of my master's journey, I am leaving with more confidence than I arrived. My time at TU Delft, enriched by transformative opportunities, challenges, and growth, has been a defining chapter in shaping me both personally and professionally.

Vedankur Kedar
Delft, The Netherlands
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Summary

The thesis investigates the trade-off between car parking accessibility and exposure to green environment by integrating street level imagery into analysis. In the quest for a sustainable development, car-free residential neighbourhoods are increasingly becoming a central element of urban planning, helping to reduce environmental impact and promote healthier, more liveable communities. This makes it essential to understand how sensitive people are towards parking accessibility and their willingness to replace it with green spaces. To solve this challenge, this study aims to provide insights into residential settings that are in resonance with the requirements of people.

In previous research on Residential Location Choice (RLC), text-descriptive stated choice experiments have been widely employed. But these approaches can fall short, as textual descriptions may be difficult for participants to fully comprehend, often resulting in inaccuracies. Although some studies have suggested the strong influence of environment affecting residential location decisions, only a few have incorporated and translated it into choice preferences. A vivid visual cue towards residential transition or development provides a clearer understanding on people's choices. The recently developed state of the art method called computer vision-enriched discrete choice model (CV-DCM) combines computer vision with conventional discrete choice models to analyse decision-making scenarios that incorporate both numerical information and visual data.

Within this study, CV-DCM is employed to better understand the preference of residents. In the experiment, the participants completed a series of decision tasks in which they selected between two residential transformation situations. Every alternative represents a residential setting defined by three attributes: walking time to the car, associated parking cost and the residential environment, which is depicted through street-level images. To uphold a consistency in the responses, participants were shown the translation of current neighbourhood to new a neighbourhood, keeping everything else the same with the image reflecting the visual qualities of the transformed neighbourhood.

A database of street view imagery was developed by acquiring images from high-density regions of the Netherlands, after which they were matched with the 12 neighbourhood categorizations each representing varied residential environment. With each combination of unique match for quality and neighbourhood categorisation, 12 set of 40 images were collated which were then used for developing 5 transformations using generative artificial intelligence (GenAI). This curated a strong image database of 2400 images which were then deployed in the survey. The experiment employed a manually developed efficient design. The usage of GenAI rendered street level images along with robust survey design proposes a new method in research arena.

Although the sample size is not fully representative of Dutch population, the findings show that the CV-DCM surpasses conventional discrete choice models by accurately capturing the impact of image-based features on residential environment selection. This method offers important insights into resident's preferences of different housing settings. The discrete choice model enabled the identification of how specific attributes influenced setting choice. It is importantly observed that young people are willing to walk almost 1.2 minutes more if their neighbourhood is translated into more greener space. Further this same measure is found be to merely 42 seconds for old age group who are more sensitive to car access. This is also observable in the Value of Time, where the old aged were willing to pay 13 Euros more than the young population for the same degree of increase in proximity to their cars. This gives a strong evidence that residents in general prioritise accessibility to their car over a preference for greener environment especially the elderlies.

This research makes an important advancement in combining computer vision with discrete choice modelling, offering policymakers a valuable tool to assess and design residential complexes. This also caters to the broader objective of car free neighbourhoods and mobility hubs. By identifying the features painting a sensitive tone for people, policies can be developed and steered around for a sustainable growth and urban development.

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1 Introduction

1.1. Background

Cities today are home to more than 55% of the world's population (Vilar-Compte et al., 2021), where the growing wealth in western economies has been pushing the demand for better quality of housing and residential environment (Dowling, 2008). This apparently translates into a preference for more space as people desire to live in suburban residential environments, characterized by peace, tranquillity, and green area (van Cranenburgh & Garrido-Valenzuela, 2023). Moreover, across the Netherlands, increasing demand for space is significantly reflected in the widespread preference for single family homes with higher green exposure. In this purview, gardens and frontal green spaces are perceived as a significant housing feature, as many individuals view it as an essential prerequisite rather than a choice (Boelhouwer et al., 1998). This further implies that prospective movers are unwilling to consider a new home unless it includes a garden or reasonable access to green spaces (Coolen & Meesters, 2012).

Households with higher incomes tend to prefer having a car (Maltha et al., 2017). This is notable because the preference for a personal vehicle is still substantial even if the country provides various transportation options (Fioreze et al., 2019) and many residents favour active forms of travel (Haas & Kolkowski, 2023). Even if these trends reflect a positive aspect of growth and satisfaction in quality of life, they hand in hand increase the pressure on already scarce resources like land and infrastructure, aggravated in high-density urban systems (Scheiner et al., 2020).

Consumers often desire large homes with more exposure to green spaces and parking, but the government encourages compact, mixed-use cities to support sustainability, considering the often shortage of land for housing (Götzeand et al., 2024). This creates a mismatch between what people prefer and current housing policies (Coolen & Meesters, 2012). Moreover, under the constraints of limited available land resources, the allocation of public land for specific infrastructure development essentially requires data-driven decisions to understand, modulate, and steer urban development paradigms. Defined in this context, "Green environment" refers to all types of public green spaces that can be provided in the residential neighbourhood, whereas "car parking accessibility" refers to the distance to car parking infrastructure from the house. With the contemporary debate about balancing competing demands for car parking accessibility and access to green environment, this trade-off made by residents has transcended to become a critical factor in residential location decisions. This also mirrors a broader urban planning dilemma, where the need to accommodate vehicles conflicts with the desire to possess or access leisurely green spaces.

The field of Residential Location Choice (RLC) has been thoroughly researched since its inception in different dimensions of transport modelling, land use, mobility patterns, and preferences. This discourse specifically lacks consideration of intricate factors like accessible car parking or access to green spaces, and how the nexus of these competing amenities shapes the choices. Moreover, there is a paucity towards how individuals or households belonging to different income, age, lifecycle status and sociodemographic groups, as an entity, balance the need for either of these amenities. The study attempts to delve deeper into this aspect of research. With the construction of distinctive neighbourhoods like the car-free district in Utrecht ("Start bouw autovrije wijk Utrecht, 'parkeerplekken nemen veel ruimte in"', 2025), which envisages a no-car policy, research concerning these factors becomes relevant to the overarching spatial decisions. Moreover, a strategic approach to this problem helps reveal people's preferences in light of government policies.

1.1.1. Car Free Neighbourhoods

Shifting cities from being car-focused to creating spaces where cars are limited is difficult but important for sustainability. Around the globe, cities are following car-restricted zones for traffic purposes in historical or commercial areas (Crawford, 2009). The concept of a car-free neighbourhood represents a reformist approach not by imposing restrictions, but by envisioning a society that functions without reliance on private automobiles (Paijmans & Pojani, 2021), where studies have shown that such neighbourhoods reduce car ownership and car usage patterns (Nobis, 2003; Scheurer, 2001). Marcheschi et al. (2022) finds that car-free street initiatives can evoke both acceptance and resistance: improvements in site quality tend to foster acceptance, while disruptions to place attachment may lead to rejection. The study also underscores the critical importance of incorporating residents' perceptions into the decision-making process when designing and implementing such interventions.

In the 21^{st} century, the car-free lifestyle is gaining momentum in different parts of the world. Paijmans and Pojani (2021) using an in-depth interview of 24 car-free people, investigates the motivation for a voluntary sans car attitude in the city of Brisbane, where they find a collective belief of having more advantages in terms of health, fitness, convenience and savings over owning a car. Moreover, this attitude is exhibited by people from all kinds of income levels, genders, and ages. On similar lines, Borges and Goldner (2015) analysed the best conditions for the suitability of a car-free neighbourhood considering the profiles of potential residents for Florianopolis in Brazil, where the location, size, and proximity to the centre are some of the vital parameters deciding the success.

As Mureau et al. (2022) and Andringa et al. (2022) in their study analysed the impact of low-car residential neighbourhoods on mobility behaviour, which takes into cognisance the car-free district of Utrecht and many other cities across the Netherlands. The recent trends in the Netherlands towards making car-free zones have gained traction and are being researched. According to Nederveen et al. (1999) 26 cities (including Amsterdam, Delft, Dordrecht, Enschede, Utrecht, and Zeist) have new plans to enlarge the traffic-calmed areas, and 25 cities (including Amsterdam, Arnheim, Delft, Gouda, Groningen, and Rotterdam) want to extend their car-free areas.

1.1.2. Challenges in the Netherlands

The dearth of land resources and the surmounting pressure of urbanisation in the Netherlands have kept the planning organisations on the edge. As discerned by Nabielek et al. (2013), the urban-rural continuum is exhibiting a 5 times higher development rate per square kilometre compared to the urban regions, especially for the residential development zones. With the targets to transform the majorly unutilized space under the parking infrastructure into green spaces, many municipalities are working towards the objectives of sustainability and efficient land usage (DutchNews.nl, 2025; Leidse Pers, 2025).

Apart from this debate, the other challenging part is to understand the notion of people towards these reformist ideas of development, as urban policies shaped in resonance with people's needs are more receptive and helpful for the development (Booth & Richardson, 2001). Although literature has proved that the benefits of a car-free neighbourhood transcend mobility, rendering a more socially cohesive environment, a safe habitat for children with cleaner air (Hazel, 1998; Melia et al., 2010; Ornetzeder et al., 2008). Yet no study has delved into how people weigh the necessity of car parking accessibility against their exposure to green spaces, and how this behaviour is reflected in their overall choice of residential location.

1.1.3. Analysing Residents' Preferences

Multiple factors influence residents' choice of a housing location; these factors can operate at different scales - city, neighbourhood, or residential level - and encompass a range of physical, cultural, social, and economic dimensions. A considerable amount of research has been conducted to date on the combination of these scales and dimensions (See Schirmer et al. (2014) for an exhaustive review). Reinforcing this, an in-depth understanding of residents' perceptions towards new concepts like car-free neighbourhoods is essential for future policy development.

Residents' preferences often reflect a trade-off between the convenience offered by accessible car parking over physical and mental well-being along with neighbourhood aesthetics provided by green spaces (Hematian & Ranjbar, 2022; Kerimova et al., 2022; Phillips et al., 2023). Moreover, apart from this, the socio-demographic variation in the population also leads to different sensitivities and preferences, which are of paramount importance in overall transport planning.

1.2. Knowledge Gaps and Insights from Research Pool

A considerable amount of research has been conducted on the aspects that affect RLC decisions. This involves a variety of factors, including the size and cost of the home, noise conditions (Hunt, 2010), as well as broader considerations such as the characteristics of the neighbourhood, proximity to key destinations, commuting distance to work, and population density (Kronenberg & Carree, 2010). Additionally, personal circumstances with regards to income (Traoré, 2019), connections with extended family (Acheampong, 2018), and changes in household composition over time (Wu et al., 2021) also play important roles. However, there is a lack of detailed research on how people trade off amenities like access to car parking and green spaces, and how sensitive they are to this choice. In essence how do they choose a residential setting based on the variation in constituting attributes (See Figure 1.1). A residential area can be visually appealing and welcoming, but limited access to parking can deter those who value car convenience above all else. This critical trade-off is frequently overlooked in existing studies, making its examination essential for the successful planning of new urban residential developments. To bridge this gap, it becomes essential to further understand individuals' preference for such housing amenities.

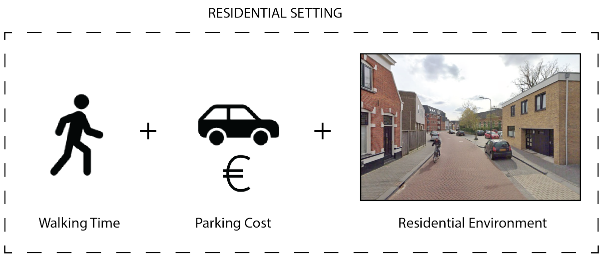


Figure 1.1: Residential Setting

A majority of these studies have employed stated and revealed preference surveys and discrete choice models (Acheampong, 2018; Frenkel et al., 2013; Hanni & Rao, 2024; Hunt, 2010; Tillema et al., 2010; Traoré, 2019). However, they often rely only on text, leaving respondents to imagine the options for themselves (Cherchi & Hensher, 2015; Johnston et al., 2017). It has been highlighted by Dongen and Timmermans (2019) that imagery is highly suitable for stated choice experiments in the built environment. With the help of imagery datasets, a visual simulation of the alternative can render the respondents a better idea of their choice, which in turn helps in understanding their preferences regarding the urban setting. Recent research has created evidence that people's preference for the visual appeal of their residential setting influences their sequential decisions (Yang & Tian, 2024), but limited research on how these aspects are important has been done. Although a perception study using an imagery dataset was used by Danish et al. (2024), no study has investigated preferences explicitly, to the author's knowledge, except van Cranenburgh and Garrido-Valenzuela (2023).

The contemporary trend of scientific research in computer vision and street view imagery has introduced new structures and methods to interpret and analyse how visual cues are integrated in people's cognition of their surrounding environment (Dubey et al., 2016; Ma et al., 2021; Rossetti et al., 2019). According to an exhaustive literature review presented in Biljecki and Ito (2021), a reasonable number of studies have used street view imagery and computer vision in the arena of spatial data infrastructure, greenery analysis, health and well-being, urban morphology, transportation and mobility, walkability, real estate, urban perceptions and others. Except for van Cranenburgh and Garrido-Valenzuela (2023), there exists a scarcity of studies which explicitly discuss how the visual perception of the residential setting influences the preference in RLC.

The Computer Vision-Enriched Discrete Choice Model (CV-DCM) introduced in van Cranenburgh and Garrido-Valenzuela (2023) is capable of handling choice tasks that include both numerical data and images by incorporating computer vision techniques into the conventional discrete choice framework. The CV-DCM can generate a utility score for the residential setting for each image, offering a useful metric for assessing how the residential environment is perceived. Due to the usage of computer vision, the comprehensibility of the model remains complex, as it is difficult to translate how scores are given. Therefore, it is of paramount importance to validate its resonance with realistic human decision-making. Moreover, it is pertinent also to analyse how different modulation in residential settings affect the utility score. For the decision maker's perspective, like the municipality or the government, decipherability of the model is significant where a lucid translation of which factors affect the decisions and their sensitivity allows for better development designs.

1.3. Research Objective and Research Questions

The objective of the research is to understand the trade-off between the accessibility of car parking locations and green environment under the scope of RLC decisions. While some individuals might value proximity to green spaces more, others might prioritise convenient car access. By understanding these dynamics, the study endeavours to provide substantial policy insights to the government and urban developers in steering the residential planning in cognizance to the need of the people.

This can be achieved by answering the following main research question.

How do individuals trade-off accessibility to car parking against green environment in residential setting preference?

To answer this research question, a number of sub-questions have been formulated, which are defined below.

1. **What are the attributes which affect the preference for a residential location ?**

   This question investigates different attributes which affect residential location choice furthering focusing on residential environment.

2. **What trade-off do individuals make regarding attributes of residential setting?**

   This question investigates the trade-off individuals make with respect to parking costs, walking time and residential landscape. This is significant in understanding the preference for a residential environment.

3. **How well CV-DCM is able to explain individuals' decision-making behaviour with respect to residential setting preference?**

   This question assesses the extent to which CV-DCM can accurately interpret and represent individuals' preferences regarding various residential settings. It also attempts to understand which residential setting has more or less preference for selection and satisfaction for respondents' personal needs.

4. **How do individuals belonging to varied socio-demographic groups such as different age segments, lifecycle status, income and political alignment prioritise these attributes when making their decision for residential setting suitability?**

This question throws light on demographic analysis, understanding how covariates like age, lifecycle, income and political alignment influence on the trade-offs individual make regarding their decisions for a suitable residential setting. One segment might prioritise keeping their car accessible to themselves irrespective of greenery, while another places exposure to a green environment as their top choice. This analysis can provide relevant insights to develop tailored and cluster specific policies.

1.4. Scope

The Netherlands is taken as the research base of the study. The image acquisition is specifically done from the high-density regions, as it provides a setting apt to identify competition between greenery and car parking accessibility. High density regions in this context are defined as those regions with 2500 or more addresses per square kilometre (Statistics Netherlands (CBS), 2024), which is translated to 8000 people per square kilometre. A detailed discussion about the process is given in Section 5.1. All residential neighbourhoods except Villawijk and Bedrijven are considered, due to the low presence of residential infrastructure. Furthermore, the study targets understanding the preferences of residents in the Netherlands.

1.5. Reading Guide

The opening chapter outlines the study's background, highlights existing knowledge gaps, and states the primary research aim. It introduces the central research question, which is further broken down into several sub-questions. Chapter 2 reviews previous research on RLC, further scoping down to the research question and the application of computer vision with street view imagery, concluding with a summary of remaining knowledge gaps. Chapter 3 details the methodological approach used to address these gaps and questions. Chapter 4 describes the process of gathering street-level images. Chapter 5 explains the design of the stated choice experiment aimed at assessing residential environment preferences. Chapter 6 reports the findings from the stated choice experiment, including the outcomes of the CV-DCM. Finally, Chapter 7 summarises the study, discusses the results, and offers suggestions for future research

COLLECTIVE KNOWLEDGE GAP & WAY FORWARD

In RLC research, no study has explored how individuals balance the need for convenient car parking with the benefits of exposure to green environment, and how this evaluation influences their ultimate residential setting preference. Also there exist a scarcity in the research pool which integrates imagery dataset in discrete choice models for understanding such dynamics in details. This gap is bridged in this research by exploring the nexus between accessible car parking and exposure to green environment using Computer Vision enriched Discrete Choice Model (CV-DCM).

2

Literature Review

The focus of this review is to shed light on the kind of research done in this arena and what gaps still exist to be bridged. The literature review first understands the factors affecting the RLC and then scopes in on the main research question and relevant studies done in this aspect. Moreover, the review also sheds light on the computer vision methods and street-level images. Culminating this, a concise summary compiles the contemporary state of knowledge, emphasising the areas where future research is entailed, and guiding direction for potential future research.

2.1. Factors affecting Residential Location Choices

Residential Location Choice (RLC) refers to the process by which individuals or families evaluate and select a place to reside based on personal preferences and extrinsic factors. In econometric terms, an individual/ a household tries to maximise the utility they gain from the particular residential property to achieve a satisfaction equilibrium. This decision corresponds to the sequential set of choices made on different scales and levels, aligned with the necessities of the resident. Moreover, such decisions on an individual level have a cascading effect on the physical size and spatial configuration of urban economies, which in turn shapes the skeleton of mobility patterns, travel behaviour, energy consumption and travel-induced impacts on the environment and society (Pagliara et al., 2010). Therefore, understanding the dynamics of residential choice and factors affecting it is of great significance (Cockx & Canters, 2020).

A household's residential choice is a function of several factors ranging from dwelling size, price, noise levels (Hunt, 2010) to overarching factors like neighborhood, proximity to major places of interest, distance to job location, density (Kronenberg & Carree, 2010), incorporating the personal variables like income (Traoré, 2019), extended family ties (Acheampong, 2018) and the composition and evolution of household structure over time (Wu et al., 2021) etc (see Table 2.1 for a detailed overview). Studies done hitherto mostly belong to the developed economies. Furthermore, families and individuals with diverse socio-demographic profile possess different priorities and intentions, associating varying importance to location, and personal attributes (Liya et al., 2013; Pagliara et al., 2010).

2.1.1. Scales of Residential Location Decisions and factors influencing them

Through the exhaustive literature review, it was observed that these attributes can be categorized into overarching scales providing a strategic eyesight to view the location choice problem; therefore they are classified into three scales of the influence.

- **Macroscopic Scale**: These refer to overarching, broad scale factors that shape the urban living and inhabiting decisions and they are related to regional or city-wide characteristics like accessibility to amenities, job opportunities, transportation, social networks and spatial preferences.

- **Mesoscopic Scale**: These envelopes those attributes which function at the neighborhood or zonal levels. They represent the characteristics of specific zones or areas within the city such as built density, safety and quality of Life.
- **Microscopic Scale**: These encompass factors significant on household and individual level, aligning with personal housing preferences which cover attributes like property characteristics, financial considerations and environmental requisites.

Table 2.1 elucidates different scales, factors and constituent sub-factors along with the literature providing evidence for the observations. According to the literature review, the macroscopic scale identified factors like

- ***Accessibility to supporting infrastructure and amenities*** that include all the vital services that enhance the attractiveness and suitability of a location for residential living. Literature suggests a strong evidence of proximity to public transit stations, job location, central business district reasonably influencing the RLC preference. Additionally easy access to services with respect to healthcare, education, recreation and urban parks underscore an important point in residential location decisions.
- It was observed that people prefer to locate themselves in a region possessing residents from same ethnicity, income levels and class which is categorized in ***Family ties and social network***.
- Some individuals choose to reside in urban and metropolitan areas, while others favor rural or countryside settings. This large scale decision are kept under ***Lifestyle Preferences***.
- All the associated costs which secondary costs for the choice maker like commute travel time, fuel cost are clustered under ***Costs Incurred***.

Mesoscopic scale consists of factors such as

- ***Spatial Character*** that broadly talks about the neighborhood attributes such as land use, density, etc. From different literature it was observed that these attributes of neighbourhood do have a strong impact on residential location decision making. Mixed Land use indicating convenient availability of various services is underlined to be very important factor followed by built density.
- ***Social Character*** that takes attributes like safety and aesthetics of neighborhood into account.

Microscopic scale deals with elements concerning the details of residential property which corresponds to

- ***Housing Amenities*** collating all the services considered significant under a residential premise like housing size, building age, number of bathroom/bedrooms, etc.
- ***Environmental Amenities*** consisting of greenery or green frontages.
- ***Residential Cost*** which clusters all the attributes like housing costs and associated taxes.

Reinforcing the current discussion apart from external variables associated to the residential location, the implicit variables like various socio-demographic variables also strongly influence the residential location priorities which is illustrated in Table 2.2. Evidence from multiple research suggest age and income levels strongly influencing the residential location priorities. Moreover, household size and life cycle which corresponds to different stages of individual life like marriage, child birth affect their inhabiting decisions. Additionally apart from the above attributes, activity patterns, education levels, migration background, car ownership and employment status also is found to shape the location decisions.

A multitude of factors, spanning various scales, shape RLC. Table 2.3 illustrates the influence of such factors on location priority. Apart from proximity to roads, which has been found preferable in most cases except (Hamersma et al., 2015). Easy access to supporting infrastructure, amenities, and social and family ties is always favorable for people who want to settle down at a location. Preference on the spectrum of urban or countryside lifestyle is subjective to the respondents, therefore dual effect can be observed, which is also dependent on socio-demographic factors like age as iterated in van Cranenburgh and Garrido-Valenzuela (2023). A high commute travel time, fuel cost and infrastructure toll cost is always found to have disutility. The propensity to choose a location is highly likely on the mixed land use, quality of traffic safety, availability of open spaces and air pollution levels observed in the neighbourhood. Built density has both positive (observed in (Kerstens & Pojani, 2018)) and negative (observed in Willing and Pojani (2017)) effect on the location choice, which majorly is a function of the regional characteristics and personal preferences. It was found in Willing and Pojani (2017) that the foreign student populace specifically from Asia prefer to have a dense built environment over sparse Australian urban planning as most of the Asian cities are highly dense and concentrated urban settlements. Safety and aesthetics are found to have a positive impact on the choice probability, whereas noise levels observed in the neighbourhood show a negative utility for location choice.

Under the housing amenities, an increase in housing rental cost or housing cost is found to reduce the likelihood of choosing a location, which is also similar for the age of the building. Different strata of populace have affinity to different housing types based on their personal taste and residential attitudes, but they possess an increase in location choice probability with a reasonable increase in housing size or number of bedrooms/bathrooms. Car parking is subject to car ownership, is preferential for a location choice as observed in Acker et al. (2014), Hamersma et al. (2015), and Yuntao and Srinivas (2020). Greenery and green frontages are found to increase the likelihood of a location, whereas the residential cost associated creates reluctance for the specific location choice.

Table 2.1: Scale and Factors influencing location choice

SCALE	FACTORS	SUB-FACTORS	REFERENCES
Macroscopic	Accessibility to Supporting Infrastructure and Amenities	Proximity to public transit stations	Acheampong (2018), Acker et al. (2014), Faber et al. (2021), Humphreys and Ahern (2019), Kerstens and Pojani (2018), Schirmer et al. (2014), Willing and Pojani (2017), Wu et al. (2013, 2021), and Yuntao and Srinivas (2020)
		Proximity to Job Location	Acheampong (2018), Beckers and Boschman (2019), Frenkel et al. (2013), Hanni and Rao (2024), Kronenberg and Carree (2010), Traoré (2019), Wu et al. (2013), and Yuntao and Srinivas (2020)
		Proximity to Central Business District	Acker et al. (2014), Beckers and Boschman (2019), Faber et al. (2021), Frenkel et al. (2013), Humphreys and Ahern (2019), Kerstens and Pojani (2018), Schirmer et al. (2014), Willing and Pojani (2017), and Wu et al. (2013, 2021)
		Proximity to Roads	Acheampong (2018), Beckers and Boschman (2019), Hamersma et al. (2015), and Wu et al. (2021)
		Proximity to Educational institute	Beckers and Boschman (2019), Schirmer et al. (2014), and Yuntao and Srinivas (2020)
		Proximity to Urban Parks	Schirmer et al. (2014), Traoré (2019), and Yuntao and Srinivas (2020)
		Proximity to Recreational Activities	Schirmer et al. (2014) and Yuntao and Srinivas (2020)
		Proximity to Hospital	Wu et al. (2021) and Yuntao and Srinivas (2020)
		Proximity to Amenities	Schirmer et al. (2014), Y. Yang et al. (2025), and Yuntao and Srinivas (2020)
	Family ties and social network	Proximity with people of same class	Acker et al. (2014) and Beckers and Boschman (2019)
		Proximity to family, friends or same ethnicity	Acheampong (2018), Acker et al. (2014), Frenkel et al. (2013), Kerstens and Pojani (2018), Traoré (2019), and Willing and Pojani (2017)
	Lifestyle Preferences	Urbanity	Frenkel et al. (2013) and Tillema et al. (2010)
	Costs incurred	Commute Time	Tillema et al. (2010), van Cranenburgh and Garrido-Valenzuela (2023), and Wu et al. (2013)
		Fuel Cost	Tillema et al. (2010)
		Toll Cost	Tillema et al. (2010)

SCALE	FACTORS	SUB-FACTORS	REFERENCES
Mesoscopic	Spatial Character	Mixed Land Use	Acheampong (2018), Acker et al. (2014), Beckers and Boschman (2019), Frenkel et al. (2013), Hanni and Rao (2024), Humphreys and Ahern (2019), Schirmer et al. (2014), and Wu et al. (2013)
		Built Density	Beckers and Boschman (2019), Faber et al. (2021), Frenkel et al. (2013), Kerstens and Pojani (2018), Schirmer et al. (2014), Willing and Pojani (2017), and Y. Yang et al. (2025)
		Traffic Safety	Hamersma et al. (2015)
		Air Quality	Hamersma et al. (2015) and Hunt (2010)
		Open Spaces	Schirmer et al. (2014)
		Noise	Acker et al. (2014), Hamersma et al. (2015), Hunt (2010), and Schirmer et al. (2014)
	Social Character	Safety	Acheampong (2018), Acker et al. (2014), Schirmer et al. (2014), Wu et al. (2013), and Yuntao and Srinivas (2020)
		Aesthetics	Acker et al. (2014) and Yuntao and Srinivas (2020)
Microscopic	Housing Amenities	Housing Type	Acheampong (2018), Humphreys and Ahern (2019), Schirmer et al. (2014), and Willing and Pojani (2017)
		Housing Size	Humphreys and Ahern (2019), Schirmer et al. (2014), Tillema et al. (2010), Traoré (2019), Willing and Pojani (2017), and Yuntao and Srinivas (2020)
		Building Age	Schirmer et al. (2014)
		Car Parking	Acker et al. (2014), Hamersma et al. (2015), Wiersma and Bertolini (2024), and Yuntao and Srinivas (2020)
	Environmental Amenities	Greenery	Acker et al. (2014), Hamersma et al. (2015), van Cranenburgh and Garrido-Valenzuela (2023), Wiersma and Bertolini (2024), and Wu et al. (2021)
	Residential Cost	Housing Cost	Kerstens and Pojani (2018), Y. Yang et al. (2025), and Yuntao and Srinivas (2020)
		House Rental Value	Acheampong (2018), Frenkel et al. (2013), Hanni and Rao (2024), Schirmer et al. (2014), Tillema et al. (2010), Traoré (2019), van Cranenburgh and Garrido-Valenzuela (2023), and Wu et al. (2013)
		Municipal Taxes	Hunt (2010)

Table 2.2: Socio Demographic Factors influencing location choice

FACTORS	SUB-FACTORS	REFERENCES
Socio-Demographic	Household Size and Type	Hanni and Rao (2024), Schirmer et al. (2014), and Traoré (2019)
	Lifecycle	Kerstens and Pojani (2018), Willing and Pojani (2017), Wu et al. (2021), Y. Yang et al. (2025), and M. Zhang et al. (2024)
	Activity Patterns	Frenkel et al. (2013)
	Education Levels	Wu et al. (2013)
	Migration	Wu et al. (2013)
	Age	Beckers and Boschman (2019), Humphreys and Ahern (2019), Kerstens and Pojani (2018), Kronenberg and Carree (2010), Schirmer et al. (2014), van Cranenburgh and Garrido-Valenzuela (2023), Willing and Pojani (2017), and Wu et al. (2021)
	Income	Acheampong (2018), Schirmer et al. (2014), Traoré (2019), and Wu et al. (2013, 2021)
	Unemployment	Schirmer et al. (2014)
	Car Onwership	Hanni and Rao (2024)
	Gender	Cui et al. (2024)

2.1.2. Factors governing Residential Choice in Dutch Context

Globally, the factors mentioned in Table 2.1 and Table 2.2 influence the choice of residential location, although with the specificity of the research question in the Dutch context, it is necessary to delve deeper into the attributes important for the Netherlands residential development outlook. In a study done by van Cranenburgh and Garrido-Valenzuela (2023) for the Dutch population above 18 years of age, through the incorporation of imagery dataset integrated in traditional choice modeling theory, people's preference for RLC was analysed. It was found that elderlies possess an affinity for a greener environment compared to the younger generation, with several other evidence for housing typology. In Faber et al. (2021), although the focus of the study was not on RLC, but a strong reason for people locating themselves in denser areas accessible to transit facilities was their individualistic priority for mobility access.

Apart from this, an important measure was the lifecycle or the current demographic stage of the household, that influences residents' choice Kronenberg and Carree (2010) and Y. Yang et al. (2025). Residents often search for such housing locations which are in resonance with their personal lifestyle priorities, travel behavior, even after possessing specific housing. As in Hamersma et al. (2015), the residents' moving intention is directed by their tolerance to the highway nuisance, although there is a strong trade-off between accessibility gains for the residents. Also in a study based on immigrants' RLC, single individuals preferred to prioritize attributes associated with the house, such as recently constructed or pre-war era and a neighborhood having high single inhabitants. Whereas, households with more than 1 member prioritized to locate themselves with people of the same ethnicity, and proximity to educational institutes (those having children) (Beckers & Boschman, 2019). Similarly, housing size and status of income (Tillema et al., 2010) and intervention of placemaking and greenery in the residential neighbourhood influence the choice (Wiersma & Bertolini, 2024) (See table 2.4 and 2.5 for more details).

Table 2.3: Effect of Factors on location choice preference

SCALE	FACTORS	SUB-FACTORS	EFFECT ON RLC
Macroscopic	Accessibility to Supporting Infrastructure and Amenities	Proximity to Public transit stations	
		Proximity to Job Location	
		Proximity to Central Business District	
		Proximity to Roads	
		Proximity to Educational institute	
		Proximity to Urban Parks	
		Proximity to Recreational Activities	
		Proximity to Hospital	
		Proximity to Amenities	
	Family ties and social network	Proximity with people of same class	
		Proximity to family, friends or same ethnicity	
	Lifestyle Preferences	Urbanity	
	Costs incurred	Commute Time	
		Fuel Cost	
		Toll Cost	
Mesoscopic	Spatial Character	Mixed Land Use	
		Built Density	
		Traffic Safety	
		Air Quality	
		Open Spaces	
		Noise	
	Social Character	Safety	
		Aesthetics	
Microscopic	Housing Amenities	Housing Type	
		Housing Size	
		Building Age	
		Car Parking	
	Environmental Amenities	Greenery	
	Residential Cost	Housing Cost	
		House Rental Value	
		Municipal Taxes	

Influence	Color Code	Influence	Color Code	Influence	Color Code
Positive		Negative		Both	

2.2. Green Environment versus Car Parking

2.2.1. Parking and Associated Policy

On an overarching scale, car ownership decisions are molded by long-term lifestyle preferences, moderate-level residential location decisions and short-term mobility behaviors, indicating a nexus of travel and housing choices (Acker et al., 2014). An in-depth explanation is given in Table 2.6. Contemporary research across the world and especially in the Netherlands has mentioned various perspectives looking at the parking dynamics. Car parking requires a huge amount of land resource, making it crucial to judiciously invest in such a project. As mentioned by Wiersma and Bertolini (2024), the parking permit allocation should be based on future spatial needs rather than current parking availability, hand in hand recommending parking hubs in the neighborhood's edge where car ownership is high. It also provides the insight that hindrance to place-making intervention increases when car ownership exceeds 0.8 cars per household.

Moreover, according to van der Waerden and Agarad (2019), drivers' willingness to pay for such amenities is a function to design related factors, payment flexibility and cleanliness. But the utility of such infrastructure to the residents is sometimes questionable. Residents prefer to keep their car specifically accessible to them or to their destination, implying their preference for in-front or proximal on-street parking (Kobus et al., 2012; Ommeren et al., 2011), where an enabling solution is to have on-street parking prices (Scheiner et al., 2020).

Furthermore, on similar lines, evidence from Christiansen, Fearnley, et al. (2017) suggests that increasing the distance between home and parking substantially reduces car usage, specifically for dense urban areas, which encourages promoting urban development policies of physical separation of car parking and homes. This puts forth a duality of infrastructure development decisions, where a parking hub suitably located at an accessible distance can provide more place-making efficiency to the neighborhood as well as simultaneously reducing the car-based trip for its residents.

2.2.2. Green environment or Personal gardens

Importance of green spaces in urban, especially high-density regions, is immense (Baur et al., 2013; Jim, 2004), but these regions, due to their intrinsic characteristics, exert pressure on the available green spaces rendering sometimes inequitable access to these spaces. Also, Zhang et al. (2015) suggests that despite having equal amounts of green spaces, differences in accessibility to these spaces lead to varying levels of mental well-being and green attachment, underlining greater importance for equal access to such spaces. Additionally, it has been found out in Lauwerijssen et al. (2024), that the green spaces value in an individual's eye and his/her interaction with it are a function of individuals' personal and social persona, where a decline in everyday green exposure may negatively impact their livability and well-being.

In the Dutch setting (see table 2.7), there is an overwhelming preference for single family homes with private gardens, as they are considered to provide essential living space, complemented with privacy, freedom and outdoor activities (Beumer, 2018). Specifically those families with children often prefer suburban environments Coolen and Meesters (2012) as the propensity of children's subjective well-being depends upon their exposure to greenery (Wu et al., 2021).

Table 2.4: Dutch Case Studies

Source	Theme	Methods	Data	Sampling	Insights	Limitations
(van Cranenburgh & Garrido-Valenzuela, 2023)	The study incorporates imagery dataset integrated in traditional choice modeling theory and is applied on residential location choice theory	Computer Vision enriched discrete choice modeling: Stated Preference data inclusive of imagery	Google street view imagery, Stated preference, Socio-demographic and travel dataset	Purposive Sampling from Dutch ministry of Statistics: Age Range the : Above 18 years	For older people, an affinity towards greener leafier areas with sparse residential density is observed compared to young people, whereas the young people prefer to reside in areas with reasonably high density. This underlines the importance of including the street-level conditions of the target population for urban development policy perspectives.	The computation of the standard error associated with the elements in the feature map is challenging due to the sheer size of the covariance matrix.
(Faber et al., 2021)	The study compares the influence of travel related location reasons and generic mode attitudes on the built environment choice	Cross-sectional and a longitudinal Structural Equation Model using data	Mobility diaries from Netherlands Mobility Panel (MPN)	Total: **4,238** for crossectional analysis, **1,677** completed data for wave 4 therefore included in longitudinal studies.	The cross-sectional model suggests that choice of built environment is much more dominantly affected by travel-related location reasons than travel attitudes for all three modes. Furthermore, people who prioritize public transport access in their location decision are much more likely to reside in denser areas with shorter distance to central facilities and transit infrastructure.	
(Kronenberg & Carree, 2010)	This study identifies and evaluates determinants of employees' job and residential mobility. The study found that a long commuting distance motivates for a simultaneous job and housing mobility.	Multinomial Logistic Regression	Purposive sampling finding people indulged in various industries, The samples were restricted to individuals aged 15 and older	The samples range from **16,682 to 85,821** employees,	Lifecycle, proximity to job locations not only impact residential location but also the income.	The corresponding limitation is that information regarding the reasons underlying employees' job changes are not available.
(Hamersma et al., 2015)	The study sheds light on the influence of highway nuisances, accessibility gains and other residential characteristics on motivation of residential change	Structural Equation Model	likert scale based datasets	Distributed: **5500**, received: **1396**	The influence of perceived highway nuisance on moving intention is very strong via mediating role of residential satisfaction although the role of accessibility gains appeared limited. Residential characteristics like satisfaction with the attractiveness of buildings, traffic safety and with social contacts were moving inhibitors	

Source	Theme	Methods	Data	Sampling	Insights	Limitations
(Beckers & Boschman, 2019)	This study explores the influence of the local living environment, particularly neighborhood and urban regional characteristics, on the residential choices of highly skilled foreign workers.	negative binomial regression model	Dutch Social Statistical Database (SSD)	**45,473** foreign highly skilled workers	Singles: opt for housing from pre-war and most recent construction events, neighbour where most singles live, Non-Singles: mix household types neighbourhoods, with high income levels, proximal to international school.	
(Tillema et al., 2010)	The paper investigates the impact of travel costs, in specificity the toll cost, on residential location choice of households	Stated Preference Surveys with Munitnomial Logit and Mixed Logit Models	stated choice experiment	**564** respondents	Respondents are more sensitive to travel costs than to equally high monthly housing expenses. Additionally, travel time appears to have a lesser impact, as reflected by a low value of time (VOT). Overall, this suggests that respondents generally prefer to pay slightly higher housing costs and endure longer travel times rather than incur high travel expenses. Moreover, location-related factors, such as the type of area and the number of bedrooms, also play a significant role in residential location choices.	
(Y. Yang et al., 2025)	This paper presents a comprehensive dynamic model utilizing a Dynamic Bayesian Network (DBN) to analyze the factors influencing residential and work-related mobility while accounting for their connections to other life events	Dynamic Bayesian network (DBN) mode	The DBN is trained and validated using **Dutch micro-population data** from 2015 to 2019	Microdata Population	The study confirms that life events such as marriage, divorce, the birth of a baby, changes in employment type, and workplace relocation significantly impact residential relocation.	Limited direct intertwining of relocations: Residential and workplace relocations in the Netherlands do not appear to be directly intertwined.
(Wiersma & Bertolini, 2024)	The paper investigates the trade-off between car parking spaces and public spaces in Dutch neighborhoods	Descriptive statistics	spatial dataset from 4 Dutch neighborhoods	Inhabitant density of 50 households per hectare	The intervention of placemaking in neighborhoods is only possible if car parking is provided in a walkable location.	

Table 2.5: Annotated Bibliography for factors affecting residential location choice in Dutch context

Source	**Economic**	**Residential**			**Neighbourhood**			**Accessibility**			**Sociodemographics**		
		Greenery	Parking	House Size	Mixed Land Use	Pollution (Air/noise/-traffic)	Density	City Centre/CBD	Education or job	transit station or roads	Age	Income	Lifecycle
(van Cranenburgh & Garrido-Valenzuela, 2023)	✓									✓	✓		
(Faber et al., 2021)							✓	✓		✓			
(Kronenberg & Carree, 2010)									✓			✓	✓
(Hamersma et al., 2015)		✓	✓			✓				✓			
(Beckers & Boschman, 2019)					✓		✓	✓	✓	✓	✓	✓	✓
(Tillema et al., 2010)	✓			✓						✓			
(Y. Yang et al., 2025)	✓				✓		✓						✓
(Wiersma & Bertolini, 2024)		✓	✓										

People's preference to have personal green space contradicts with the government's norms, creating a mismatch in the desire of residents and the policy vision of the government. Therefore, spatial development needs to balance both sides of the coin to have a sustainable yet satisfied urban development.

Overall evidence from the literature suggests that although car parking and green frontage/parks are essential amenities for the residents, which strongly influences their residential location decisions, no study has been found concerning the trade-off between these two aspects. Moreover, in an ideal situation, residents would desire to have both car parking and green space, yet the high density urban planning reinforced with sustainable guidelines does not align with these inclinations. Therefore, urban planning decisions regarding such residential and parking hub development entail a data-driven approach reflecting the opinion of residents while catering to the needs of sustainable governance.

2.3. Street View Imagery and Computer Vision

This section delves deeper into the studies which have incorporated real-world images and computer vision to analyse the environment.

2.3.1. Overview of Street View Imagery and Computer Vision

Over the years, the availability of large street imagery datasets, advances in computer vision, machine learning, and high-end computational power have enabled translation of methodologies in understanding how landscape attributes affect the perceived environment (Biljecki & Ito, 2021; Ramírez et al., 2021). Moreover, street view images (SVI) and computer vision (CV) have been applied in a myriad of domains that include urban health (Kang et al., 2020), quality of the built environment (S. Li et al., 2021), urban activities (Yao et al., 2021; F. Zhang et al., 2020), urban mobility (M. Li et al., 2022; F. Zhang et al., 2019), urban change (Byun & Kim, 2022; Naik et al., 2017), urban perception (Qiu et al., 2022; Wei et al., 2022), urban climate (Ignatius et al., 2022), transportation (Wang et al., 2022), greenery (Branson et al., 2018), energy (Sun et al., 2022), geospatial artificical intelligence (Liu & Biljecki, 2022), and many more.

2.3.2. Street View Imagery and Computer Vision in Greenery and Car Parking Analysis

Several studies have incorporated street view images and computer vision specifically for greenery assessment and green exposure. X. Li et al. (2015) integrated Google Street View (GSV) in the existing green view index (GVI) to understand green exposure in the East Village of Manhattan district in New York City, where its superiority over conventional image-editing software method has been reported in Aikoh et al. (2023). Similarly, Xia et al. (2021) proposed a method based on the semantic segmentation of street view images to evaluate the GVI of urban streets and a new measure called Panoramic View Green View index (PVGVI) is developed. Using the DeepLabv3+ neural network model, L. Zhang et al. (2022) has improved the accuracy of this measure further. The street view images were also used by Yu et al. (2022) to monitor spatio-temporal changes in the vegetation on the street in Tai'an, China, where the study introduced a novel vegetation index (VGI) that allows accurate quantification of urban greenery along the streets. In terms of the research pool, He and Li (2021) has put forth an exhaustive review of articles that discuss the usage of SVI in the evaluation of urban neighbourhoods, as SVI can aptly capture elements embedded in the urban fabric of systems. An exhaustive review of the literature on how street view data is used in urban greenery analysis has been mentioned in Lu et al. (2023). As per the literature, not much evidence regarding how the presence of car is perceived in urban environment is studied.

2.3.3. Computer Vision Enriched Discrete Choice Modelling

In most of the studies mentioned above, a quantitative translation of the street view image is done, understanding how the visual cues impact the perception of green exposure or view for the respondents. Although perception in urban planning research is of paramount importance, yet it does not signify the trade-offs which people make in real life. Moreover, perception as an indicator corresponds to certain ambiguity. Contrary to this, preferences render a direct manifestation of people's behaviour, as there is a balancing of various factors in decision-making.

Table 2.6: Literature on Parking Accessibility as a Residential Amenity

Source	Case Study	Theme	Methods	Data	Sampling	Insights
Wiersma and Bertolini (2024)	Urban residential neighborhood in **Maastricht, the Netherlands**	The paper investigates the trade-off between car parking spaces and public spaces in dutch neighborhoods	Descriptive Statistics	spatial dataset from 4 dutch neighborhoods	residents of neighborhood where density is 50 household per hectare	The intervention of placemaking in neighbourhoods are only possible if car parking is provided at a walkable location.
Scheiner et al. (2020)	Urban residential neighborhood in **Dortmund, Germany**	The study investigates parking behavior of residents in a neighborhood and extracts insights regarding the policy implication to improve the situation.	Descriptive Statistics	Face to Face Survey collecting Household in demographic, car ownership and accessibility dataframe.	households approached: **3566**, Households participated:**840**	It was found that residents prefer on-street parking in front of their house for convenience, specifically with context to multiple trips in a day.
Kobus et al. (2012)	Central Business District of in **Almere, the Netherlands**	The analysis explores the preference of people for curb parking over garage parking and estimates their willingess to pay for such travel behavior preference	Discrete Choice Modelling and Probit Model	Parking transaction data from January to December 2009	**475,899** parking transactions over **258 days**	The study reveals that drivers have a strong preference for street parking when supply of street parking is ubiquitous and garage parking is discretely located over space. This preference is due to street parking being closer to driver's final destination like home or shop. Moreover for such behavior there is an observable willingness to pay of 0.35 - 0.58 €.
Ommeren et al. (2011)	**Amsterdam, the Netherlands**	The study empirically examines the residents' willingness to pay for on-street parking with respect to the house price for the region of Amsterdam	Hedonic housing pricing function	Dataset provision by NVM containing 29,606 housing transactions that took place between January 2004 and December 2008	**24,804** observations for the analysis, with an average house price of **€251,159**	The marginal willingness to pay for on-street parking permits were found to be €10 per day for the non-residents. This also supports the intuition that people prefer to keep their cars accessible to themselves in residential locations.
van der Waerden and Agarad (2019)	**The Netherlands**	The study investigates the willingness to pay for the design attributes of the parking space.	Stated Preference surveys and Multinomial Logit Model	Dataset from Dutch parking organisation, Vexpan	**315** respondents who evaluated in total **3,150** choice tasks	Out of all observations, longer walking distances between parking garage and final destination, lowered the utility of parking garage.

Table 2.7: Literature on Greenery as a Residential Amenity

Source	Case Study	Theme	Methods	Data	Sampling	Insights
Lauwerijssen et al. (2024)	Elderly residents living in **Breda and Tilburg, the Netherlands**	The paper attempts to explore the garden identities across the life span of elderlies in the Netherlands	Thematic Analysis and in depth interviews	Participants for this study were recruited from two neighbouring medium-sized cities, in the province of Noord-Brabant, southern Netherlands: Breda and Tilburg	20 residents of neighborhood	The evidence suggest that garden identity, both personal and social are a function to individual perceptions, experiences, meaning, values and expressions, where the importance of such gardens in contemporary urban planning paradigm is undeniable for a better and healthier livability.
Beumer (2018)	Urban residents living in **the Netherlands**	This paper examines Dutch viewpoints on gardening for biodiversity and the development of sustainable urban environments	Cultural Theory used as a heuristic framework	A semi-qualitative survey, incorporating multiple-choice, open-ended, and visual questions, was conducted with a representative sample of the Dutch population	**517** respondents	The evidence suggest although there is a cognitive dissonance between what respondents want as gardens and what they have, yet they all demarcate an importance to possess a recreational space in their residential amenity set.
Zhang et al. (2015)	**De Hoogte and Corpus Noord in Groningen, The Netherlands**	The study explores the aspects of urban green space availability and attachment on residents' self reported mental, physical and general health.	Confirmatory Factor Analysis with one way MANOVA analysis	Socio-demographic data and likert scale based questionnaire	**223** respondents	The results indicate a stronger attachment to local green spaces and improved self-reported mental health in the neighborhood with greater access to usable green areas. However, no differences were found between the two neighborhoods in terms of physical and overall health.
Coolen and Meesters (2012)	**The Netherlands**	The paper talks about the mismatch between the consumer preference of desiring a swelling with garden and the government's policy agenda of high-density and mixed-use cities.	Descriptive Statistics	Woon Onderzoek Nederland 2006 housing database	**1,799** respondents who are 18 years or above	The paper highlights that different meanings are associated with the domestic gardens and public green spaces based on their functions. The essence of public green spaces is the contribution to the livability of the dwelling environment, whereas domestic gardens are considered to be an outdoor extension of the dwelling that can afford casual leisure.
Stobbelaa et al. (2021)	130 municipalities of **the Netherlands**	It explores urban greening, with a particular focus on the removal of garden pavement in Dutch cities.	Descriptive Statistics	Qualitative and Quantitative data from municipalities	35% of the participating municipalities	People's preferences for gardens are shaped by multiple factors, such as proximity to green spaces and understanding of environmental advantages.

To understand these preferences, it is important to include the factors which are essential in answering the research question, such as accessibility to car parking, associated costs in the investigation. van Cranenburgh and Garrido-Valenzuela (2023) introduced a novel approach that combines computer vision techniques with traditional discrete choice models, enabling the analysis of choice tasks that include both numerical data and image-based attributes. The study investigated how people choose where to live by conducting a stated choice experiment in which participants selected between two residential options, each characterised by a street-level image, monthly rent, and commuting duration. This research is among the earliest to incorporate visual imagery into discrete choice modelling. For those analyses where solitary use of numerical attributes might not fully capture the nuanced nature of choice situations, and visual cues are essential, this approach proves to be very appropriate. The CV-DCM is capable of generating predicted utility scores for residential environments based on images. However, because the model's decision-making is driven by computer vision algorithms, the rationale behind the assigned scores is not transparent or easily interpretable, making it difficult to understand why a specific score is given to an image.

2.4. Conclusion and Discussion

The initial section of the literature review discusses various factors which affect the RLC, ranging from macroscopic factors like accessibility to amenities, job opportunities, transportation, social networks and spatial preferences to microscopic variables like property characteristics, financial considerations and environmental requisites.

The surge in availability of street view imagery databases, with computational advancements in the field of computer vision and machine learning, has reinforced the replicability and robustness of methodologies which investigate how visual cues affect perceptions. Out of all attributes, it was observed that visual perception strongly affects residents' decisions with respect to any change in their residential environment.

There is a paucity of such research in the literature pool. Although in the field of RLC, most studies have applied a textual format to the stated choice experiments. Presenting information about the residential environment solely through text allows respondents to interpret details subjectively, shaped by their imagination, which can introduce structural bias into the analysis. The usage of images in such a context has been proven to effectively capture the true image of the research environment. An ample amount of studies have been done in this context, but specificity to understand residents' preference for car accessibility or greenery has not been properly investigated. Analysing preferences is significant as they are a direct translation of the choice behaviour. On the other hand, perceptions are merely the impressions but do not necessarily imply a choice. A residential neighbourhood can be perceived as aesthetically beautiful, yet it does not indicate whether residents would still prefer such an environment over their access. Perception intrinsically lacks the trade-offs, which are significant in formulating any data-driven policy. Therefore, it becomes essential to take preference for individuals in cognisance over perceptions.

Using images to visualise residential environment transitions can yield important insights regarding individuals' preference for a greenery setting over personal vehicle accessibility. No study hitherto has raised and studied this point. Information from such an analysis can help the urban development and decision-making bodies in steering the spatial plans accordingly. The model recently proposed by van Cranenburgh and Garrido-Valenzuela (2023) enables the integration of both numerical data and imagery in choice experiments by embedding computer vision within traditional discrete choice models (CV-DCM). However, because the model's reasoning is driven by computer vision, its internal decision-making is not easily interpretable. Therefore, supplementing the model with qualitative, spatial, and quantitative analyses can help clarify its outcomes and enhance understanding.

INSIGHTS

With the help of an exhaustive literature review it is observed that attributes like proximity to public transit stations, job location, central business district, roads, educational institutions, urban parks, recreational activities, hospital, same ethnicity and class strongly define the optimal residential location. Apart from this the commute time, urbanity, land use type, built density, traffic safety, general safety, air quality, noise, housing type, car parking availability, greenery and housing cost has reasonable influence. The socio-demographic factors like household size, lifecycle, educational levels, migration, age, income, employment status, gender and car ownership is also a deciding factor for the whole dynamics.

3 Methodology

This chapter presents the methodology used to reach the research objective. It begins with an overview of the methodological framework, followed by a detailed explanation of the specific methods employed.

3.1. Research Methodology Framework

The aim of this study is to investigate preference for residential setting and assess how walking time to the car, parking cost and residential environment affect these choices. The objective is to provide recommendations for developing new sustainable residential areas which cater to the needs of population. To achieve this, the research follows a structured methodology, beginning with review of attributes and data for designing the stated choice experiment. The impacts of key attributes are analysed using the CV-DCM model, a latent class model with results from these analyses thoroughly examined. This methodology leads to a comprehensive understanding of preference of environment and influence of different things on the choice. This paves a way for the policy makers, urban planners to steer urban development with respect to the people's motivation and attitudes. A structured methodology is explained in Figure 3.1. This structure is designed to give readers a clear overview of the analysis and its purpose throughout the study.

3.2. Stated Choice Experiment (SC)

The development of residential neighbourhoods that reflect the preferences and priorities of residents is essential. This requires a deeper understanding of their choices over different neighbourhood changes. A stated choice experiment isolates and measures the separate effects of different variables on the choices respondents make by presenting them hypothetical scenario with a systematic variation in attributes (Kløjgaard et al., 2012). The enlistment of variables is done via literature review and discussion with the varsity supervisors and experts at the company. The overall design, attributes and their respective ranges decided are detailed in Chapter 4. Convenience sampling is used to recruit individuals for the survey. The sampling does not involve financial remuneration to the respondents for their participation in the survey. A reflection of the Dutch population in the sampling is paramount to understanding the decision preferences in different sub-groups within the population.

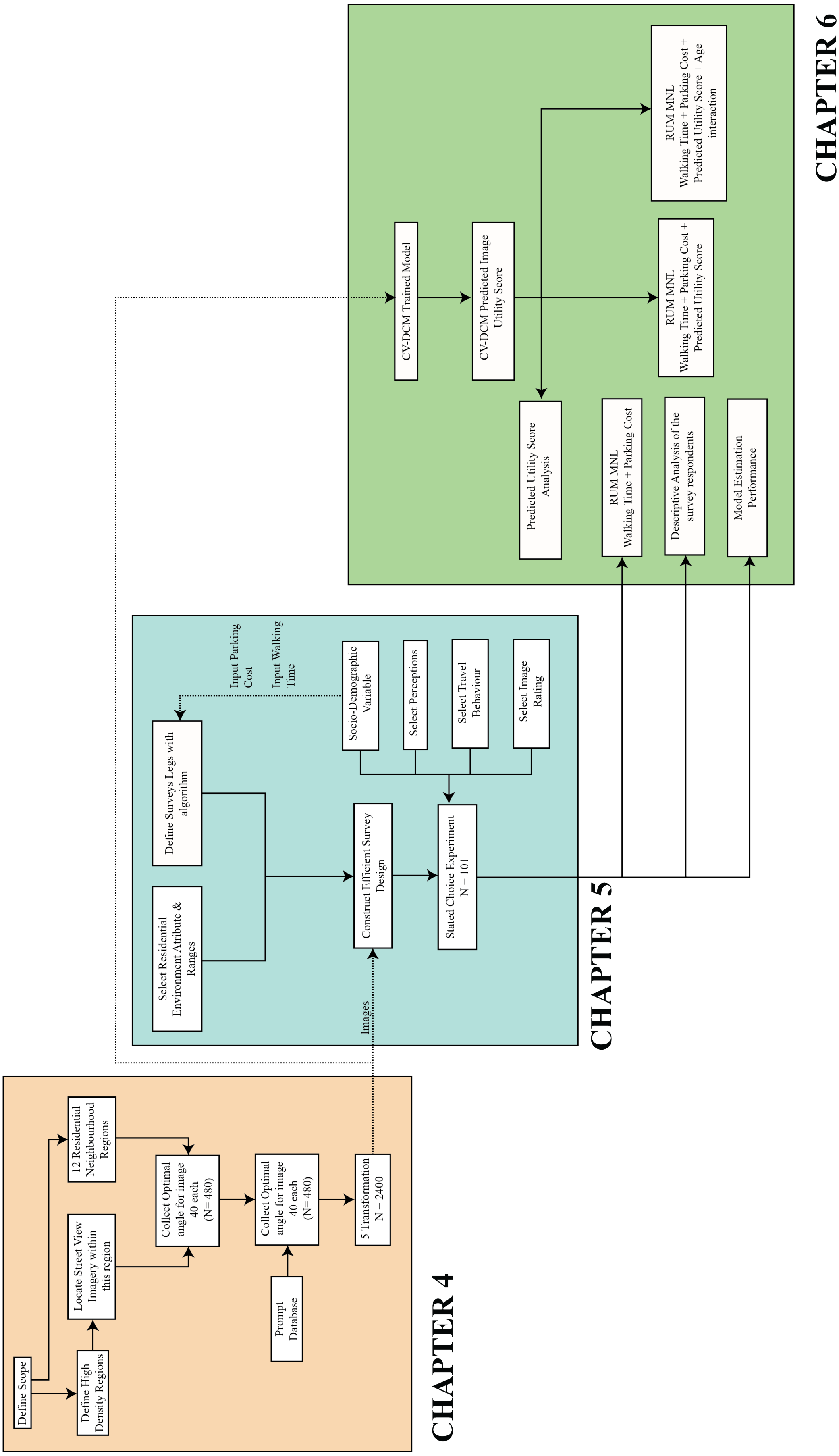


Figure 3.1: Research Methodology

3.3. Street-Level Image Retrieval

Street-level images are incorporated in the stated choice model to simulate the visual neighbourhood environment. The study follows method mentioned in Wang et al. (2022) for street level imagery collection, after which generative artificial intelligence (GenAI) is used for transformation generation. Transformations basically are the synthetically developed images which represent visual changes in the base image. Section 5.1 delves deeper on the collection strategy of street-level images.

3.4. Discrete Choice Models (DCM)

For this study, to predict the residential neighbourhood transformation choice, a computer vision-enriched discrete choice modelling (CV-DCM) method is employed. Furthering the discussion, first, the traditional Multinomial logit discrete choice model based on the random utility maximisation principle (RUM MNL DCM) is discussed.

Discrete choice models are extensively applied to capture individual decision-making across a range of fields, including transportation, energy economics, and agricultural economics (Kim & Bansal, 2024). It has been used for over four decades as a mathematical manifestation of the choices that people make, employing an economic and quantitative framework. It assumes every decision results from a rational decision-making process (Prato, 2009).

Daniel McFadden in his seminal paper McFadden (1974) introduced the widely recognised Random Utility Maximisation (RUM) model, which posits that individuals select the option that yields the highest utility. In this framework, the utility for each alternative is composed of two parts: a component that can be observed—based on measurable attributes influencing the decision—and an unobserved component that captures all other factors affecting choice. The unobserved portion is treated as a random variable, which introduces stochasticity into discrete choice models. This is typically expressed as the utility U for alternative i being the sum of its observed and unobserved utilities (Equation 3.1).

Maximum likelihood estimation seeks to determine the set of beta parameters that best explain the observed data by maximising the log likelihood (LL) function. This process assigns weights to each observed attribute in the model. The typical linear additive form of the Random Utility Maximisation (RUM) model is shown in Equation 3.2. With these estimated weights, the probability that a respondent selects a specific alternative can be calculated, most commonly using the multinomial logit (MNL) model. In the MNL framework, the error terms are assumed to be independently and identically distributed as Extreme Value Type I, with a variance of $\pi^2/6$. The associated alternative probabilities are therefore evaluated using the softmax function given in equation 3.3.

$$U_i = V_i + \varepsilon_i \tag{3.1}$$

$$U_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{3.2}$$

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} \tag{3.3}$$

3.4.1. Latent Class Choice Models (LCCM)

Although the RUM-MNL model has been extensively used in the decision-making arena, it possesses some lacunae. A major drawback of the conventional MNL model is the ”one size fits all” paradigm, rendering the same taste parameter. As evidenced by Mouter et al. (2017), individuals do possess different preferences over the same choice tasks. The Latent Class Choice Model (LCCM) can overcome this gap by identifying varied subgroups of the population that show similar characteristics and sensitivities (Hess, 2024). In other words, LCCM is capable of reflecting the diversity found among different population groups. Because of this, they often outperform traditional RUM-MNL models in terms of data fit, leading to more dependable parameter estimation and choice forecasting. Moreover, the segmentation provided by LCCM enables policymakers to develop resonant interventions for each group, supporting the government’s strategic goals. Considering that there are S classes with varied values of taste parameters $\beta_s = \{\beta_1, \ldots, \beta_S\}$. The probability that respondent n belongs to class s is denoted by $\pi_{ns} \in [0,1]$ and $\sum_{s=1}^{S} \pi_{ns} = 1$.

This is formulated using a softmax function on r_{ns} represented by class-specific constants for class s, δ_s and the parameters γ_{sq} estimated for covariates q such as age, lifecycle status, where z_{nq} is the variable (See Equation 3.4 and 3.5)

$$\pi_{ns} = \frac{e^{r_{ns}}}{\sum_{l=1..S} e^{r_{nl}}} \tag{3.4}$$

Such that

$$r_{ns} = \delta_s + \sum_{q=1...Q} \gamma_{sq} z_{nq} \tag{3.5}$$

The Formulation for the latent class choice Model is shown in Equation 6.3, where $P_n\left(i \mid \beta_s\right)$ is the closed logit function of Equations 3.2 and 3.3 on class-specific (s) taste parameters for m attributes β_s.

$$P_n(i \mid \beta) = \sum_{s=1}^{S} \pi_{ns} P_n\left(i \mid \beta_s\right) \tag{3.6}$$

3.5. Computer Vision enriched Discrete Choice Modelling (CV-DCM)

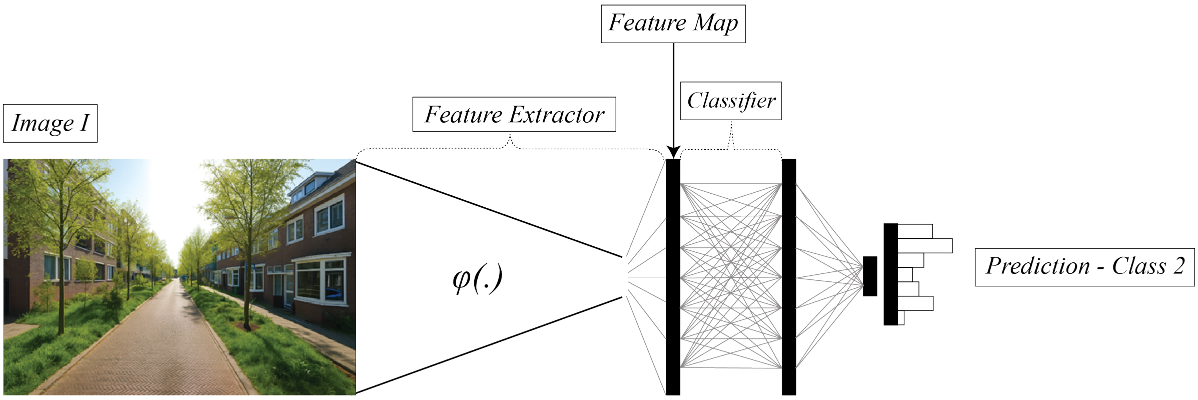


Figure 3.2: Feature extraction and classification adopted from van Cranenburgh and Garrido-Valenzuela (2023)

Visual data provides an important supplementary source of insight for analysing individuals' decision-making processes. In numerous decision-making scenarios, it is difficult to choose without access to visual information. Imagery usage via computer vision has garnered much attention in the recent years towards its utility in urban planning, where a systematic review done by Marasinghe et al. (2024) has thrown light onto this aspect of research. Computer vision (CV) plays a vital role in extracting insights from visual content. Advanced CV models are capable of recognising scenes and objects, with the most complex models utilising over a billion parameters. For the current study, Computer Vision enriched Discrete Choice Models (CV-DCM) introduced and detailed out by van Cranenburgh and Garrido-Valenzuela (2023) is used.

For the research, an original baseline situation is given for which a multi-attribute choice task with J mutually exclusive alternatives (in this study, 2 alternatives) is provided to a decision maker, n. Each alternative i is defined by M numeric attributes $X_i = \{x_{i1}, x_{i2}, \cdots, x_{iM}\}$, which can be walking time, cost of amenities and by coloured image $\mathscr{I}_{in}$ having a resolution of $H \times W \times C$ (Height, Width, Colour). The image effectively grasps the perceptible attributes like quality, form and shape.

A standard image is made up of millions of pixels, but feeding raw pixel data directly into a computer vision (CV) model is inefficient because of the sheer data volume and the limited value of individual pixels. To address this, the CV model used in this study incorporates both a feature extractor and a classifier. The resulting feature map is a reduced-dimensionality vector representation of the image that encapsulates its most salient characteristics. This feature map condenses the essential visual information from the image into a format that is both machine-readable and computationally manageable. Figure 3.2 illustrates the structure of the CV model.

The feature map of the image $\mathscr{I}_{in}$ is denoted as $Z_i = \{z_{i1}, z_{i2}, \cdots, z_{iK}\}$ where $\varphi(w) : \mathbb{R}^{H \times W \times C} \to \mathbb{R}^K$ is a function that transforms the image into its feature map. Here, ϕ refers to the feature extraction process of a computer vision model, and w is referred to as the weights that are its learnable parameters that extract the relevant image attributes.

The assumption that decision-makers act according to the principles of Random Utility Maximisation (RUM) as described by McFadden (1974) and illustrated in Equation 3.7 are followed. Here, U_{in} represents the total utility that the decision-maker n derives from alternative i. The component V_{in} reflects the utility attributed to observable factors, while an additional error term ε_{in} is included for each alternative to capture influences on utility that are not observed by the analyst (Train, 2009).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{3.7}$$

Additionally, it is also considered that decision-makers derive utility from both the numerical attributes X_{in} and the features represented in the image $\mathscr{I}_{in}$, as shown in Equation 3.8. Here, ν denotes a preference function that translates both the numeric and image-based attributes of an alternative into utility.

$$U_{\text{in}} \left(X_{\text{in}}, \mathscr{I}_{\text{in}}\right) = \nu \left(X_{\text{in}}, \mathscr{I}_{\text{in}}\right) + \varepsilon_{\text{in}} \tag{3.8}$$

The research posits that the contributions to utility from numerical attributes and from image-encoded features are independent and additive within the utility framework, as shown in Equation 3.9. In this setup, the function f assigns utility to the observed numeric attributes (Equation 3.10) while the function g does so for the information contained in the images (Equation 3.11). Since images generally capture several different features, these can be treated collectively as a composite good. Both the numeric attributes X_{in} and the feature map Z_{in} are incorporated into the utility function in a linear and additive way. In this equation, β_m represents the marginal utility of a numeric attribute m; x_{imn} is the value of the numeric attribute m for the alternative i faced by the decision maker n and β_k is the coefficient for the k^{th} component of the feature map Z_{in}.

$$U_{in} \left(X_{in}, \mathscr{F}_{in}\right) = f\left(X_{in}\right) + g\left(\mathscr{F}_{in}\right) + \varepsilon_{in} \tag{3.9}$$

$$f\left(X_{in}\right) = \underbrace{\sum_m \beta_m x_{\text{imn}}}_{\substack{\text{Systematic utility} \\ \text{derived from} \\ \text{numeric attributes}}} \tag{3.10}$$

$$g\left(\mathscr{F}_{in}\right) = \underbrace{\sum_k \beta_k z_{ikn}}_{\substack{\text{Systematic utility} \\ \text{derived from attributes} \\ \text{encoded in the image}}} \tag{3.11}$$

where $Z_{\text{in}} = \varphi\left(\mathscr{I}_{\text{in}} \mid w\right)$

Consequently, the outputs at the final layer of the network can be interpreted as utility values. However, the parameter β_k does not essentially reflect the same meaning as that of β_m. Although β_k can be considered a marginal utility, since it quantifies the change in utility resulting from a unit change in an attribute, its behavioural meaning is ambiguous because the elements of the feature map Z_i are not defined in this context.

An assumption importantly made in this study is that the baseline scenario does not intuitively affect the choice probabilities. It just informs the respondent regarding the changes which the status quo situation undergoes to transform into the new alternatives, but the end choice is made based on the comparative characteristics of the new options.

Figure 3.3 illustrates the architecture of the applied CV-DCM model, where the network, in the baseline scenario and the other alternatives, is the same. The structure of CV-DCM in this research also upholds the consistency with RUM. The inclusion of a baseline scenario does affect the utility function of the alternatives, but the basic criterion that the utility of one alternative is not affected by another alternative's attributes is retained. Even though the difference in utilities of alternatives and the baseline scenario is taken, yet the ordinality of the whole system is maintained, as discussed in van Cranenburgh and Garrido-Valenzuela (2023).

INSIGHT

To answer the research questions, a stated choice experiment integrated with imagery dataset is designed. A strategic process for image retrieval is followed. To analyse the acquired data set and seek answers, discrete choice models (DCM), latent class choice model (LCCM) and computer vision-enriched discrete choice model (CV-DCM) are used.

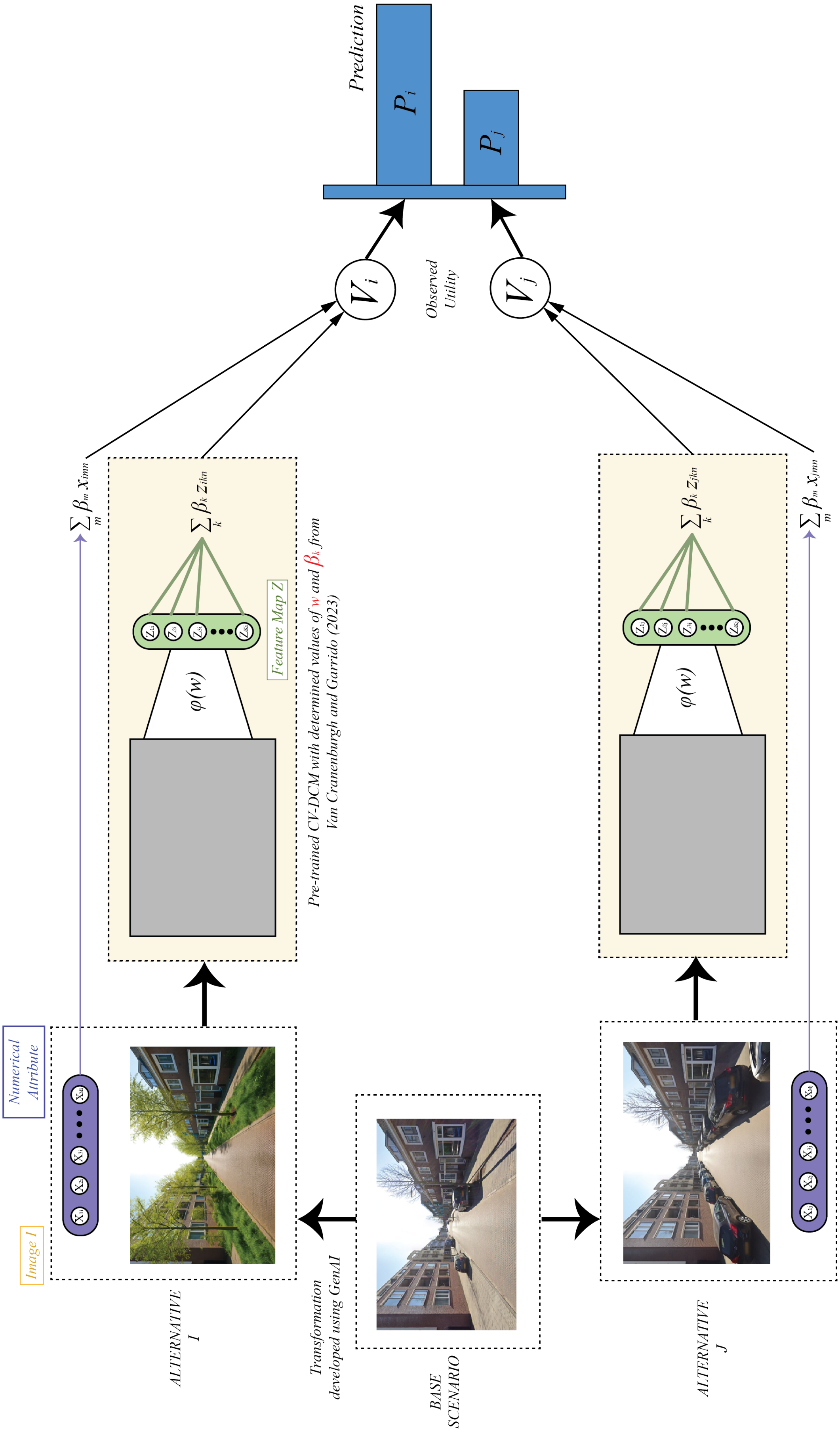


Figure 3.3: Model Structure for CV-DCM for the study

4 Stated Choice Experiment Design

This chapter details the structure of the residential setting choice experiment. The objective of the survey is to analyse the impact of the residential environment on the neighbourhood choice, and to determine the trade-offs made by individuals between the residential environment and characteristics of amenities. This is done with the help of a survey by asking the people for their preferred choice of residential environment, depending on the image of the neighbourhood and the associated attributes.

The study follows a stated choice experimental approach described in the book ”Stated Choice Methods: Analysis and Application” (Louviere et al., 2000). Designing the survey involves several challenges. One of the primary difficulties in stated choice (SC) experiments is developing choice scenarios that realistically reflect actual decision-making situations. This requires careful examination and evaluation of the relevant attributes and their possible values. With the objective to ensure that the utility functions can be accurately estimated, resulting in reliable parameters with low standard errors, a variation in the choice scenario is essential. For this kind of optimality in the analysis, the selection of an appropriate experimental design is quite significant (Bliemer & Rose, 2011). Moreover, balancing this, it is essential to maintain the number of choice tasks which are practically doable by the respondents and do not overwhelm them.

4.1. Selection of Attributes

An appropriate set of attributes not only steers around the policy and design but also is highly relevant to the needs and conditions of the individuals (Nielsen et al., 2021). The initial step is to identify the attribute, which is done via literature analysis and exhaustive discussions.

Christiansen, Engebretsen, et al. (2017) highlights that apart from accessible parking availability at workplace destinations, individuals are also highly sensitive to residential parking availability, which influences car usage in the long term. Moreover, it is evidenced by Z. Guo (2013) that within households with similar car ownership, those who have convenient availability of parking are twice as likely to use cars compared to the other case, making convenience an important aspect for residents. In a similar context, Millard-Ball et al. (2022) explains that the availability of accessible parking shapes the travel behaviour especially car ownership, for people. Although with a high accessibility, accompanied high cost are de-motivators for households which prioritise car ownership (Ostermeijer et al., 2019). van der Waerden et al. (2013) suggested that people value free or low-cost parking spaces ($Utility = 2.4523$) much higher than even a slight increase in the parking cost ($Utility = -2.3488$). Therefore, the research pool suggests that accessibility to car parking and the associated costs are very important attributes in the choice of residential environment. This detailing is also discussed in Section 2.2.1.

Furthermore, access to greenery is deemed to be one of the most important aspect looked for by families in their residential neighbourhood choice (Beumer, 2018). Additionally, in practice, placing urban green spaces next to major roads to serve as a green buffer for residential areas seems to be the most favoured approach, based on the housing preferences of homeowners (J. Li et al., 2024). In the economics literature, the identification of preference for any specific real estate amenity has been identified with a high cost or willingness to pay for such amenities, where Chen et al. (2022) has clearly suggested that proximity to green spaces has been reflected in high property prices in residential zones. This also tags green space accessibility as one of the important aspects for people in location choice decision making.

As discussed in the Section 2.1.1, there exist several factors which govern the preference towards a specific residential setting. The residential environment encompasses factors such as the aesthetics, greenery, car parking presence, availability of open spaces and built environment, all visually observable through images. Also, as suggested by van Cranenburgh and Garrido-Valenzuela (2023), the attractiveness of the images is a function of the season they are obtained. Therefore, most of the images used in the study are captured during daylight hours to remove this bias in preference.

Reinforcing the current narrative, subjective perceptions such as aesthetics, social safety, traffic safety and peacefulness are also captured in the survey. Aziabah et al. (2025) and Henderson et al. (2016) elicit that these factors have a reasonable effect on residents' preferences for any location. These three perceptions cannot be measured directly or extracted by the model from the images themselves. Since these three perceptions cannot be directly quantified or automatically derived from the images, participants are subsequently asked, after the stated choice experiment, to rate the images they saw based on aesthetics, safety, and peacefulness.

As detailed in Section 2.1.1, residents possess diverse preferences over residential environment choices; moreover, the location choice decisions are highly dependent on the lifecycle status of the respondent, rendering it necessary to capture socio-demographic aspects (Cockx & Canters, 2020; J. Guo & Bhat, 2001). Therefore, attributes like age, gender, income, partnership status, and age of youngest child (if yes) are recorded. It is pertinent to mention that during a brainstorming session with experts advier, a reasonable suggestion of political alignment influencing the residential preference is put forth, which is also included in the analysis. Moreover, Freemark (2024) and Clegg (2021) have provided evidence that political views can steer the planning outcomes and attitudes toward urban development.

Drawing on the attributes identified from the literature and insights from van Cranenburgh and Garrido-Valenzuela (2023), multiple versions of the survey are developed. To identify the optimal design, 4 sample choice tasks are developed based on the captured images, their transformation and associated numerical attributes. The information regarding this is presented in Appendix A. The surveys were piloted with experts from the company, and subsequently reviewed by my supervisors at TU Delft. Based on this process, several conclusions were drawn and documented in the report.

- Accessibility option of ”More than 3 minutes” was very ambiguous as it could be interpreted as 3.01 minutes or 10 minutes. Moreover it did not add much to the research design, as walking for 3 minutes itself was too much for any respondent.
- The survey design using image transformations with car presence was logical, but the ones which exhibited greenery were inconsistent and very similar. Therefore, it was decided to refine them further.
- In the transformation images, both car presence and greenery created a dilemma in the survey logic. If the car was visible in the image, but the respondents were asked to park it away, the basic query would be why can not they park it there. To overcome this situation, out of the five transformations, 2 were kept strictly incorporating car presence and the other 3 were made with respect to greenery.
- In some survey designs, the presence of a base image was creating confusion, as this is not taken into account in the CV-DCM mathematical model. As a result, the baseline scenario was treated solely as a reference point, with the assumption that it does not affect the choice probabilities of the alternatives. This is discussed in detail in Section 3.5

The final set of survey attributes was established through expert feedback and collaborative discussions with my supervisors. The images of residential neighbourhood, the associated parking costs and accessibility measure are the incorporated attributes.

4.2. Attribute Level Selection

The levels and range for these three attributes must be specified. The images themselves cannot be associated with the attribute levels that are essential for implementing an experimental design. Therefore, similar to the procedure followed by van Cranenburgh and Garrido-Valenzuela (2023), the image database as a whole is taken into account. Out of the 5 transformations, 2 are specifically kept oriented to car presence and 3 are associated with greenery as mentioned in Section 5.2

It has been noted in Bliemer and Rose (2024) that a wide attribute level range (1-5 min) has higher statistical efficacy over a low range (1-2 min). This is due to the low standard error, resulting in better parameter estimates. On the other hand, a wide attribute level range might also encompass dominant alternatives, which is problematic for the estimation. As iterated in Christiansen, Engebretsen, et al. (2017) and Ostermeijer et al. (2019), residents who are overtly dependent on cars prioritize their accessibility.

For accessibility, initially, 4 ranges of walking times are decided (0-1 min, 1-2 min, 2-3 min, more than 3 min) to capture expected non-linear effects. Time is preferred over distance here to measure accessibility because people find it easier to understand how long something takes rather than how far it is (Pot et al., 2021). During expert consultation at the company and with the supervisors, it is indicated that a discrete set of attribute levels is most suited for this study, as the range in itself would cause ambiguity in understanding. Moreover, the stratification of the base ”0 to 1 minute” range is done into ”in front of house,” ”30 seconds,” and ”1 minute” because people see ”in front of house” very differently from the other options. The ”More than 3 minutes” option is also removed from the study because it is too vague and already considered too far for residents to walk. It is important for a design to allow comparison across all levels, from the lowest to the highest, to ensure that no alternative is dominant (Rose & Bliemer, 2009). Therefore, the accessibility is defined with ”In Front of House”, ”30 Seconds”, ”1 Minute”, ”2 Minutes”, and ”3 Minutes”. This also aligns the attribute balance as 5 image transformations are used.

With a thorough analysis, it was found that there is a variation in the residential parking permit fee for different cities and for different areas within the city (See Table 4.1). It is decided to use a pivot design for the cost as they can tailor scenarios to each respondent’s real-life context, rendering their decisions more realistic and relatable (Rose & Hess, 2009). During the process of cost level finalisation, the proposal of using a percentage is given, but this is discarded due to the complexity which is incurred in the final analysis. The major challenge in designing the attribute levels is their relevance to the majority of the respondents. At first, residents were going to be asked about their current permit parking fees so that attribute levels could be adjusted accordingly. However, this idea was dropped after the pilot survey showed that most residents do not pay a parking fee. To better fit the residents’ situation, the parking fee question was changed to a simple yes or no question. Accordingly, attribute levels are decided as -100 €, -50 €, -25 €, -10 €, +10 €, +25 €, +50 €, +100 €.

Table 4.1: On-Street Residential Parking Permit Fees taken from Ostermeijer et al. (2019)

Permit fee (€/yr)	Amsterdam	Rotterdam	The Hague	Utrecht
Centre ($<$ 2 km)	500	70	40	70
Urban ring (2–5 km)	200	70	40	30
Periphery ($>$ 5 km)	0	0	0	0

4.3. Survey Layout and Process Flow

Based on the initial baseline image, the respondents are asked to compare the two different transformations and associated numerical attributes. During the Decision-making process, they are asked to consider the following situation:

- Imagine that you live in the neighbourhood shown in the current situation, which is going to get transformed into 2 alternative neighbourhoods.
- With the transformation, there is a new cost for a parking permit, a new walking time to access your car and a new neighbourhood environment, which is shown in the image.

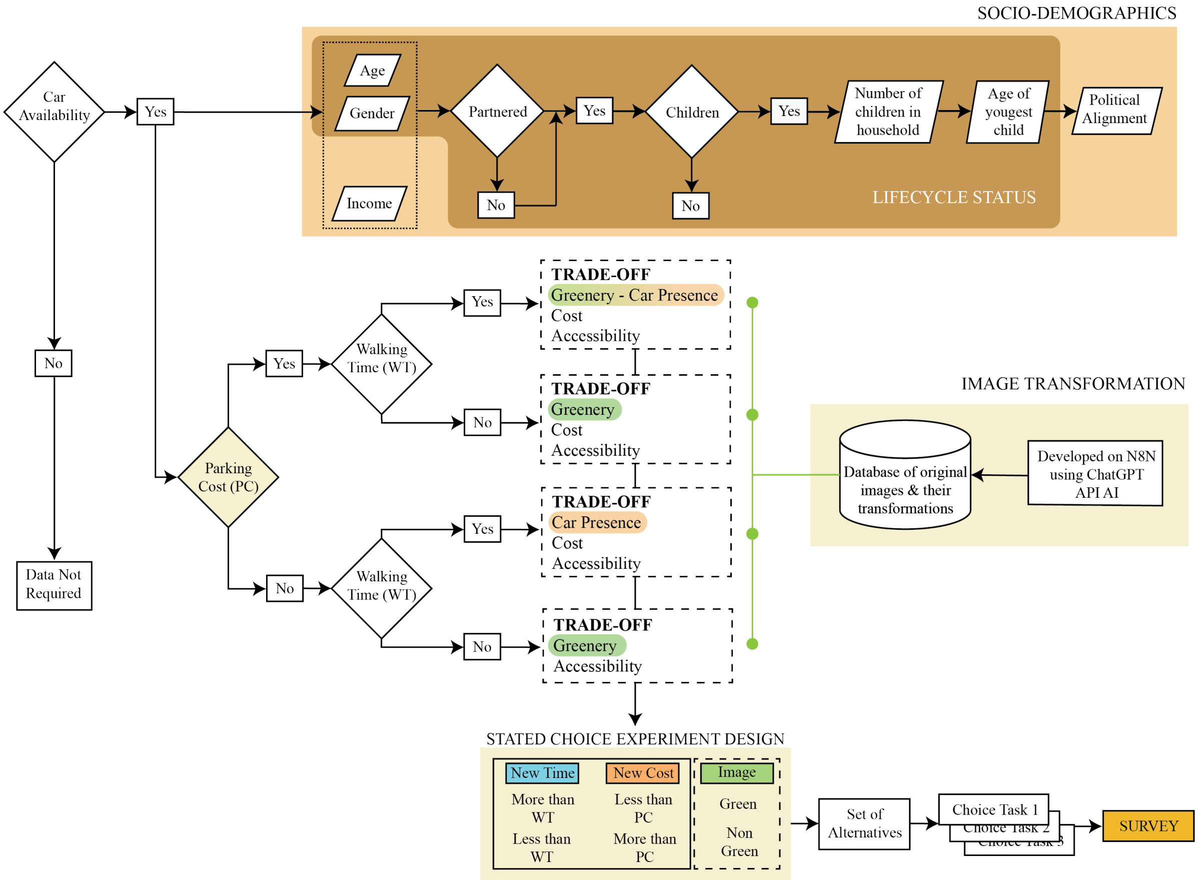


Figure 4.1: Survey Information Flow Design

- All other aspects of the house, locality, and accessibility to different facilities remain the same.
- **Which transformation would you choose?**
- The following assumptions are made:
  - You are taking this decision, seeing the requirements of your household.
  - The photo gives a good idea of what the transformation would look like.
  - Since the alternatives are generated using Artificial Intelligence, there is a chance that some images may contain logical inconsistencies. Therefore, please prioritise the relevance of the image to the topic rather than focusing solely on its accuracy.

The survey is designed into different phases to understand the characteristics of respondents, capture their preferences, and collate perceptions associated with imagery. Figure 4.1 describes the logical flow of the survey design.

- The survey is initialized with questions regarding to the ownership or possession of car. Those respondents are not furthered who do not own the cars, as this study focuses on the residents who might experience or are experiencing the trade-off for greenery and car parking accessibility. .
- One the basis of the questions regarding parking permit payment and current walking time, four legs for the survey are designed which is explained in details in Section 4.4 and in Figure 4.1
- With an appropriate images combined with set of attribute levels, alternatives are generated, which are then bundled as choice tasks. Oehlmann et al. (2017) recommend administering between 10 and 15 choice tasks per respondent, as this range strikes a balance between obtaining sufficient data and avoiding excessive cognitive burden. Therefore, 15 choice tasks are set in the survey.

- The survey culminates with basic questions associated to current travel behaviour, self-reported importance of images and other numerical attributes.
- Finally, all the Socio-demographic dataset is collated through the questions.

4.4. Experimental Design

In a stated choice (SC) study, various experimental design options are available. Among the commonly used types are full factorial designs, random fractional factorial designs, orthogonal designs, and efficient designs.

A full factorial design for such study results in a large choice tasks. There are more effective and organized ways to develop a design that produces more trustworthy parameter estimates. One such method is the orthogonal design, which focuses on minimizing correlations between attribute levels in the choice tasks (Rose & Bliemer, 2009). This approach helps reduce standard errors, leading to more reliable parameters. However, orthogonal designs can sometimes include dominant alternatives—options that are obviously ”best” or ”worst” and therefore do not provide useful information about trade-offs. These should be excluded, but doing so can introduce correlations between attribute levels, which decreases the efficiency of the design (Hensher et al., 2015). Efficient designs address this issue by excluding dominant alternatives and aiming to balance the utilities of choices within each set. This strategy maximizes the information about trade-offs and keeps the standard errors of parameter estimates as low as possible.

Although employing an efficient design is not a feasible in this study as it requires ordinal or categorical level data, whereas images do not fall into this data category. Therefore, a random experimental design is used similar to the one formulated in van Cranenburgh and Garrido-Valenzuela (2023). The Figure 4.2 is the basic schema of alternative development. With the initial question associated to car parking permit and accessibility, the baseline scenario for the respondent is defined. This also defines the leg of survey which the respondent faces as logical flow for survey needs to be maintained.

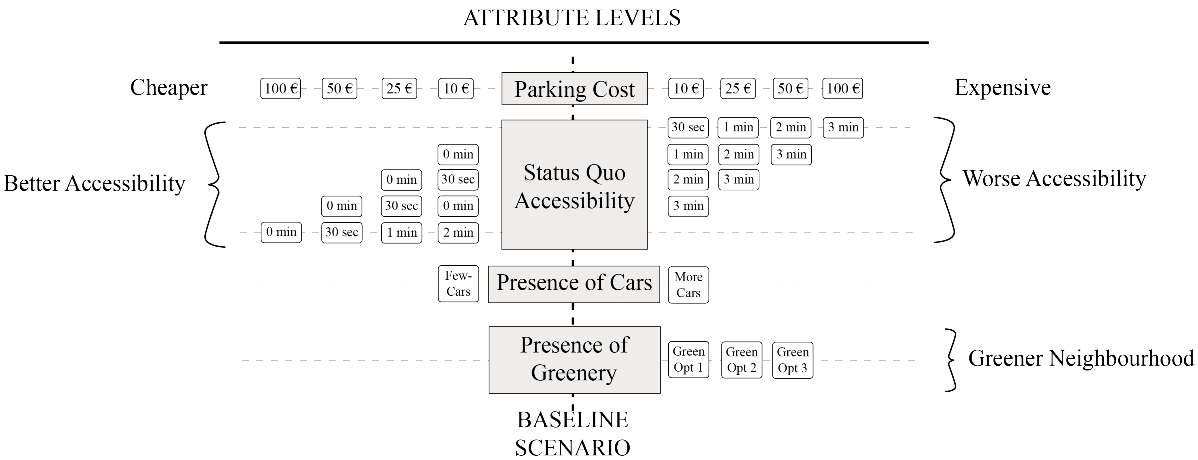


Figure 4.2: Alternative Schema

4.4.1. Leg 1

This leg of the survey is made for those respondents who assign ”Yes” for parking cost and have to walk some distance to access their cars. Under such condition, they are required to trade-off accessibility to car with greenery and parking permit costs. As illustrated in 4.3, the option of status quo = ”in front of house” is blocked. For a random base image, its transformation with the presence of a car is pulled and combined with an increase in cost and decrease in accessibility and in case of greenery the vice versa is done. Example of alternative 1 describes that if a respondent reports 1 minute as the current walking time. Alternative 1 envelops transformation with car (any of the two), an increase in the parking cost (25 €) and increase in accessibility (Walking Time = 0 minute/ ” In front of House”). Similarly, alternative 2 combines a random green transformation (out of 3 transformations) with worse accessibility measure (Walking Time = 3 minutes) but a decrease in parking cost (50 €). In this algorithm, other alternatives are made in same manner and then paired to form one choice task.

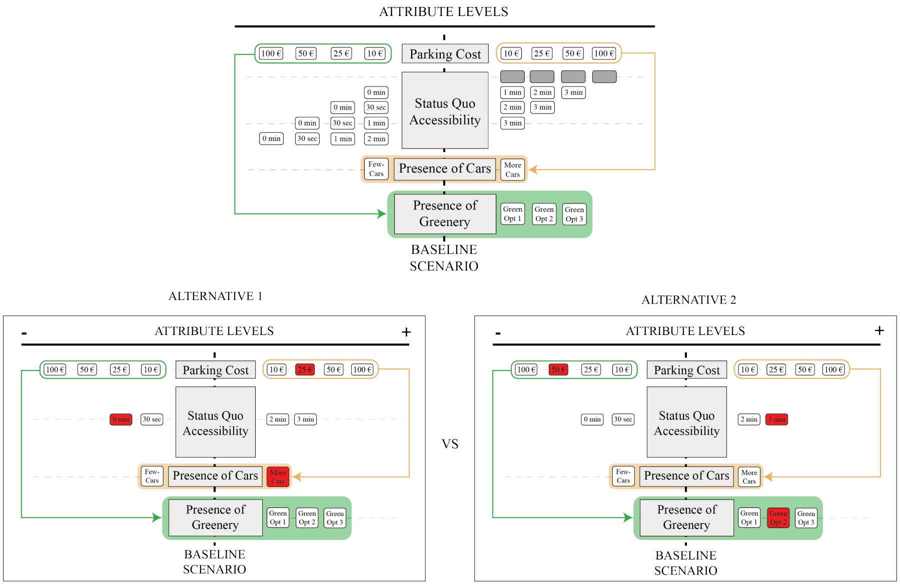


Figure 4.3: Alternative Development: Leg 1

4.4.2. Leg 2

This leg corresponds to respondents who pay some parking cost, and parking their cars in front of the house. It is pertinent to mention that in such context, the trade-off is between parking permit costs reduction, increase in walking time, and greenery. The example for this leg is shown in Figure 4.4. For a respondent who pays something and parks their car in front of house. Either they are provided with option 1, with 10 € reduction in parking cost complemented with increase in greenery and walking time by 1 minute, or 100 € reduction with 2 minute accessibility and other green transformation. The alternatives are developed in such a manner that there is no repetition of same attribute level for any chosen attribute, therefore a trade-off always exists.

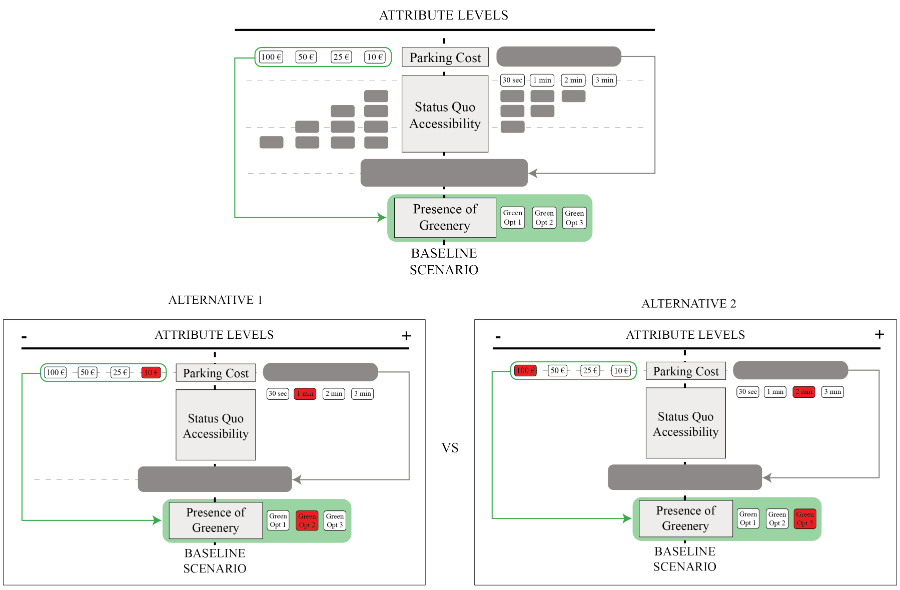


Figure 4.4: Alternative Development: Leg 2

4.4.3. Leg 3

Those respondents for whom the status quo is defined by not paying any parking cost, but have to walk certain distance to access car. The trade-off for them is of car accessibility against their willingness to pay for such access. Therefore the alternatives always have an increase in parking permit price coupled with higher accessibility time than status quo, and image with presence of car. This intuitively indicates how the situation would be if the respondents wants to priorities their car over anything else. As shown in Figure 4.5, with a current walking time of 2 minutes, alternative 1 subjugates an increase in parking cost (25 €) and a walking time reduction of 1 minute and alternative 2, with a hike of 100 € but no walking time.

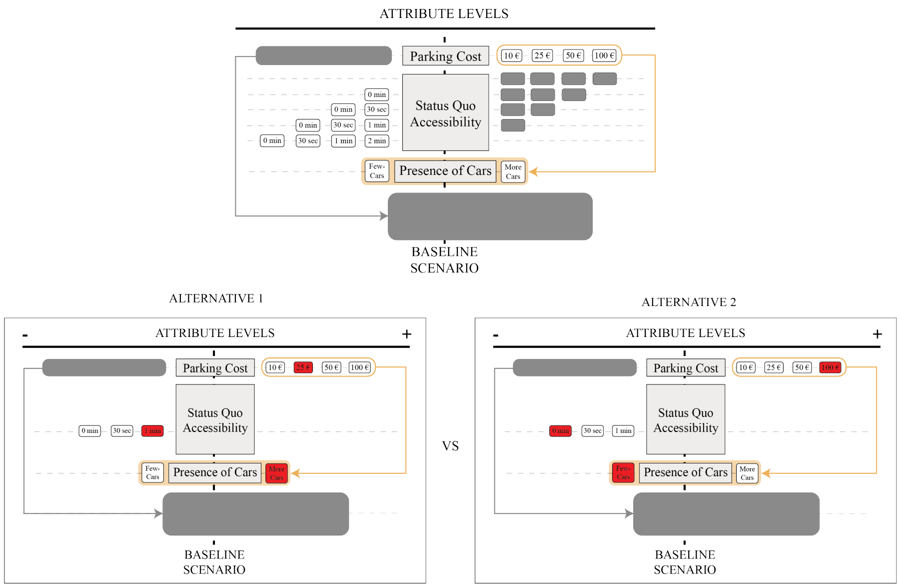


Figure 4.5: Alternative Development: Leg 3

4.4.4. Leg 4

This last leg of survey addresses those respondents who neither pay a parking permit, nor have a walking time. Therefore, the trade-off is only between greenery and accessibility to their cars. It records their willingness to keep their cars away if they get a greener environment in front of their house. Figure 4.6 gives this example where alternative 1, increases the walking time by 3 minutes but in return provides a greener environment. Similar is done with Alternative 2.

These four legs attempt to cater to the logical dynamics of all kinds of respondents and generally understand the variation in trade-offs. Following the guidelines of van Cranenburgh and Garrido-Valenzuela (2023), the study calibrates all the choice tasks such that

1. All the developed alternatives in any leg are different to each other (varied attribute levels), so that there always is a trade-off in the generated choice tasks.
2. All dominant choice tasks are removed since the study relies on strong prior assumptions about the expected signs of the preference parameters for parking cost and walking time.
3. All the choice task where involved alternatives have one or more equal attribute levels are removed, which ensures that every choice situation has a mandatory trade-off involved.

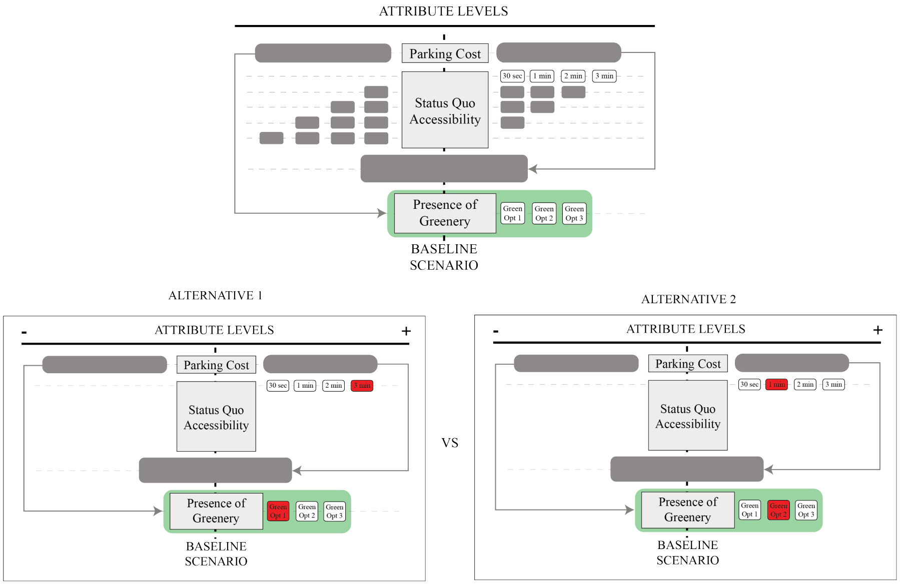


Figure 4.6: Alternative Development: Leg 4

4.5. Survey Design and Implementation

The algorithm takes random images and their transformations into account so that no two choice tasks are the same in any way, and a variation in the preference over a set of images is observed. Based on the information input by the respondents, the algorithm coupes images with proper survey leg.

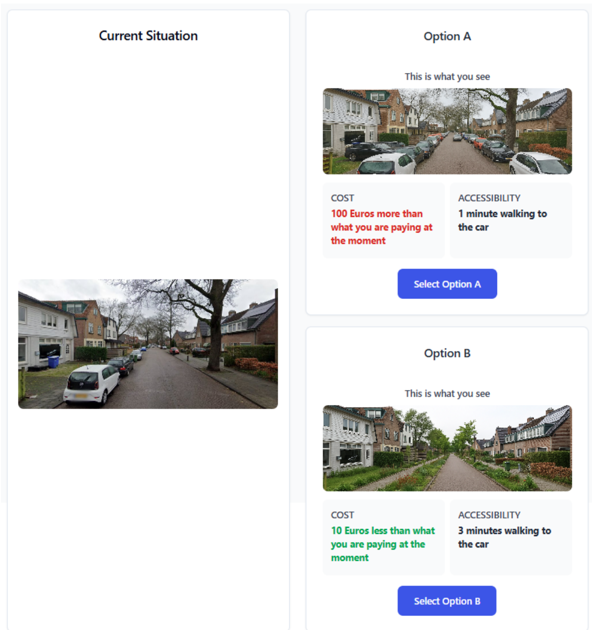


Figure 4.7: Example of a Choice Situation

Every choice task uses a random image and its transformation based on the survey leg. It is ensured that a respondent sees an image and the alternatives only once during the choice tasks. Also the order of choice questions is randomized for every respondent. Moreover, the order of upper/lower alternatives as defined in the underlying design is randomized between and within respondents.

The survey was developed on Lovable (Lovable, 2025) which uses React with TypeScript, Vite, Tailwind CSS and shadcn/ui for the frontend and Supabase, PostgreSQL, Deno with TypeScript as backend.

This survey was developed in a collaboration with Head of IT at Advier, Niels de Vries (de Vries, 2025). The survey is phased in 5 sections.

1. Introduction : Detailing about the survey with potential information for the respondents to begin before the study.
2. Fifteen choice situations: For which participants are required to select their preferred neighborhood transformation.
3. Five Image Rating questions : Observing the previously mentioned perceptions of aesthetics, social safety, traffic safety and peacefulness for already shown images.
4. Mood Impact, Importance rating and Travel Behaviour: Collecting all the information of current travel behaviour, the impact on mood because of different types of images, and significance of images, cost and accessibility in decision making.
5. Socio-Demographic Information : Capturing the basic information about the respondents.

The survey can be seen in Appendix B. The link for the survey is https://image-choice-compass.lovable.app/.

INSIGHTS

To design the stated choice experiment, appropriate attributes are selected. With an objective to answer the research question, through an exhaustive review, 3 attributes are found suitable for the experiment. Walking time to the car from house, the annual parking cost for the car and the residential environment which is illustrated using the images. In accordance with the context, attribute levels are defined. For walking time 5 attributes levels : in front of house, 30 seconds away, 1 minute away, 2 minute away and 3 minute away are found suitable. The attribute levels for parking costs are assigned from -100 €, -50 €, -25 €, -10 €, 10 €, 25 €, 50 €, 100 €. The survey design targets population with different parking cost and walking time situation, therefore to cater to this, 4 different legs of surveys are developed. The respondents were allocated to these legs based on their input to survey questions which ask their status quo condition. These survey legs were logical combinations of images, parking cost and walking time different with respect to their current situation, such that respondents always have a trade-off to be made. Apart from the choice experiment, other socio-demographic and travel behaviour information is also collected.

5 Street Level Imagery Acquisition

For the stated choice model, street-level images are incorporated to illustrate the residential environment and their respective changes. To capture the preference for greenery and accessibility to cars, a street-level image of the residential environment and its surrounding settings is required. Following the method in Garrido-Valenzuela et al. (2023), Google Street View (GSV) are handled with IDs, and then the images are used (Google, 2023). The images are selected based on the suitability for transformation, clarity and variation. Of all angles, the most suitable angle is selected where the image captures the characteristics of the residential neighbourhood.

5.1. Image Collection

Inclusive of the street-level images, the high-density residential regions of the Netherlands are in the scope of the study. To have a specific definition of high population density, different resources are checked yet a spatial translation of high population density is not directly available. Statistics Netherlands (CBS) (2024) defines extremely urbanized as those regions with 2500 or more addresses per square kilometre, but no translation into population per square kilometre is given. By matching the dataset with a 100 * 100 square meter dataset, defined in Centraal Bureau voor de Statistiek (CBS) (2025), those datasets are only taken where the addresses are more than 25 (corresponding with 2500 addresses per km^2) and a range of population per square 100 meter is obtained. The minimum population per 100 square meters ranges from 5 to 1465; therefore, within 1 square kilometre the population ranges from 500 to 146500. The median is found to be 80, therefore 8000 people per square kilometre is taken as the threshold. As illustrated in Figure 5.1, the regions correspond to high-population density areas of the Netherlands, and the images are collected from these particular areas.

To have a uniform representation of all kinds of residential neighbourhoods in the survey analysis, images are initially categorized on the basis of residential neighbourhood data available on "Klimaateffectatlas Kaartviewer" (2025) shown in Figure 5.2. The high-density imagery and residential neighbourhood database are then collated on a geographic information system (GIS) environment (QGIS, 2025). Out of 14 neighbourhoods, two, Villawijk and Bedrijven, are not considered in the data collection. This is due to the lesser presence of residential neighbourhoods in these categorizations. After clipping the database, the image capture year is set for 2022, as this is the year with the latest and most captured images. With the query database, 40 images from each neighbourhood (n = 480) are randomly selected, keeping the clarity, variation, and transformability of the image in mind. The images are in the form of 360º panorama photos, from which four individual 90º photos are configured. Figure 5.3 illustrates an example of the panorama street-level image, which is configured into four individual 90º photos. The selection of the unique image with the highest residential characteristics is done.

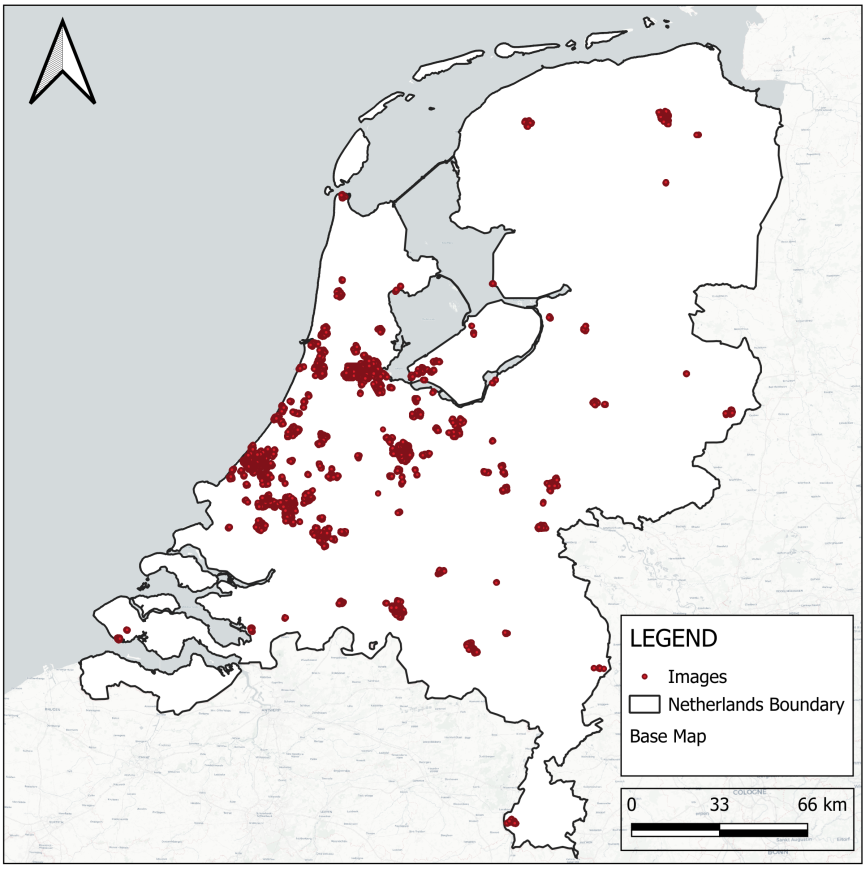


Figure 5.1: Spatial Distribution of Selected Images for the study

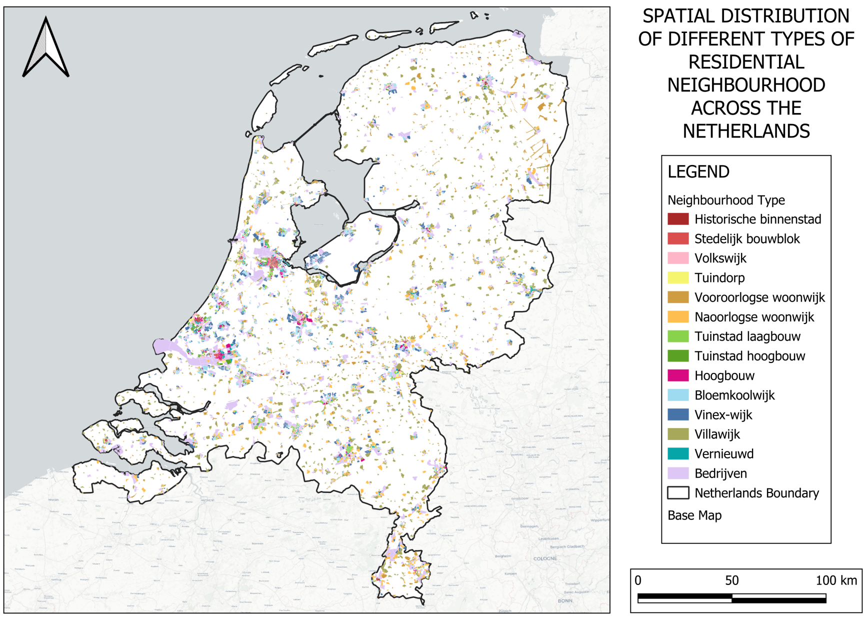


Figure 5.2: Spatial Distribution of Different Types of Residential Neighbourhoods across the Netherlands

Figure 5.3: A 360° panorama view sourced from Google Street View (GSV)

5.2. Image Transformation using Generative Artificial Intelligence (GenAI)

Recent advancement in artificial intelligence has nudged urban planners to incorporate it in several areas, but one prominent field where artificial intelligence is proving its relevance is simulations. Studies till now have employed traditional architectural software such as computer Aided Design (CAD) (Valença et al., 2025) and 3DSMAX (Dongen & Timmermans, 2019) for presenting street design concepts. Studies have used such software for developing simulations and testify people' perceptions (Dongen & Timmermans, 2019; Phillips et al., 2023). However, these programs are effort intensive for creation of intricate layouts and the visualizations cannot be produced within limited amount of time.

Figure 5.4: N8N Work Flow

A lot of platforms have gained prominence for producing real-time visualizations within a stipulated amount of time. This has substantially made it easier for stakeholders and citizens to indulge in design process by allowing them to preview potential street transformations and assert their preferences. While also making the dataset and resources development less time and cost intensive. As the current study requires large amount of imagery dataset for the CV-DCM model, GenAI was employed to develop different transformations which were used in the survey. This is discussed in detailed in Section 4.4

Out of 480 images taken in the database, initial runs observed that there existed some blank images which changed between the phase of data collection and survey testing. To remove these discrepancies, a Python code is developed that removed all blank photos from the original base dataset. After this, the images are subjected to the N8N version 1.99.1 workflow pipeline ("N8N: Workflow Automation Tool", 2025) plugged with the API version of the CHAT GPT-4o (OpenAI, 2025) for development of 5 varied transformations. Every transformation is developed by keeping a variation of the attribute (car presence, greenery, landscaping and trees) in mind (See Table 5.1). The first transformation is modelled to have more cars than the original image, with no greenery and landscaping. The number of trees are same as in the original image. The second transformation has less car than the original image, with all other attribute levels same to transformation 1. For third transformation, a no-car scenario is modelled, with 50% increase in greenery and more presence of trees. Transformation 4 corresponds to a no car scenario, with 50% increase in both greenery and landscaping. The landscaping here refers to benches, small gardens, pergolas, pavilions which adds aesthetic and quality of life to the neighbourhood. With no car presence, and 50% increase in the greenery transformation 5 is illustrated. Only the difference between transformation 4 and 5 is that there is no landscaping and lesser presence of trees. The model is structured to retain the base image as much as possible and only varying these attributes, so that bias does not creep into the model analysis.

Table 5.1: Transformation Information

Transformation	Car Presence	Greenery	Landscaping	Trees
Transformation 1	More	0%	0%	Same
Transformation 2	Less	0%	0%	Same
Transformation 3	0%	50% More	0%	More
Transformation 4	0%	50% More	50% More	More
Transformation 5	0%	50% More	0%	Less

All values are with respect to status quo situation. As the transformations are modelled on the original image, if the original images have trees, then they are also illustrated in transformations.

The workflow process is shown in Figure 5.4. This automated workflow sequentially processes every image by producing transformations, assigning URLs for every image and then storing it against the base image. The Open AI uses a text to image version, where the textual prompts used for the transformation are detailed out in Appendix C. For every image, it roughly took 4 - 5 minutes for transformation, yet some images were not possible to be transformed. The model observed perpetual failure in transforming such images, which is plausible due to logical inconsistencies while creating such images. Therefore such images were dropped out again from the analysis. In the end, the whole database consists of 449 images with their respective 5 transformations that resemble a data retention of 93.54%. Example of original image and their respective transformations is shown in Figure 5.5.

INSIGHTS

To complement the stated choice experiment and construct the survey, a database for imagery is developed. For this, 40 street level images from 12 neighbourhood are selected based on variation and quality. They are specifically taken from high density region in the Netherlands defined with a population density of 8000 or above per square kilometre. With a database of 480 street level images, an automation workflow using N8N is developed for creating 5 transformations based on textual prompts. The considered attribute levels for transformation development are presence of car, greenery, landscaping and presence of trees. This is done to showcase the transition of the status quo residential environment into greener or a car intensive one. A database of 2400 images is planned to be developed and deployed in the survey, but due to discrepancies 2245 images are developed and used.

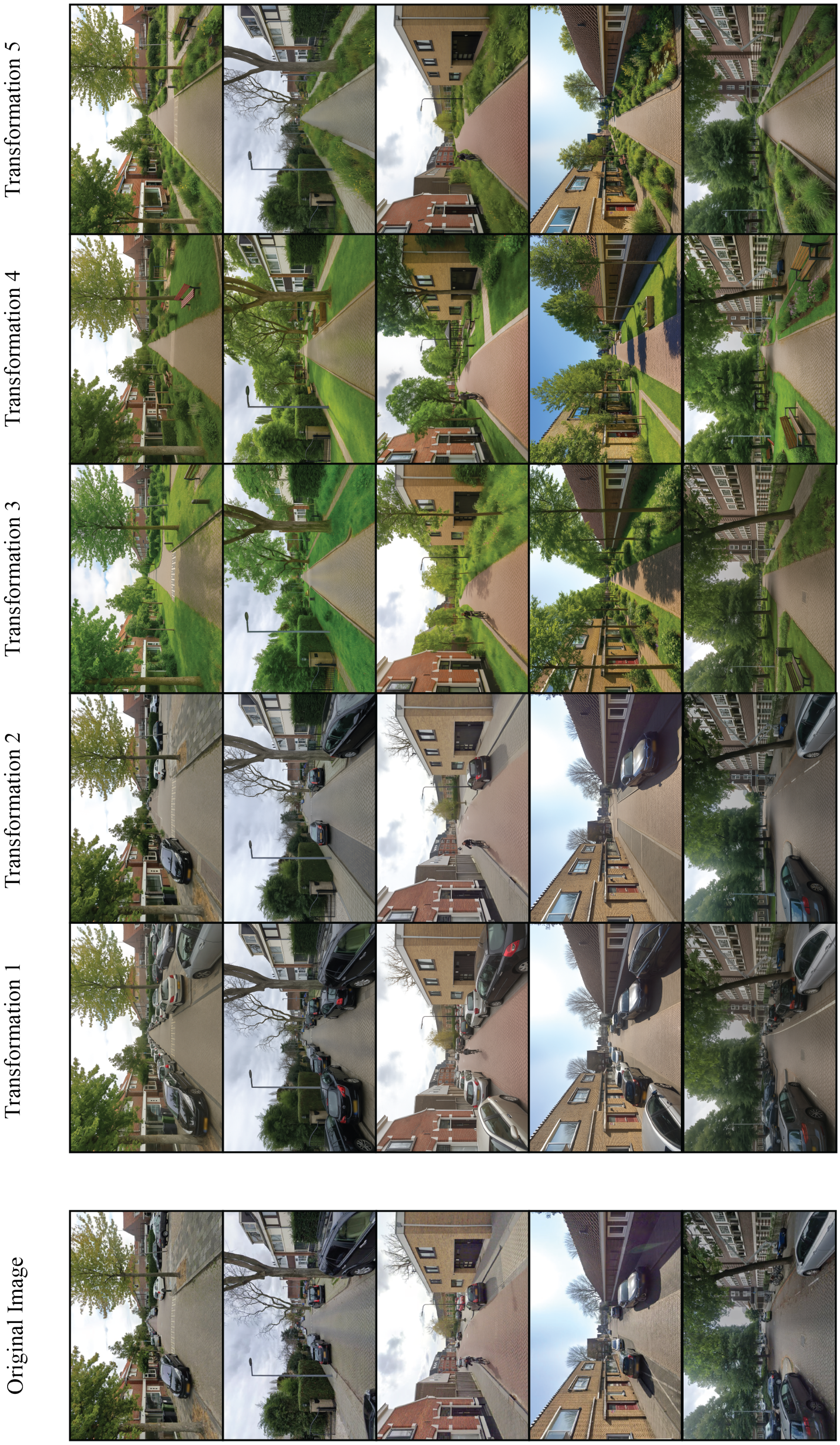


Figure 5.5: Original Images and their Transformations

6

Results of Stated Choice Experiment

This chapter highlights the results of the analysis. Section 6.1 offers a summary of the respondents, highlighting the key attributes of the individuals who participated in the survey. Section 6.2 elaborates the CV-DCM training process. The estimation results for different models are elucidated in Section 6.3. The focus of Section 6.4 is on the results from CV-DCM. The chapter culminates with Section 6.5 emphasizing on the findings of latent class model.

6.1. Descriptive Analysis

In totality, the survey was fully completed by 101 individuals between end of June and beginning of August, 2025. Convenience sampling was used to gather the appropriate dataset where the survey was circulated on different social media platforms like LinkedIn, Reddit, Facebook and also shared among the 1^{st} and 2^{nd} degree acquaintances. Apart from this, the survey was posted on open survey groups like survey swap (Surveyswap, 2025) and survey circle (Surveycircle, 2025) for more response inputs. People who possess a car in their household (by themselves or by the company) are specifically targeted in the survey. Therefore, individuals who do not own or use cars were unable to participate in the survey.

To capture variation in the population and a true reflection of the society, the survey was also uploaded on Dutch research groups and city discussion groups. The socio-demographic data follows categorisation detailed out by CBS (2025). Apart from preference information, the respondents were also required to provide socio-demographic information and insight about their current travel behaviour.

6.1.1. Socio-Demographics

Maximal amount of efforts were made to gather a pan Netherlands dataset, but due to the type of sampling employed, majority of the data captures respondents' information with same age, educational background and other socio-demographic category. Figure 6.1 illustrates the cumulative categorisation of the data. Majority of the respondents were males (67.32%) and 66.33% of all respondents belong to the age range of 20 - 40. A higher proportion of young respondent is due to the fact that the survey was spread in the professional and personal network of the author corresponding to more people in similar age group. This is evidently visible in Figure 6.2 and 6.3. According to the statistics recorded in 2019 (Statistics Netherlands (CBS), 2019), adults ranging from 18 - 40 years have more issued driving license, partly reflecting the dominance of this age range in the survey.

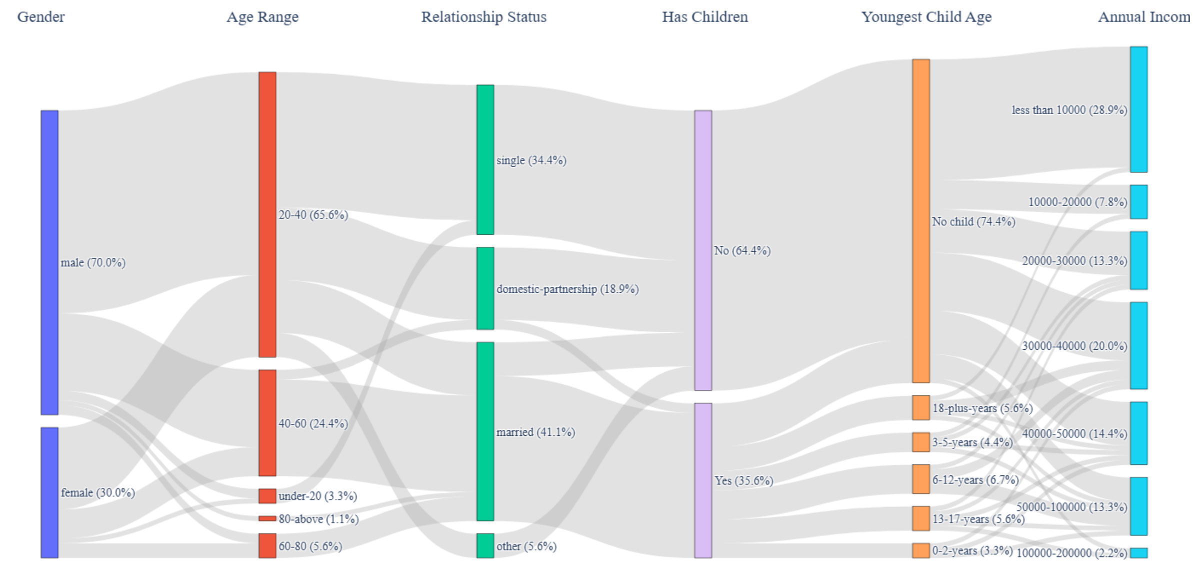


Figure 6.1: Sankey Diagram of Socio-Demographic Data

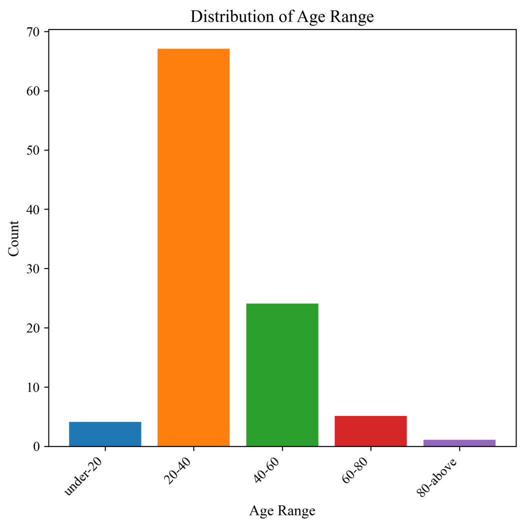


Figure 6.2: Age Range Distribution

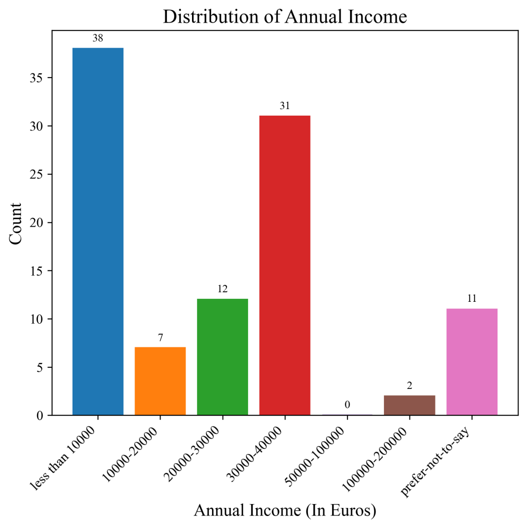


Figure 6.3: Annual Income Distribution

Lifecycle Status

For the decision over preference of car accessibility and green space, it has been evidenced that life cycle status has a very strong influence (Beckers & Boschman, 2019; Kronenberg & Carree, 2010; Y. Yang et al., 2025). A plausible reasoning to this phenomenon is that with changing household size, age and maturity, the needs and priorities of the household also change hand in hand. The dynamics are then reflected in the preferences, which in this case is about the trade-off between greenery and car accessibility.

Numerous life cycle models have been developed since the 1950s and have been extensively utilized in various research studies. Some models like Gilly and Enis (1982), Glick (1955), and Murphy and Staples (1979) have explored the hierarchical stages of households and associated individuals involved in them in a sequential manner. Larouche et al. (2020) and Zhao and Yuan (2023) have talked in detail on the effect of family structure on the contemporary travel behaviour. Taking insights from these seminal studies, this research also incorporates a simple life cycle model, which is categorized in six stages (See Figure 6.6)

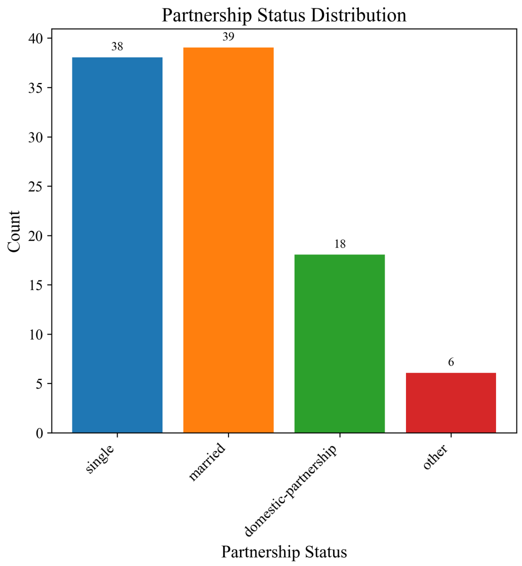


Figure 6.4: Partnership Status

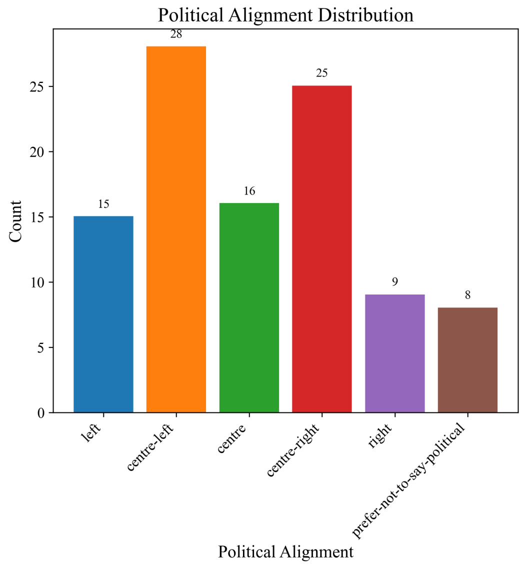


Figure 6.5: Political Alignment

1. Stage 0: This refers to the phase where an individual is single. The phase where an individual is married but currently does not cohabit with partner (divorced or widowed) also lies in this category.
2. Stage 1: The phase where the individuals are married or in a domestic partnership, cohabiting with each other. In laymen terms, they are in their solitary couple phase.
3. Stage 2: This phase corresponds to young parent couple phase with their youngest child in their infancy.
4. Stage 3: It corresponds to the growth stage for couples with youngest child in median phase.
5. Stage 4: The mature stage where youngest child is in the teenage.
6. Stage 5: Old phase for couple, where the youngest child is a mature adult, rendering an empty nest.

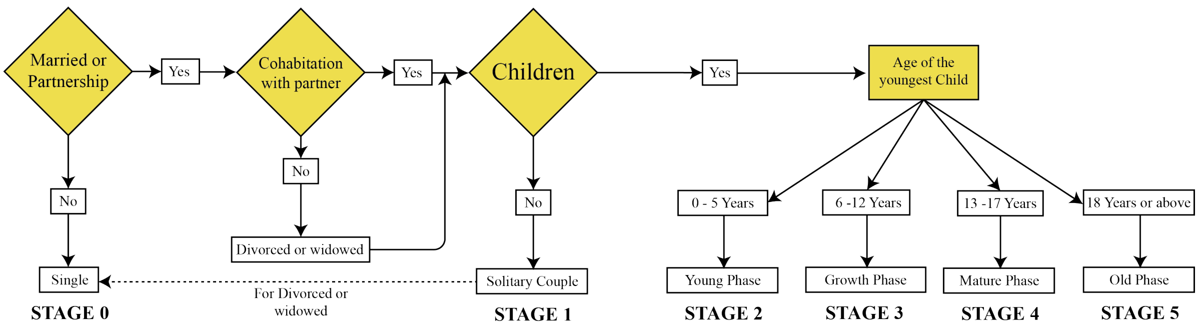


Figure 6.6: Lifecycle Status

This classification helps in understanding the current status of respondents and eventually makes it possible to observe its effects on their preference and choice priorities. There are several logical hypothesis which can put forth such as respondent in their elderlies would find both car parking accessibility and greenery significant in their decision making. Respondents in their solitary couple single phase might not mind keeping their cars at a specific distance. These hypothesis can be proven by considering the lifecycle status into the model.

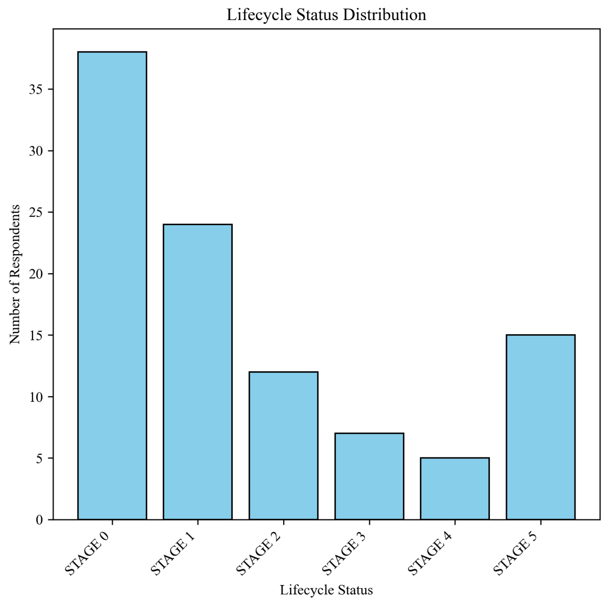


Figure 6.7: Lifecycle Distribution

As illustrated in Figure 6.7, the highest number of respondents belong to Stage 0 of the lifecycle. Many more respondents are found in the Stage 1 and Stage 5 categories, denoting the solitary couple and empty nest phases respectively. The lifecycle status was not asked directly to the respondents but was determined by combining responses to various questions related to partnership status, cohabitation status, number of children in the household, and age of the youngest child (if applicable). This indirect approach ensured a more nuanced classification based on the actual living arrangements of the respondents. Consequently, the resulting distribution provides a comprehensive overview of the diverse household compositions present in the sample.

6.1.2. Travel Behaviour

Apart from the socio-demographics information, the respondents were also asked about their current travel behaviour. It was indicated that cycling/bike was the most important mode of transport followed by car and public transport. Furthermore, a quarter of all respondents use their cars several times a week, where the primary reason for this usage is found to be work/business trips followed by personal reason like meeting friend and social gathering. This also reflect the fact that those respondents who have been given lease car by the company use it for their work purpose.

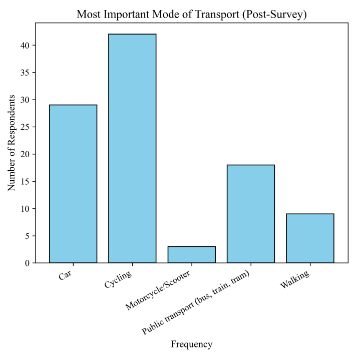


Figure 6.8: Most Important Mode

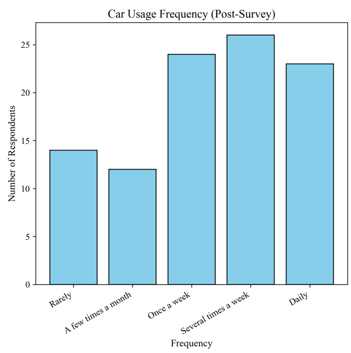


Figure 6.9: Frequency of Car Usage

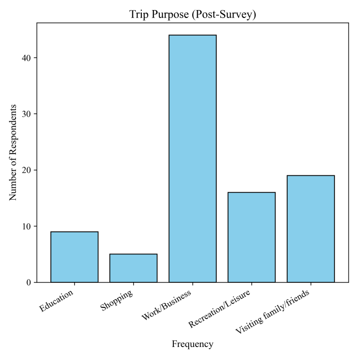


Figure 6.10: Purpose of Trip

Apart from this the respondent also highlighted that although images were useful to decide, they were certainly not able to relate to the choice task sometimes. This was due to the fact that all the images were taken from high-density regions. Therefore those respondents who belonged to other parts of Netherlands like rural areas, could not properly relate. As a result such responses might not fully reflect the characteristics of car driving population in a whole.

6.1.3. Effect on the Mood due to Imagery

The respondents were asked how the presence of greenery and cars in the images influenced their feelings and how they perceived those images. Apart from this they were also asked how strongly neighbourhood planning influenced their perceived quality of life. A reasonable amount of people iterated that the green images somewhat had a positive affect on the mood whereas in similar context, the presence of cars in the images induced a negative feeling in general. This emphasises that respondents were aware and were taking the perceived feelings induced due to the environment in consideration for their decision making process.

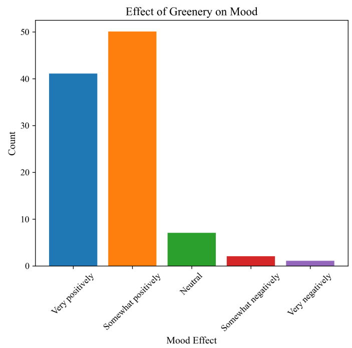


Figure 6.11: Effect of Greenery on Mood

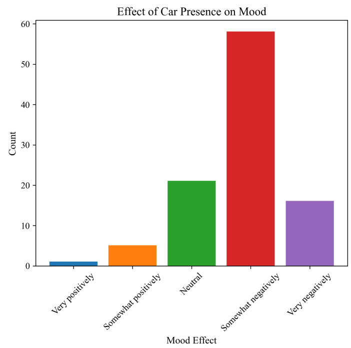


Figure 6.12: Effect of car presence on mood

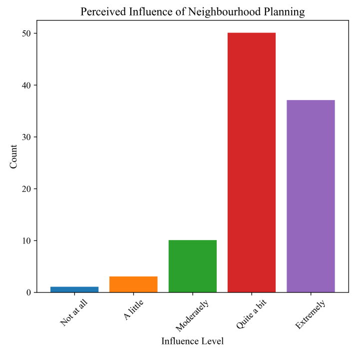


Figure 6.13: Neighbourhood Influence

6.1.4. Self Reported Importance

Respondents were also asked to report their perceived importance for the attributes accessibility, parking cost and images in fixing their preferences. This method is effective in understanding the nexus of prevalent patterns. Figure 6.14, 6.15 and 6.16 illustrate the distribution of self-declared importance of attributes. In general the residential environment is given greater importance than other factors. In a comparative perspective the average of image importance is 8.18, whereas it is found to be 6.91 and 6.82 for walking time and parking costs respectively.

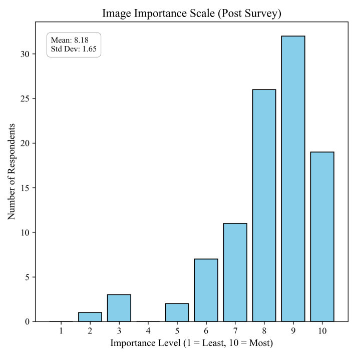


Figure 6.14: Self-declared importance of the image

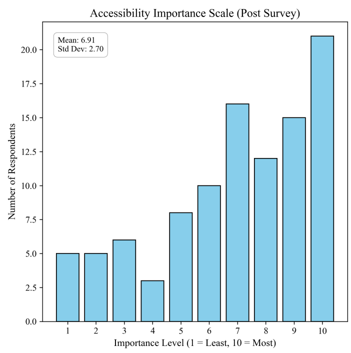


Figure 6.15: Self-declared importance of the walking time

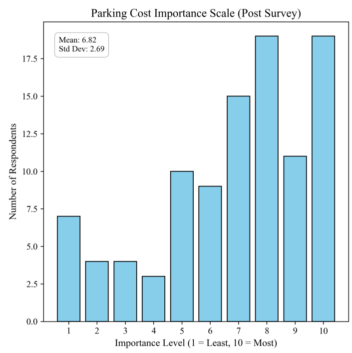


Figure 6.16: Self-declared importance of parking cost

Earlier studies like the one done in van der Waerden et al. (2013) evidenced that people prefer free parking close to their dwellings. However, in this study, a greater number of respondents have iterated a higher importance to residential environment than to both parking cost and walking time.

Correlations to understand the association between different socio-demographic variables and other self declared importance attributes. Figure 6.17 shows the correlation between socio-demographics and self declared importance. Gender is encoded as 1 for male and 0 for female. Income and political alignment are encoded with increasing levels.

A positive correlation between attributed importance to image with age and lifecycle is observant. This applicably highlights that people on the higher side of age spectrum and lifecycle weight environment significantly in their choice. Moreover, the effect of cars presence on mood records a negative correlation for almost all socio-demographic variables and self-declared attributes.

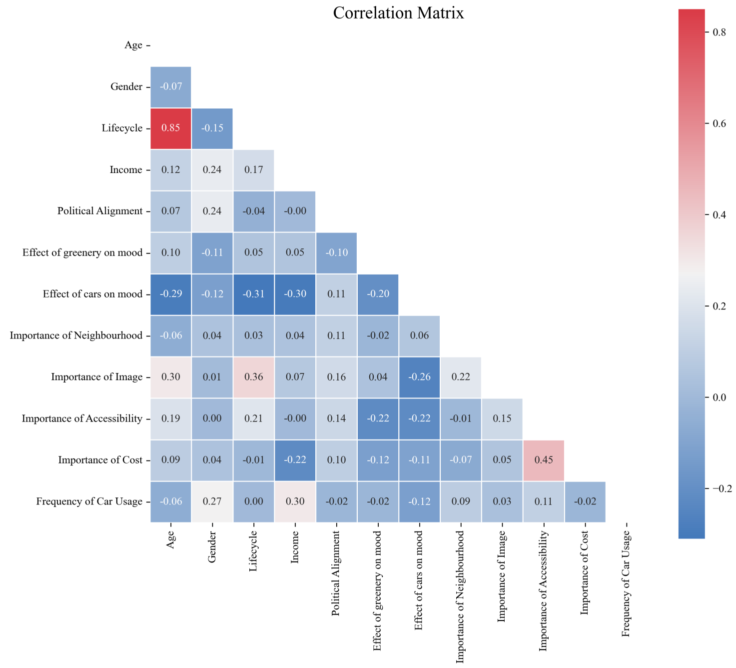


Figure 6.17: Correlation Matrix

This is in line with the current literature strands which suggest people show an aversion to visual clutter caused due to high car presence (Klein et al., 2024; Mulalic et al., 2020). Furthermore, importance of cost records a positive correlation with importance to accessibility, meaning that both the attributes are essential in the choice preference. Although Income records a positive correlation with usage of car, it possess a negative correlation with the importance to cost. This is in resonance to the research which suggest people with high income generally are indifferent to cost attribute (Ostermeijer et al., 2019) but have a higher car usage (Maltha et al., 2017). Furthermore, a peculiar yet important aspect about importance of accessibility is its negative correlation with the effect of greenery on car presence on the mood. This implies that the respondents who prioritize accessibility are indifferent to the effects of environment. For such respondents accessibility is more important that the environment setting.

6.1.5. Distribution of Choice Situation and image induction in the survey

As highlighted in Section 4.4, the choice situation is developed for specific legs of survey, with logical combination of attribute levels and transformation images. The distribution of unique and appropriate numerical choice situations is shown in figure 6.18. Furthermore, Figure 6.19 illustrates the induction of 449 different image and their transformation in the survey. As the images are randomly deployed in the survey by the developed algorithm, the distribution is homogenous. One of the image has been shown more than 16 times, representing the highest frequency.

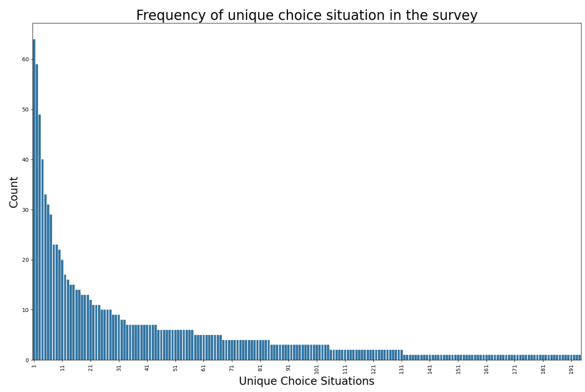


Figure 6.18: Distribution of Unique Choice Situation

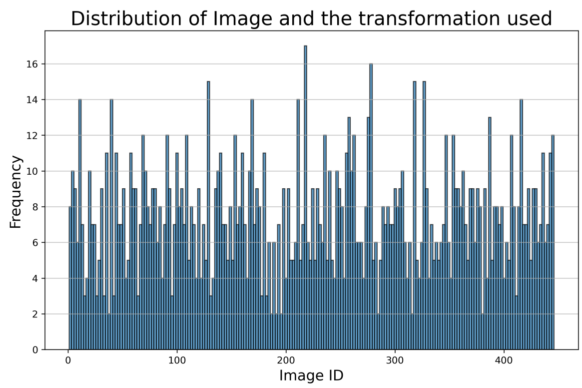


Figure 6.19: Distribution of image induction in the survey

6.2. Employing the CV-DCM

A pre-trained model provided the initialization for the CV-DCM, employing transfer learning to minimize computational resources and training data volume by prioritizing learned visual features. Specifically, the DeiT base model Touvron et al. (2021) was utilised, having already been pre-trained on the extensive ImageNet dataset ImageNet (2024), which contains 1.2 million images. By starting with this well-established foundation, the training process was both more efficient and resulted in strong model performance. The images are now represented by a feature map containing 1,000 values, which captures most of the important visual information needed for training the CV-DCM model. These feature map values are then standardized to follow a normal distribution with a mean of zero and a standard deviation of 0.1.For the study done in van Cranenburgh and Garrido-Valenzuela (2023), the training of CV-DCM followed the above process.

It is pertinent to mention that for current study, pre-trained CV-DCM from van Cranenburgh and Garrido-Valenzuela (2023) was taken. This was done majorly for the following two reasons.

1. The present study leverages GenAI to generate various image transformations using tailored prompts. However, due to certain inherent limitations, not all outputs maintain logical coherence across every generated scenario. Therefore, training the model on defective training dataset not only lets the fault creep into the model, but also leads to inconclusive results.
2. The CV-DCM in van Cranenburgh and Garrido-Valenzuela (2023) is trained on real residential neighbourhood image dataset. As the weights and taste parameters rendered in the model are in resonance to what is required in the study. This can be directly used for extracting the utility values for images.

6.2.1. Cross-Entropy Loss Function

As iterated in Section 6.2, the pre-trained model from van Cranenburgh and Garrido-Valenzuela (2023) is used for analysis. For this pre-trained model, the most suitable beta parameters for the 1000 elements of the feature map are found where the respective cross-entropy loss is minimised. The cross-entropy loss function seeks to minimise the difference between the true and predicted results (Mao et al., 2023), where a lower cross-entropy value signifies better model accuracy. Minimizing this loss is essentially the same as maximizing the log-likelihood (LL), as discussed in Section 3.4. Equation 6.1 shows the cross-entropy loss function, where the second term represents L2 regularization. L2 regularization is used to prevent over fitting by adding a penalty based on the magnitude of the model's weights, with the penalty's strength determined by the parameter γ. This regularization is applied only to the feature extractor weights w, and not to the preference parameters β_k and β_m, since regularizing these could introduce unwanted bias into the model (van Cranenburgh & Garrido-Valenzuela, 2023).

$$w, \beta = \arg\min_{w,\beta}(\underbrace{\frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{J} y_{nj}\log\left(P_{nj} \mid X_{nj}, S_{jn}, \beta\right) +}_{\text{Cross-entropy loss}} \quad \underbrace{\gamma\sum_{r=1}^{R} w_r^2}_{\text{L2 regularisation}} \quad) \tag{6.1}$$

Already established values for w, β from the van Cranenburgh and Garrido-Valenzuela (2023) are directly imputed in the model which provides the utility values as shown in Figure 3.3

6.3. Estimation Results for Different Models

Four models were constructed to predict the residential environment choice. Section 6.3.1 explains the models and the estimates of parameters. Section 6.3.2 navigates through the importance of attributes used.

6.3.1. Estimation of Parameters

Model 1 estimates the likelihood of data using just the information from parking cost and walking time. This model acts as an benchmark to understand the improvement in the models and predict precision of CV-DCM. Model 2 is an extension of Model 1 but it also takes the image type into consideration. For this purpose, the 5 transformations are encoded into 2 set, one for car intensive neighbourhood transformations (Transformation 1 and 2) and two for green neighbourhood transformations (Transformation 3, 4 and 5). This helps in estimating a numerical understanding towards the type of residential neighbourhood environment preferred by respondents. Model 3 estimates the data using predicted utility scores rendered by CV-DCM for each image, where the interaction of age with the utility score is taken into consideration. This emphasises on the varied sensitivity across different age groups. The age grouping is done in accordance with van Cranenburgh and Garrido-Valenzuela (2023) [Young : 18 - 40 years; Middle: 41 - 60 Years and Old: Above 60 years]. This establishes a threshold on how better CV-DCM is able to explain the data over other traditional discrete choice models. Subsequently, Model 4 is estimated by incorporating the CV-DCM scores as well as the interaction of age group with walking time. This is done to understand and therefore find the age specific marginal rate of substitution for environment over walking time. The estimates are elucidated in Table 6.1

Model Equations

$$\text{Model 1}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility for walking time}} + \varepsilon_{in} \tag{6.2}$$

$$\text{Model 2}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility for walking time}} + \underbrace{\beta_{Car\ Green} \cdot (Img)_{in}}_{\text{Utility for type of image}} + \varepsilon_{in} \tag{6.3}$$

$$\text{Model 3}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility from walking time}} + \underbrace{\sum_{age} \beta_s^{age} \cdot S_{in} \cdot age}_{\text{Utility from predicted utility score}} + \varepsilon_{in} \tag{6.4}$$

$$\text{Model 4}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\sum_{age} \beta_{wt}^{age} \cdot wt_{in} \cdot age}_{\text{Utility from walking time}} + \underbrace{\sum_{age} \beta_s^{age} \cdot S_{in} \cdot age}_{\text{Utility from predicted utility score}} + \varepsilon_{in} \tag{6.5}$$

Model 1: Walking Time and Parking Costs

Model 1 only takes walking time and parking costs into account which has a ρ^2 value of 0.121. Although it is within acceptable range but this still can be improved to make the model robust. The value of time (VOT = β_{wt}/β_{pc}) in this context is evaluated to be 26.36 Euros, indicative of the fact that means respondents are willing to pay 26.36 euros extra annually to increase their accessibility by 1 minute.

Model 2: Walking Time, Parking Costs with Image Type

The ρ^2 for this model increased to 0.153, relatively higher than Model 1. Therefore, it can be considered that inclusion of type of image as a numerical attribute is able to estimate the data and the type of residential environment does have a significant influence on the choice behaviour. The observed parameters are consistent with expectations, especially concerning the negative effects of walking time and parking costs. The VOT is found to be 54.80 Euros. Here, the marginal rate of substitution (MRS = $-\beta_s/\beta_{wt}$) essentially represents the trade-off between any two attributes while maintaining the same level of utility. It is found to be 2.230 minutes in context of walking time traded off with type of image, implying that respondents are willing to walk for almost 2 minutes in exchange of greener residential neighbourhood.

Model 3: CV-DCM derived Utility

The estimated ρ^2 value of for Model 3 is found to be 0.164 with a BIC value of 1776.15 which is lower than the earlier models. This supports the argument that CV-DCM can reliably estimate the utility of images. Moreover, the visual characteristics of the residential environment play a notable role in shaping individuals' choice behaviour. A detailed explanation regarding this is done in Section 6.4. The VOT is equivalent to 44.93 Euros whereas the segmentation of predicted utility in accordance with the age provides three unique MRS values. Young respondents are willing to walk for almost a minute for balancing greenery against car presence (unitary increase in predicted image score is equal to

1.039 minutes), but elderlies are more sensitive to the accessibility (0.862 minutes). This aligns with the current literature pool which says that elderlies essentially value a proximity to car as this can be helpful in any situation and reduces social isolation (McFeeters-Krone, 2024).

Model 4: CV-DCM derived Utility with Age interaction

Model 4 predicts the data based on the utility scores, parking cost and interaction of walking time with the age categorisation as done for the predicted utility score. The ρ^2 value is found to be highest among all the models that is 0.178 with the lowest BIC value of 1762.50. The utility score and walking time interaction with age substantially predicts the data, which is in accordance with the expectation as the image score encompasses data about the environment. The segmentation of walking time also allows a precise estimation VOT and MRS. The VOT is found to be 36.52 Euros for young respondents whereas this is higher for the elderlies it is 49.63 Euros. This essentially implies that elderlies are willing to pay almost 13 euros extra for the same accessibility increase, proving their sensitivity and reliance on cars. Similar to Model 3, the MRS value is found to be around 1.2 minutes for young respondents whereas the sensitivity of elderlies is for accessibility shrinks this value to approximately 42 seconds. The estimate for middle-aged people is not found to be statistically significant for both Model 3 and 4.

Table 6.1: Model Comparison and Results

	Model 1			Model 2			Model 3			Model 4		
Model Type	RUM-MNL			RUM-MNL			CV-DCM derived Utility			CV-DCM derived Utility with Age		
Estimation Method	bgw			bgw			bgw			bgw		
Number of Parameters	2			3			5			7		
Set (N = 1515)												
Log-Likelihood	-914.01			-878.68			-869.79			-855.65		
ρ^2	0.121			0.153			0.164			0.178		
BIC	1842.66			1779.31			1776.15			1762.50		
Parameters	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**
β_{wt}	-0.495	0.001	0.00	-0.707	0.060	0.00	-0.650	0.065	0.00			
$\beta_{wt\ young}$										-0.536	0.062	0.00
$\beta_{wt\ middle}$										-1.036	0.100	0.00
$\beta_{wt\ old}$										-0.726	0.153	0.00
β_{pc}	-0.018	0.001	0.00	-0.012	0.001	0.00	-0.014	0.001	0.00	-0.014	0.001	0.00
$\beta_{Car-Green}$				1.584	0.192	0.00						
$\beta_{utility\ Young}$							0.626	0.237	0.00	0.649	0.241	0.00
$\beta_{utility\ Middle}$							-0.152	0.245	0.90	-0.157	0.246	0.94
$\beta_{utility\ Old}$							0.561	0.202	0.00	0.505	0.205	0.01
Value of time	26.36			54.80			44.93					
Young										36.52		
Middle										71.41*		
Old										49.63		
Marginal Rate of Substitution				2.230								
Young							1.039			1.225		
Middle							-0.234*			-0.152*		
Old							0.862			0.701		

**not Significant*

6.3.2. Relative Importance of Attributes

This section analyses the relative importance of walking time, parking cost and environment of the residential neighbourhood. This provides a deeper understanding towards the nexus between these attributes. Maximum utility difference imparted by each attribute over the utility function is evaluated and then they are normalised to relative percentages as presented in Table 6.2. This was performed on all the models. It is pertinent to mention that attribute with higher range would logically have a high utility difference and therefore a high relative importance.

As it can be observed that in Model 2, although the image is considered numerically but the relative importance is relatively less (26%), but in Model 3 which applies CV-DCM, this value increased to 34%. This implies CV-DCM is able to account for the importance respondents give to the environment. Moreover in Model 3 and Model 4 maintain almost same relative importance for all attributes effectively indicating that all the aspect of the stated choice tasks are considered in modelling the taste parameters.

The environment's importance could be overstated since images generally capture more attention than numerical data. This limitation is explored further in the discussion.

Table 6.2: Relative Importance

	Model 1	**Model 2**	**Model 3**	**Model 4**
Model Type	RUM-MNL	RUM-MNL	CV-DCM derived utility	CV-DCM with age
Number of Parameters	2	3	5	7
Relative Importance (%)				
Walking Time	31%	36%	32%	34%
Parking Cost	69%	38%	34%	32%
Environment		26%	34%	34%

6.4. Results of the CV-DCM

This section elaborates ability to precisely predict the utilities for different transformation in residential environment based on the images. Emphasising this stance, the aim of this analysis is to throw light into the preferences and aversion for different types of residential environment for individuals as reflected in the predicted utility scores from CV-DCM.

To discuss this in detail, initially cross-sectional analysis of understanding the baseline image from different neighbourhoods and its derived utility is performed, presented in Section 6.4.1. Subsequently, the predicted utility score analysis with respect to different transformation is done. This is elaborated in Section 6.4.3. Furthering the discussing, in depth analysis about age interaction with the utility score is given in Section 6.4.3

6.4.1. Descriptives of the utility score

CV-DCM is applied to the imagery dataset developed using GenAI consisting 2245 images for 449 original images across different neighbourhoods in the Netherlands. The process used to generate these images is detailed in Chapter 5. Here, a brief summary will is provided. Initially, in accordance with the definition for high density region, images are enlisted. A set of 40 images each from all 12 kinds of neighbourhood is collated to have variation and heterogeneity in the samples. Then, an N8N base workflow plugged with ChatGPT API AI version is used to create 5 transformation for each image. Subsequently, some set of images are removed due to discrepancies in the development. For a detailed explanation regarding CV-DCM, please refer to Chapter 3.5

For all the transformations and base images, predicted utility score is assigned. While the utility score does not have an absolute scale and is therefore limited in stand-alone value, it is useful for highlighting differences in utility between images. Since knowledge regarding the source neighbourhood image is known, it can also be used in analysis for comparing neighbourhoods and analysing the status quo context of the study. Additionally, analysing utility differences alongside the utility values for walking time and parking costs offers insights into the trade-off involved in residential environment selection. Figure 6.20 presents the box plot for predicted image utility score across all the neighbourhood categories.

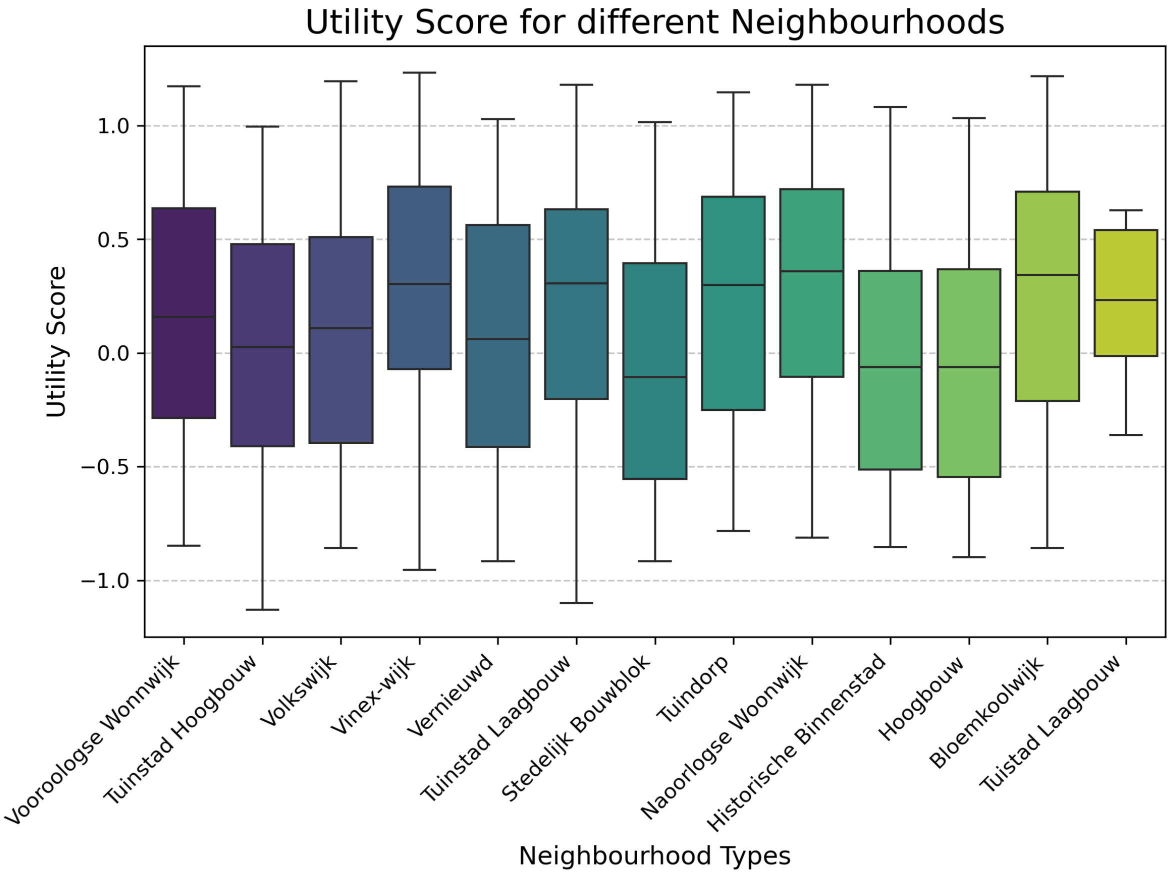


Figure 6.20: Box Plot for Utility Score across different neighbourhoods

It is observed that mean utility score of almost all images across the neighbourhoods are same indicating a same baseline scenario for transformation comparison. Furthermore, Figure 6.21 shows the distribution of predicted image utility score for all kinds of transformation developed in the study and Figure 6.22 illustrates the same but for the images applied in survey. The random deployment of images in the survey maintains a homogeneity.

The utility score for all transformation spans from -1.0 to 1.25, although this model is specific to the Dutch context and might change for any other countries or region. The mean utility score is found to be 0.467. It is pertinent to highlight that a negative utility score does not imply a poor residential environment as the stand-alone value of utility score does not impart much insight.

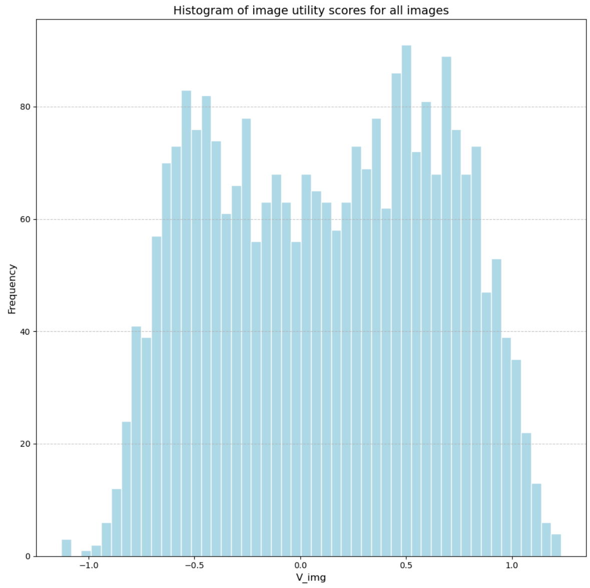


Figure 6.21: Distribution of image utility score of transformations generated

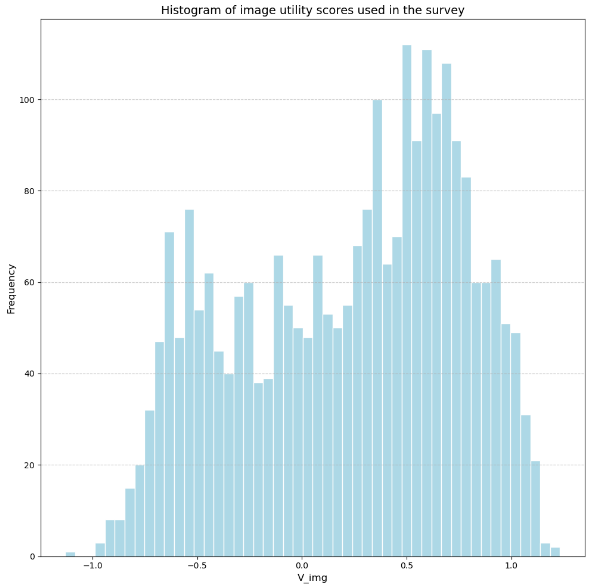


Figure 6.22: Distribution of image utility score of transformations applied in survey

6.4.2. Transformation based analysis of the utility scores

Transformation specific analysis for predicted utility score with respect to age categorisation provide a deeper qualitative insights. With the analysis of rich dataset, it is easier to understand the relationship between environment and utility scores. As observed in Figures 6.23, 6.24, and 6.25, the predicted utility scores for transformations where car presence is either higher (Transformation 1) or lower (Transformation 2) have a negative or a value very close to zero. This indicates that irrespective of lower or higher presence of car, these environment are allocated a lower utility score. There is a slight increase for transformation 2, indicating a sensitivity towards car density captured by the model. This is in resonance with the literature and the hypothesis. Xu et al. (2024) has recorded preference of people to reside in neighbourhood where less frequency of car are used and found, moreover the hypothesis expected a lower utility score for higher car presence.

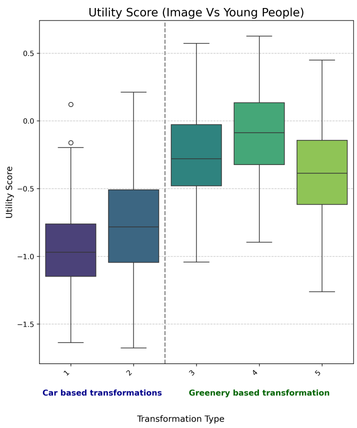


Figure 6.23: Predicted Utility Score of Images for Young Respondents

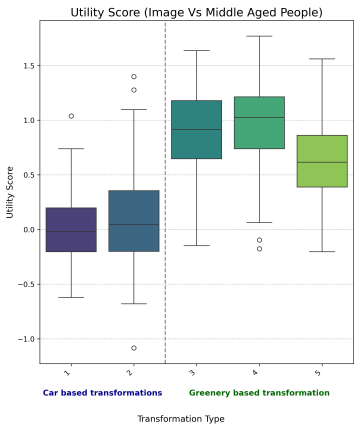


Figure 6.24: Predicted Utility Score of Images for Middle-Aged Respondents

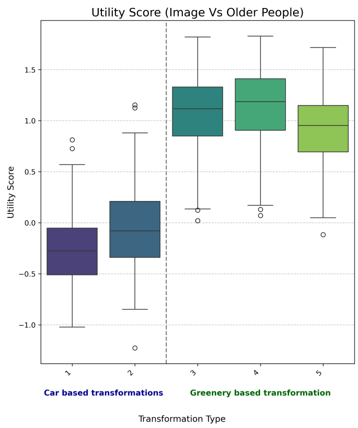


Figure 6.25: Predicted Utility Score of Images for Elderly Respondents

On similar lines it is expected that all transformation associated to greenery will get relatively higher score. Transformation 4 which exhibits residential environment with greenery with landscaping records a highest out of all transformation for all age groups. This is then followed by transformation 3 which corresponds to simple green transition and lastly transformation 5, with no trees. It has been evidenced by Giannico et al. (2021) that individuals with access to green spaces like parks or well-kept communal gardens near their homes tend to experience greater happiness, enhanced mood, and an increased sense of well-being. They directly connect exposure to greenery with improvement in quality of life (Wolch et al., 2014). A similar trend is observed when the difference between predicted utility score for the baseline image and all transformation are recorded. Most of the image transition from the baseline image to transformation 1 and 2 is recorded negative or close to zero utility score, whereas for all green transformation this score is positive. On an average the difference between the lowest and highest utility transformation is recorded to be 1.073 utility points. By applying the parameter for walking time β_{wt} from Table 6.1 which is -0.495, it can be elucidated that according to the model, individuals are willing to walk almost 2 minutes extra to get a residential environment from transformation 1 to transformation 4 (highest relative utility). Also, on average there is an increase in utility score by 0.162 from transformation 1 to 2, which indicates that people are willing to trade-off merely 20 seconds for such change. However, an environment transition from car presence to greenery intensive setting leads to a mean utility increase of around 0.865 utility points which equates to a balance of 1.75 minutes of extra walking time. The transition to other green transformation does not lead to reasonable amount of improvement in the mean utility score. Although, the average utility score for transformation 5 which records greener environment with no trees is least among the green transformations. The difference between the average utility score for this and greener environment with trees (transformation 3) and greener environment with trees and more amenities (transformation 4) is found to be 0.186 and 0.283 respectively. This iterates that individuals are willing to walk extra 22 and 34 seconds for environment with trees and more amenities, respectively. This utility difference is illustrated in Figure 6.26, 6.27 and 6.28

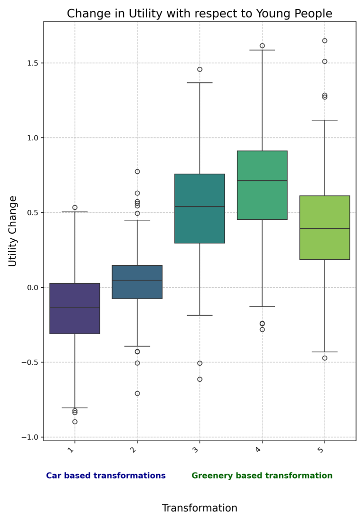


Figure 6.26: Utility Difference with respect to Base Image for Young Respondents

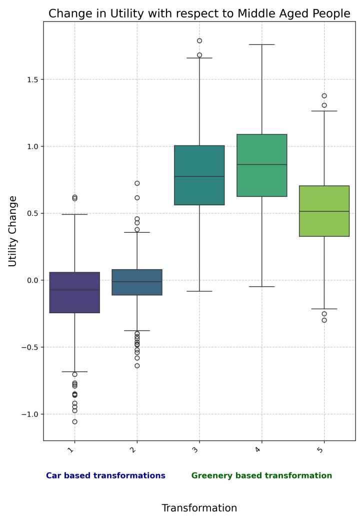


Figure 6.27: Utility Difference with respect to Base Image for Middle-Aged Respondents

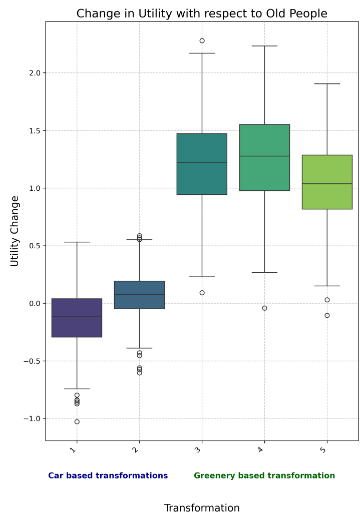
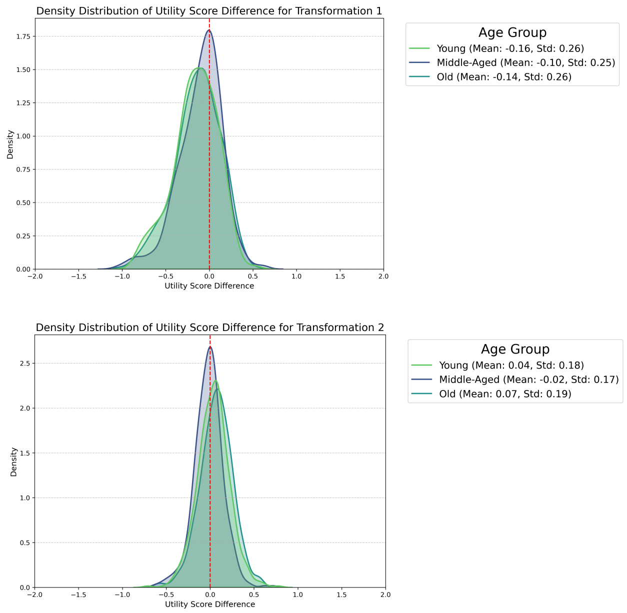


Figure 6.28: Utility Difference with respect to Base Image for Elderly Respondents

6.4.3. Age based analysis of the utility score difference



To have a deeper understanding with respect to the age based distribution of utility score difference for the images, Figure 6.29 illustrates a kernel density distribution. An increase in the utility score measurement recorded between base image and image transformation is a strong indicator towards the how the image is perceived and preferred. As observed in the figure, the impact of these transformations is perceived differently based on age. It could be due to varying needs, preferences and lifestyle requirements. The density plot for transformation 1 is observed to have small yet negative mean values for all age group, indicating that compared to the status quo, car intensive environment are unattractive. For transformation 2 as well, this trend is observed but with 0 mean value for all the age groups. The density plots for transformation 3 record highest mean score difference for elderlies (1.21) followed by middled-aged (0.79) and youngsters (0.53). This indicates a higher attractiveness of environment with greenery over the status quo situation. The same trend is followed for transformation 4 (Mean difference for youngster = 0.69; Mean difference for Middle-Aged = 0.86; Mean difference for Elderlies = 1.27) and transformation 5 (Mean difference for youngster = 0.41; Mean difference for Middle-Aged = 0.52; Mean difference for Elderlies = 1.04). It is therefore evident that the sensitivity towards the transition from a car-based to a greenery intensive environment is very strong, especially for elderlies. The average utility score for elderlies has a substantial improvement by almost 1 utility unit, indicating that elderlies are highly sensitive to the greenification. A more detailed clustering of all kinds of transformation with different utility scores is illustrated from Figure D.1 till D.5 in Annexure D

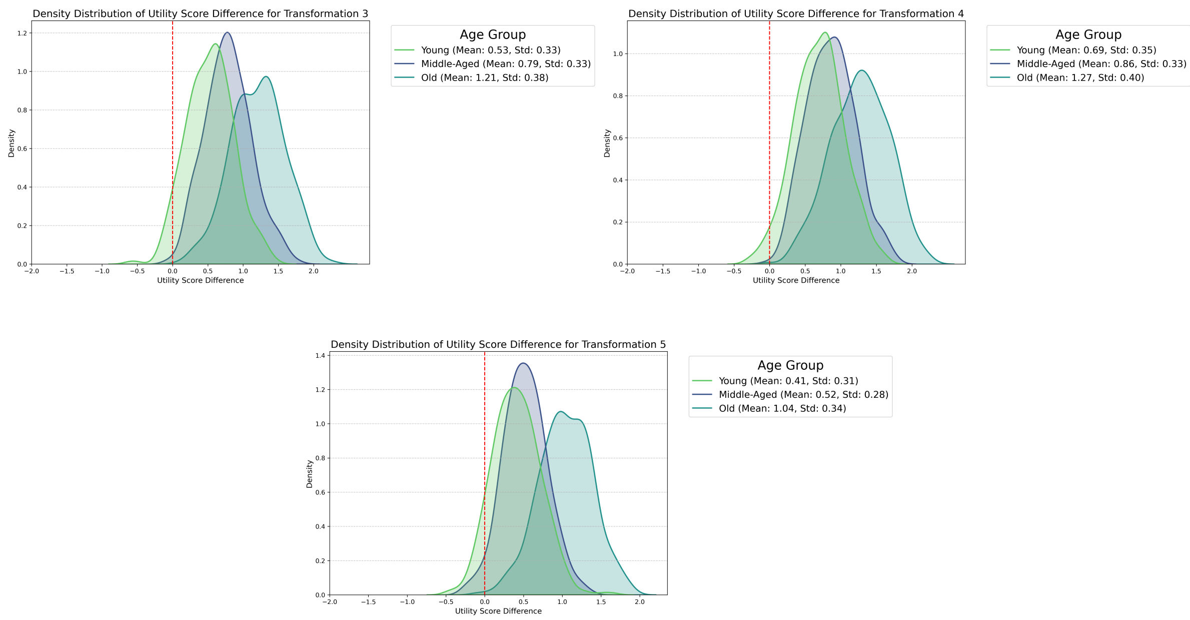


Figure 6.29: Density Plots for different Transformation with respect to Age

6.5. Latent Class Choice Models

The models discussed till now were MNL and CV-DCM, where MNL upholds the assumption of population mean and does not account for heterogeneity in it. The rich insights discussed in the Section 2.1.1 highlight that preferences vary across different demographic groups making it essential to understand and account for such perspectives. Respondents in lower lifecycle stage might prioritise accessibility to the car, whereas on the other hand more exposure to greenery is preferred. To address this heterogeneity, latent class (LC) models were used to identify distinct groups of residential seekers who share similar preferences (Bridget et al., 2020).

The estimation of latent class models involves testing different numbers of classes. Because the likelihood function for latent class choice models may not be globally concave, 5 random starting values are used. The optimal number of classes is determined using the BIC, which accounts for both model fit and simplicity, making it preferable over relying solely on the likelihood. Table 6.3 presents the estimation results. When the BIC was calculated by including the predicted utility score, and numerical encoded value of the images, the evaluation provided too high taste parameters. Therefore it was discarded. A plausible reason behind this might be less sample size which is discussed in detail in Section 7.2.3. Therefore the base model RUM-MNL 1 (See Equation 6.2) was taken into consideration for its effect in the analysis. Out of BIC value evaluation for 3 Latent class model, latent class 2 is found with least value.

Table 6.3: Model Comparison Results of Latent Class Models

Set (N = 1515)	**RUM-MNL 1**	**Latent Class 2**	**Latent Class 3**
Number of Parameters	2	5	8
Log-likelihood	-914.01	-902.11	-898.08
ρ^2	0.121	0.133	0.137
BIC	1842.66	1840.79	1854.67

To identify the effect of income, lifecycle and political alignment on the choice behaviour, they are taken as covariates. Income was not found to be significant covariate (γ_{income} = -0.524, Sig = 0.19). In both the case, it is found that class one nomenclated as ”Efficiency Gainers” are highly sensitive to increase in walking time whereas on the contrary. Tolerant walkers are not affected that much by increase in the walking time. The covariate sensitivity parameter for lifestyle : $\gamma_{lifestyle}$ and political alignment : $\gamma_{political}$ are found to be -0.177 (Sig = 0.00) and -0.270 (Sig = 0.00) respectively. The negative value indicate that an increase in the attribute levels decreases the propensity to belong to class 2. Therefore as people incrementally belong to higher stages of lifecycle and towards a right alignment in the political spectrum. They become more sensitive to the walking time. This trend is also observed with the increase in age where a strong correlation between age and lifecycle is also shown in Figure 6.17. The limitation in such insight is that due to low sample size, the results do not represent an overarching outlook towards Dutch population, which can be catered to later.

Table 6.4: Using Lifecycle and Political Alignment as Covariate in the base MNL model

Number of Parameters	6				6			
Log-Likelihood	-896.42				-895.47			
ρ^2	0.138				0.139			
BIC	1836.72				1834.83			
	Efficiency Gainers		Tolerant Walkers		Efficiency Gainers		Tolerant Walkers	
Parameters	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.
β_{wt}	-3.396	0.00	-0.440	0.00	-4.757	0.00	-0.466	0.00
β_{pc}	0.483	0.00	-0.039	0.00	0.652	0.00	-0.036	0.00
Covariate	Lifecycle				Political			

RESULTS

For model 1, which only explains the data on based on walking time and parking cost, a ρ^2 of 0.121 is recorded, with 26.36 € as VOT. This indicates that for 1 minute increase in accessibility, people are willing to pay 26.36 € extra annually. With model 2, the explainability of the data increases as ρ^2 value is found to be 0.153. In this model, the inclusion of image category as a binary variable is done (Car Intensive = 1 and Greenery based = 2). In this case, the VOT is doubled, where it can be deduced that residents are willing to walk for almost 2 minutes more if their environment is transformed from car intensive one to a greenery based. Using CV-DCM extracted utility scores added to the analysis, the explainability of model towards data increases to ρ^2 = 0.164, with a VOT of 44.93 €. Moreover, the CV-DCM segments utility scores based on age, where it is found that young residents are willing to walk 1.039 minute more for unitary increase in derived utility score from images. For the same value, elderlies are willing to walk just 0.862 minute. Model 4 with the highest ρ^2 value of 0.178 and lowest BIC of 1762.50 predicts the data based on interaction with age for both utility derived from images and walking time. The VOT is found to be 36.52 € for young residents whereas same measure is almost 13 € more for elderlies. This substantially indicates sensitivity for elderlies towards their car accessibility. On the similar lines, the MRS value for young and old residents is found to be 72 and 42 seconds respectively.

From the relative importance analysis, it is found that residential environment is equally important as walking time and parking cost in decision making. It was observed that the utility derived from the image records highest mean value for transformation 4. The utility change from transformation 1 (car intensive setting) to transformation 4 (greenery based setting) is equal to 2 minutes extra walking time. This is in resonance with the results from model 2. For a transition in residential setting from high car presence to a lower car presence, only a trade-off for 20 seconds is observed. This means that residents are willing to walk 20 seconds more for their cars, if they can get a residential setting with lower car presence in return. Even for the different green residential setting the willingness to walk is different. Residents are willing to keep their cars 34 seconds away, if they are getting the residential setting with landscaped amenities over simple green setting with no trees (Transformation 5) in return. This same value is merely 22 seconds for a transition from transformation 5 to 3. From the analysis it is observed that elderlies derive a higher relative utility from greener environment when compared to other age groups.

Further the influence of socio-demographic variables such as income, lifecycle and political alignment is evaluated using latent class choice model. It is observed that with an increase in lifecycle status the sensitivity towards car accessibility increases. Moreover, with a transition of political alignment from left to right, the sensitivity of residents towards walking time increases. This indicates that people towards the higher end of lifecycle prefer to keep their car closer. People with a liberal outlook towards urban development are flexible to keep their cars away, but with a more traditional outlook towards politics, a quicker access to car is highly valued.

7
Conclusion, Discussions and Recommendations

This chapter presents the final findings of the research along with discussion and proposition for future research.

7.1. Conclusion

The conclusion outlines the study's scientific contributions and responds to the research questions.

7.1.1. Scientific Contribution

This study advances the field of integrating image analysis into discrete choice models by applying computer vision techniques. The study utilizes the recently developed CV-DCM model by van Cranenburgh and Garrido-Valenzuela (2023) to investigate preferred residential environment among two likely options, that is high car presence or greenery based. This model enables the prediction of choice behaviour using both quantitative data and visual information. An evidence towards this trade-off not only provides insights on the preference for greener neighbourhoods, but hand in hand provides the sensitivity towards accessibility to car. With these amenities competing against each other, the willingness to walk in return of greener residential setting provides deeper understanding on people's contemporary preferences and therefore gives the opportunity to steer it better with respect to sustainable urban paradigm. Moreover, such evidence adds up to the research on car-free neighbourhood which aims to reduce the dependency on car significantly.

This research is the first to employ and examine images developed through GenAI with a base dataset of 480 distinct street-level images within the stated choice experiment using a logical efficient design. The CV-DCM is able to estimate the residential environment preference successfully, rendering in-depth insights regarding the decision making process for the study context. Compared to the contemporary stated choice experiments, this study provides more realism to the choice process and ability to measure sensitivity towards in future developments.

The study relies and further constructs on the foundational study of van Cranenburgh and Garrido-Valenzuela (2023) with three innovation pillars: the deployment of GenAI for transformation development, structuring of efficient design and an overarching data collection. The development of different transformation using GenAI ensures the variation in the images in accordance with the hypothesis. Effectively, the model is able to establish and predict the variation in residential environment. Moreover, the image analysis and categorisation enabled in formulation of strategic efficient design. This was done manually due to the limitation of not much numerical dataset, therefore careful calibration and iteration was required in the structuring of the experiment. In this manner, the study is able to improve trade-off insights simultaneously by reducing standard errors. The amalgamation of robust survey design with reasonable quantity of generated images proposes a new method in research arena.

The CV-DCM's foundation on a neural network introduces challenges for understanding how it arrives at its decisions. This study in particular tries to address the gap of asset creation especially for stated choice experiments which takes a lot of time on designing software. With the proposition of GenAI, the research proposes and validates both utility of GenAI and CV-DCM for the particular context. Also, the analysis has enabled in understanding the influence of comprehensible attributes on residential environment choice, bringing neural network, classical DCM and GenAI more closer.

The analysis substantiates valuable insights regarding the decisions taken by different individuals under different environment and different cost and accessibility setting. These findings advance scientific understanding while also offering practical value, making this research especially useful for policymakers.

7.1.2. Outcomes for the Research Questions

The study addresses the following primary research question:

"How do individuals trade-off accessibility to car parking against green environment in residential setting preference?"

To answer the main research question, the study explores five sub-questions, each of which adds to the overall response. The conclusions drawn from these sub-questions are as follows:

Q1: *"What are the attributes which affect the preference for a residential location ?"*

Residential location choice is influenced by attributes operating at three main scales: macroscopic, mesoscopic, and microscopic. At the macroscopic level, city or region-wide characteristics shape decisions, such as accessibility to amenities, job opportunities, transportation, and the presence of social networks and lifestyle preferences. Key considerations include proximity to transit, schools, healthcare, recreational spaces, and overall costs like commuting time and expenses. The mesoscopic scale focuses on neighbourhood attributes, including land use mix, built density, safety, and aesthetics, which significantly affect location preference. Finally, the microscopic scale centres on individual or household-level factors, such as specific housing amenities (e.g., size, building age), environmental features like greenery, and direct housing costs and taxes. According to the literature, each scale plays a distinct role in shaping where people prefer to live, with evidence showing that both broader urban context and finer household characteristics are integral to residential location decisions.

Q2: *What trade-off do individuals make regarding attributes of residential setting?*

A comprehensive review of existing literature was carried out to determine the most relevant factors, their dimensions and scales. In scope of this study, parking cost, walking time and residential environment are found to be the significant factors. To gain a deeper insight into these factors, the influence of these three factors on residential location choice was assessed. As a part of the survey, the importance of each attribute while decision making was asked to be rated on the scale of 1 to 10. It was found out that residential environment was considered the most important with a rating of 8.18, whereas for walking time and parking cost it is found to be 6.91 and 6.82 respectively. Furthermore, through the analysis it is found out that people are highly sensitive to walking time, compared to parking cost. This insights are in resonance with the studies done earlier regarding parking accessibility and cost.

Q3: *How well CV-DCM is able to explain individuals' decision-making behaviour with respect to residential setting preference?*

The previous research question revealed the importance of residential environment for choosing a specific option. CV-DCM was employed for this purpose, where the explained variance of CV-DCM based model records high ρ^2 value of 0.178 with the lowest BIC value of 1762.50. Therefore, it is clear that CV-DCM is able to capture characteristics embedded in the images and explain the preference towards a residential setting.

Q4: *How do individuals belonging to socio-demographic group such as different age segments, life-cycle status, income and political alignment prioritise these attributes when making their decision for residential setting suitability?*

From the analysis it is found that the value of time (VOT) for young residents are willing to pay 36.52 € for increase in accessibility by 1 minute for their cars, where the same measurement is almost 13 € higher for elderlies. For middle-aged residents, this was not found statistically significant. Furthermore, the marginal rate of substitution (MRS) value is found to be 72 seconds for young residents and 42 seconds for elderlies. This is in resonance with the above aspect that even if there is a transition from car-intensive residential setting to a greenery based one, residents show a reluctance to replace their car accessibility with greenery, and this sensitivity increases with age.

Analysis on image based utility suggests that elderlies derive a higher relative utility from greenery when compared to other age groups. Moreover, residents are willing to walk 20 seconds more for a replacement of high car presence residential environment to a lower one. This value is found to be 34 seconds when the transition is from green environment with no trees to a landscaped one and 22 seconds from green environment with no trees to normal green setting (transformation 3).

A latent class choice model was applied to identify influence of lifecycle, income and political alignment of different groups. Income as a covariate was not found significant. It was observed that residents belonging to higher spectrum of lifecycle attach higher importance to the accessibility, which is in line with the age based analysis discussed above. This is also observed for political alignment. The further an individual's political alignment moves to the right, the greater their sensitivity to issues of car accessibility tends to be. This indicates that people with a liberal outlook towards politics have greater flexibility towards keeping their cars away than vice versa.

With all sub-questions addressed, we can now answer the main research question: ”How do individuals trade-off accessibility to car parking against green environment in residential setting preference?”. This research has underlined that residential environment has an equivalent influence on the choice behaviour in comparison to walking time and parking cost. Residents prefer greener residential environment over those saturated with car presence, although they are reluctant to trade accessible parking space for a greener environment. This sensitivity increases with age signifying that young residents are quite flexible in their preference, but elderlies attach a high value to accessibility.

7.2. Discussion

The aim of this study was to investigate the residential environment preferences of different groups. This study bridges multiple gaps in the research pool. It is one of the first studies which employs generative artificial intelligence in urban development research. The study adopts an efficient design that integrates visual imagery with numerical attributes within the stated choice experiment. It also provides evidence of the trade-off between different residential setting and the balance of attributes across different age groups. Following comprehensive research, these objectives were addressed in the conclusion. The pathway to these findings involved certain assumptions, methodologies, and estimations that merit further examination. This section provides a critical discussion of these uncertainties and the findings presented in the report.

7.2.1. Limitations of the Stated Choice Experiment

The results of this study show that the quality of the residential neighbourhood environment apart from all other factors plays a crucial role. Past studies have put an emphasis on the influence of walking time and parking cost as a key driving factor of such decisions. However, this research indicates that environment is valued equally important with respect to parking cost and walking time. The significance of the environment could also be linked to how the information was presented to participants. While the environment was shown using images, walking time and parking cost were conveyed as numerical values. Studies have shown that visual images attract attention more effectively than numerical information (Dikgang, 2022; van Cranenburgh & Garrido-Valenzuela, 2023). This shift of attention from numerical attributes to imagery attributes might lead to a cognitive bias, where the significance of environment is overestimated. However, this is not necessarily reflected in the actual behaviour of respondents.

The aspect of cruising for parking which has been discussed in detail in van Ommeren et al. (2012) is not considered as a dominant factor influencing the decisions of respondents. Including cruising time for parking would have introduced a third numerical attribute, making the study more complex and potentially overwhelming for respondents. Although, the impact of parking costs might be underestimated as factors like extra fuel consumption, lost value of time in cruising are not directly considered.

One limitation of stated choice experiments is that individuals' stated preferences may differ from their real preferences (Hensher, 2010). Respondents might either overstate or understate certain preferences. For example, since respondents are not actually expected to walk in the presented alternatives, they might underestimate walking time. Using a combination of revealed and stated preference data can offer a more complete insight into decision-making and help confirm the results of stated choice experiments.

7.2.2. Limitations of the Street-Level Image Collection

During the collection of images, although the scrutinized images were taken into account yet, due to the changing database of Google imagery, some images of the neighbourhoods were found blank. Therefore such images were required to be removed from the survey database in totality.

The latest database of images was found to be recorded in year 2022 from which all the images are sourced. Also, the varying image quality, weather, lighting conditions were not accounted for in analysis. Although, these factors are very significant in decision making, but as the analysis used two transformations, both from the base image, it was assumed that these effects did not affect the choices (as both the choice had the same weather or lighting effects).

The study also overlooks how the neighbourhood environment changes across seasons. As a result, seasonal differences such as variations in greenery or street activity, are not considered in the analysis.

7.2.3. Limitations in Data Collection

Although efforts were made to collate samples which represents a population reflection pan Netherlands, yet due to the collective nature of sampling, this was not possible. As it is visible in the the collection dataset, most of the respondents belonged to the same age category as the researcher. Future research could also include residents who intend to purchase cars, examining their preferences in detail. This would provide insights into potential future car owners as a distinct group and analysing their choices could reveal trends different from current car owners.

7.2.4. Limitations of the Generative Artificial Intelligence (GenAI)

The development of transformations from the base images employs text-to-image propmt - based generative artificial intelligence as discussed in Section 5.2. Although, this exhibited a higher accuracy levels for developing the alternative images, there are limitations to what input is given and what output is received at the drawing end. This limitation was attempted to be improved by language iteration and upgradation to be very specific and precise yet, some generated images are not correct. The respondents were instructed to ignore the logical inconsistencies in the shown image and provide choice based on overall outlook of the option. Therefore, there is a plausible presence of minor systematic error in the data. The future research can cater to this gap by retaining the logically consistent images and training the CV-DCM on the rectified dataset. The benefit of such analysis would be stronger data explainability with no systematic error creeping in the results.

7.2.5. Limitations of the CV-DCM

The CV-DCM measurement are not straightforward to understand via parameters. Contrary to standardized discrete choice models, which offers a direct and measurable information through their parameters, the CV-DCM depends solely on the images' translation using deep neural network. Therefore reducing the comprehensibility of such analysis to the direct decision makers in development bodies who entail a simplistic and understandable results to reinforce their decisions. Although the model perform better in estimating the data with a ρ^2 of 0.178.

7.3. Recommendations

Building on this research, there are multiple areas that warrant deeper investigation to enhance our understanding of both the CV-DCM and residential environments. The following section outlines these potential avenues for further study.

7.3.1. Analysing Perceptions

The survey gathered respondents' views on various aspects of the neighbourhood's image, such as aesthetics, traffic safety, social safety, and peacefulness. Analysing whether and how these perceptions impact the choice of residential environment would be insightful. Additionally, identifying which specific features of a residential area are most critical for promoting traffic and social safety would be advantageous. For example, it is reasonable to suggest that vibrant neighbourhoods with limited parking and greater walkability can enhance both social and traffic safety.

7.3.2. Usage of Calibrated Images

As discussed earlier, the usage of images generated via artificial intelligence possess some logical inconsistencies and discrepancies. It would be beneficial in future studies to calibrate the images ensuring a high precision, and interpretability of the data, as this can be considered as a intrinsic error of the GenAI model.

7.3.3. Analysing Revealed Preferences

This study utilized a stated choice experiment. To determine whether residents value environmental factors similarly in real-life situations, it would be useful to compare these findings with revealed preference data. One approach could involve analyzing current real estate prices and hedonic costs, both for renting and purchasing as these reflect actual choices and preferences. By investigating how people select their residential locations based on revealed preferences, it would be possible to assess the factors influencing their decisions. This approach can help determine whether elements like greenery, the presence of cars, and other neighbourhood amenities genuinely play a significant role in their choices. Additionally, the model could be expanded to identify optimal locations by linking different segments and tracking individual choices predicted by the model, allowing for a comparison with actual residential selection data.

7.3.4. Explainable Artificial Intelligence

Investigating the application of machine learning models to examine the factors affecting residential environment scores could be highly beneficial. Methods like semantic segmentation and panoptic segmentation anything model (PSAM) can shed light on which specific attributes such as type of residential environment, presence of other amenities have influence on the scores. Further exploration of this approach could assist in identifying precise interventions to steer residential development which can render low scores.

The field of computer vision offers significant potential for further research and practical applications. For instance, in her master's thesis Yan (2024) utilized a semantic CV-DCM approach to investigate how micro-scale built environment (BE) features influence residential location choice. The semantic computer vision model employed a panoptic segmentation model that combines both instance and semantic segmentation, allowing for more precise quantification of features. The findings reveal how specific micro-scale BE characteristics impact RLC, offering valuable guidance for urban planners. Therefore, by integrating the panoptic segmentation model with CV-DCM could enhance the comprehensibility, allowing for greater insight into how particular elements within an image influence the score, instead of depending only on the raw data.

7.3.5. Heterogeneity

In the process to capture the heterogeneity, a latent class model was developed that included predicted residential environment score, but the but the effects of image attributes on various demographic groups were not examined. Different groups may have different sensitivities to aspects such as greenery or car presence. Incorporating covariates like income into the CV-DCM training process could provide deeper insights. For instance, it would be worthwhile to explore whether the predicted utility score for a particular image varies between income groups. It is possible that individuals with high income might be highly sensitised to car accessibility and have high VOT, while residents with lower incomes are still indifferent to car presence.

7.3.6. Virtual Reality in Choice Modelling

Most existing research in choice modelling relies on text-based numerical attributes. The introduction of CV-DCM paves a step forward by being the first to integrate images directly into the choice experiments, imparting more realism in choice modelling. With respect to residential environment, exploring virtual reality could further immerse participants, enabling them to experience the setting. Incorporation of olfactory and auditory factors into this experience would help paint a clear picture of the whole experience. This methodology allows participants to make decisions in environments that closely mimic real-world conditions, providing richer insights into how features such as traffic noise, contemporary setting shapes preferences. As of now, no existing choice models are known to combine virtual reality with choice experiments.

7.3.7. Relevance in Other Countries

This research can be reproduced in other countries with the notion that prerequisite data is available and accessible. It is essential to procure street - level images for this purpose, where Google maintains an extensive collection of Street View images across many countries. However concerning the usage right and copyright, utilising Google Street View images bring some challenges (Garrido-Valenzuela et al., 2023). National University of Singapore maintains an open database of 10 million street view images from 688 cities across the globe (Hou et al., 2024). Moreover many open source database such as Mapillary (Mapillary, 2025) and Kartaview (Kartaview, 2025) can be used for such research.

To evaluate the residential priorities it is essential to train the model for different countries as there exists substantial variation in the typology of housing specific to the research base. A new CV-DCM model might need to be trained using the methodology adopted in this study. However, integrating thousands of images into a survey remains difficult with the current survey platforms. For the current study lovable.dev (Lovable, 2025) application was used. However, this may pose a challenge as it entails programming expertise to design the survey logics.

7.3.8. CV-DCM for other research

Using images in stated choice experiments can enhance the prediction of choice behaviour in fields where text descriptions alone are inadequate. While this paragraph highlights two specific areas, the potential applications clearly extend to many other domains.

One area of research with high utility for CV-DCM is understanding safety as a attribute influencing walking route choices. Safety intrinsically is an attribute which can be perceived and visual cues are essential in reinforcing the stance. By integrating images of different routes with different characteristics at different time of the day, research can shed light on individuals choice of route, preferences and priorities to navigate the situation. This can substantiate ongoing research on urban safety and gendered research towards urban dynamics.

Limiting to the field of residential location choice, future research can be furthered into how visible indicators of safety or disorder (e.g., graffiti, lighting, visible security measures) in images impact willingness to choose a location. Moreover, the nexus between safety and actual crime rates can also be investigated.

7.4. Useful Policy Insights

A key objective of this research was to provide the decision makers with guidance on effective strategies for creating better residential neighbourhoods. Therefore, this section highlights how the findings can offer valuable policy recommendations for the company and decision makers in general. The crux of the research suggests for designing car-free neighbourhoods equipped with accessible parking not more than 1 minutes away, as the willingness to walk has been found 1.2 minutes in the results. It has been found in literature pool that increase in walking time towards car substantially decreases the propensity to use it (Núñez et al., 2024; Panter et al., 2013). This research puts forth a threshold for plausible walking time which decision makers can keep in mind and design residential areas in alignment to the travel behaviour objectives. Research shows that people initially show reluctance to car-free interventions but in the longer run their acceptance for such paradigm increases (Marcheschi et al., 2022). This can align with the policy perspective to nudge the sustainable travel behaviour.

7.4.1. Measuring Residential Priorities

As mentioned in the introduction, traditional approaches to assessing residential priorities typically rely on surveys and interviews. These techniques have notable limitations as they are often time - intensive, expensive, and capture only a narrow viewpoint, representing the opinions of a limited sample. Accurately understanding how individuals balance these trade - offs in residential location choice has been challenging. The CV-DCM model addresses these issues by offering a more practical and scalable quantitative approach that also incorporates visual preferences into the analysis. Although greener environments are preferred over those saturated with cars, yet accessibility to parking is reasonably preferred.

7.4.2. Evaluating Infrastructure Location Suitability

As per the studies conducted on residential location choice, no analysis has focused on this trade-off in residential amenities and associated preference. This model bring a quantitative and systematic approach to the table rendering a significant perspective for improvement.

This also provides a substantial evidence into people's preference for greenery or car accessibility and its affect on their choices. These insights can be effectively translated. This information can be turned into monetary values using value-of-time calculations, which helps compare the costs and benefits of locating a parking zones for residential complexes. These insights are useful for improving infrastructure and making future decisions.

7.4.3. Relative Importance of Attributes

Currently, residential neighbourhood suitability estimates the effects of all the attributes discussed in detail in Section 2.1. This body of research was further extended by van Cranenburgh and Garrido-Valenzuela (2023) by considering the importance of environment in decision making. Therefore, integrating best neighbourhood environment into the RLC choice models would improve their accuracy and realism.

It is advisable to evaluate this model against actual RLC data, as discrepancies may exist between what individuals claim to prefer and their real-world choices. If the model is validated, integrating the ideal residential environment into advanced RLC frameworks could lead to more accurate and practical predictions.

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A

Pilot Survey Design

Drawing on the attributes identified from the literature and insights from van Cranenburgh and Garrido-Valenzuela (2023), multiple versions of the survey are developed. To identify the optimal design, 4 sample choice tasks are developed based on the captured images, their transformation and associated numerical attributes. The base images are extracted randomly for the high-density region database and are combined with their transformation.

The survey designs are shown in Figure A.1, A.2, A.3 and A.4. All survey choice tasks reflect the realism of residential location choice decisions and contain cost and accessibility as numerical attributes. The surveys were piloted with experts from the company, and subsequently reviewed by my supervisors at TU Delft. Based on this process, several conclusions were drawn and documented in the report.

Figure A.1: Type 1

ORIGINAL IMAGE

TRANSFORMATION 1

COST: 50 Euros more than the current price
ACCESSIBILITY: 30 seconds more than the current time

☐

TRANSFORMATION 2

COST: 20 Euros more than the current price
ACCESSIBILITY: 3 minutes more than the current time

☐

Figure A.2: Type 2

ORIGINAL IMAGE

TRANSFORMATION 1	**TRANSFORMATION 2**
	
COST: 40 euros less than what you pay now per month	**COST:** 50 euros more than what you pay now per month
ACCESSIBILITY: 4 minutes' walk from the house	**ACCESSIBILITY:** 30 Seconds walking from the house
☐	☐

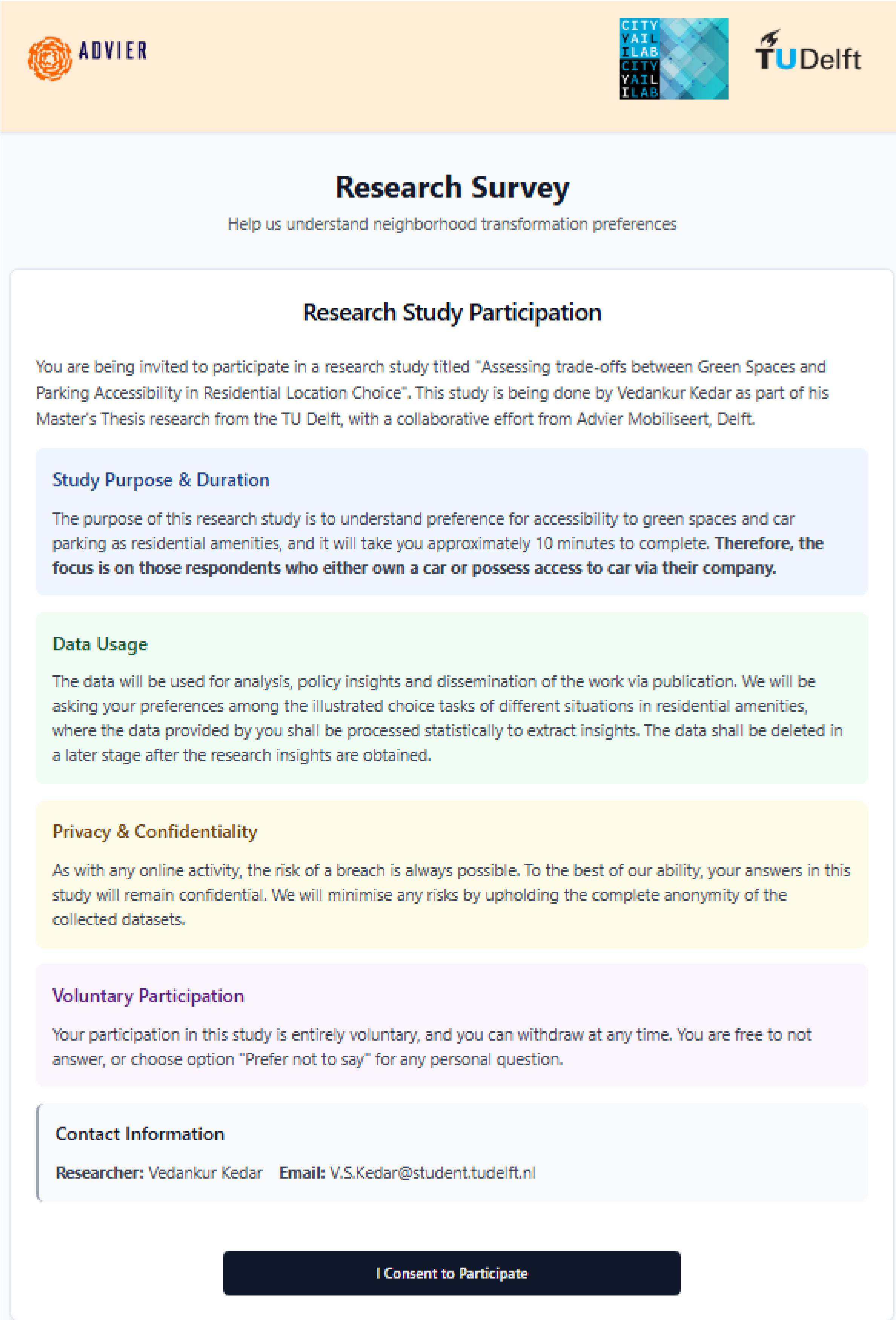
Figure A.3: Type 3

<table>
<tr><td>TRANSFORMATION 1</td><td></td><td rowspan="3">☐</td></tr>
<tr><td colspan="2">COST: 20 euros more than what you pay now</td></tr>
<tr><td colspan="2">ACCESSIBILITY: 1 minutes' walk from the house</td></tr>
<tr><td>TRANSFORMATION 2</td><td></td><td rowspan="3">☐</td></tr>
<tr><td colspan="2">COST: 20 less than what you pay now</td></tr>
<tr><td colspan="2">ACCESSIBILITY: 3 minutes' walk from the house</td></tr>
</table>

Figure A.4: Type 4

B
Survey Website

The following figure illustrates the various modules of the survey. Figure B.1 introduces the survey. The respondents were given the choice task as shown in Figure B.2. Additionally, participants were instructed to rate the images according to several different perceptual criteria (Figure B.3). Aziabah et al. (2025) and Henderson et al. (2016) elicit that subjective perceptions such as aesthetics, social safety, traffic safety and peacefulness have a reasonable effect on residents' preferences for any location. Due to the limited availability of time during this research, it was not possible to investigate these perceptions; therefore, they can be adapted in further research. Figure B.4 capture the questions associated with travel behaviour and different imagery perception for the participants. Finally Figure B.5 records the basic socio-demographic characteristics of respondents



Research Survey

Help us understand neighborhood transformation preferences

Research Study Participation

You are being invited to participate in a research study titled "Assessing trade-offs between Green Spaces and Parking Accessibility in Residential Location Choice". This study is being done by Vedankur Kedar as part of his Master's Thesis research from the TU Delft, with a collaborative effort from Advier Mobiliseert, Delft.

Study Purpose & Duration

The purpose of this research study is to understand preference for accessibility to green spaces and car parking as residential amenities, and it will take you approximately 10 minutes to complete. **Therefore, the focus is on those respondents who either own a car or possess access to car via their company.**

Data Usage

The data will be used for analysis, policy insights and dissemination of the work via publication. We will be asking your preferences among the illustrated choice tasks of different situations in residential amenities, where the data provided by you shall be processed statistically to extract insights. The data shall be deleted in a later stage after the research insights are obtained.

Privacy & Confidentiality

As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study will remain confidential. We will minimise any risks by upholding the complete anonymity of the collected datasets.

Voluntary Participation

Your participation in this study is entirely voluntary, and you can withdraw at any time. You are free to not answer, or choose option "Prefer not to say" for any personal question.

Contact Information

Researcher: Vedankur Kedar **Email:** V.S.Kedar@student.tudelft.nl

I Consent to Participate

Figure B.1: Survey Part I - Introduction

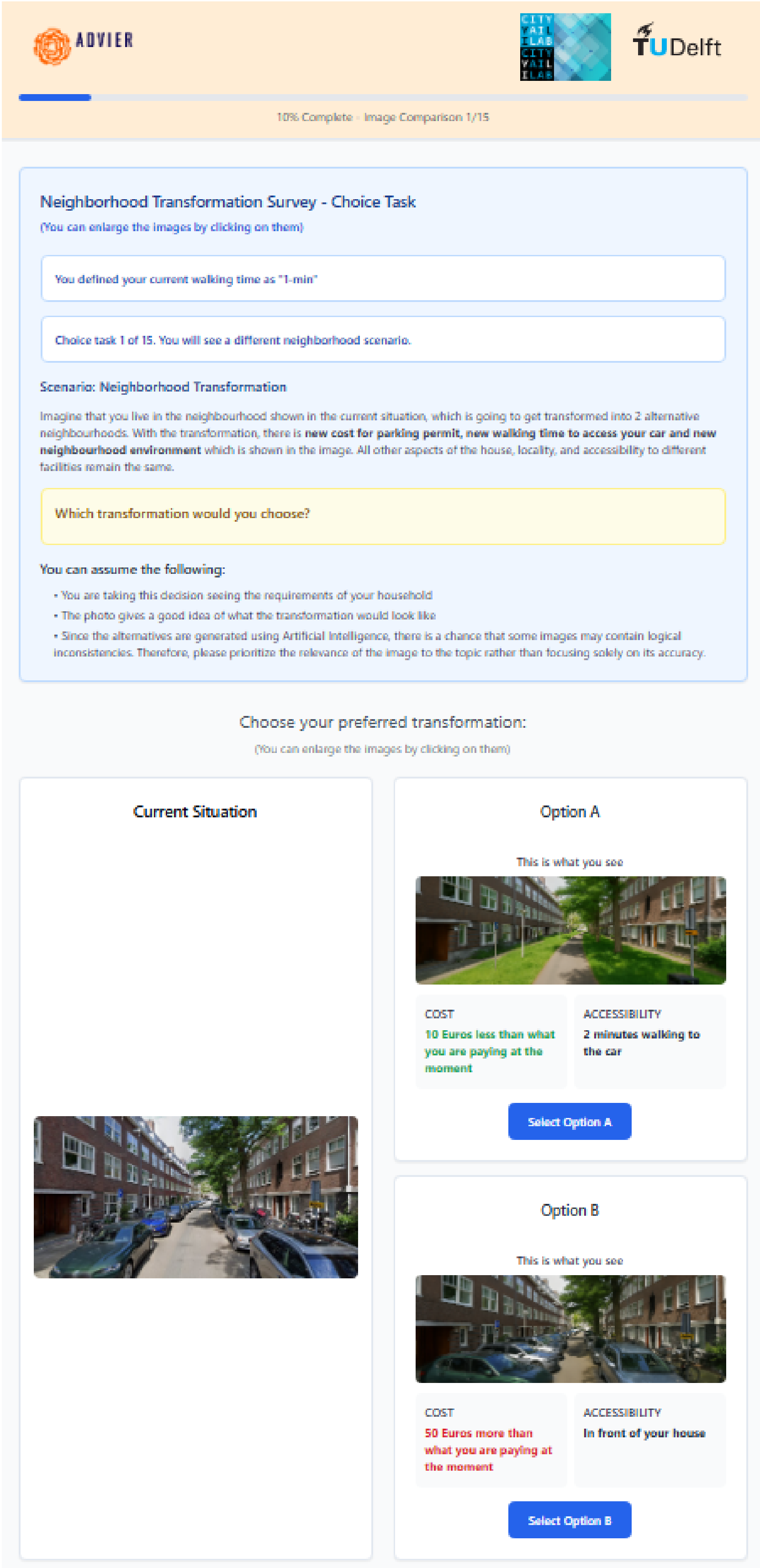


Figure B.2: Survey Part II - Stated Choice Tasks

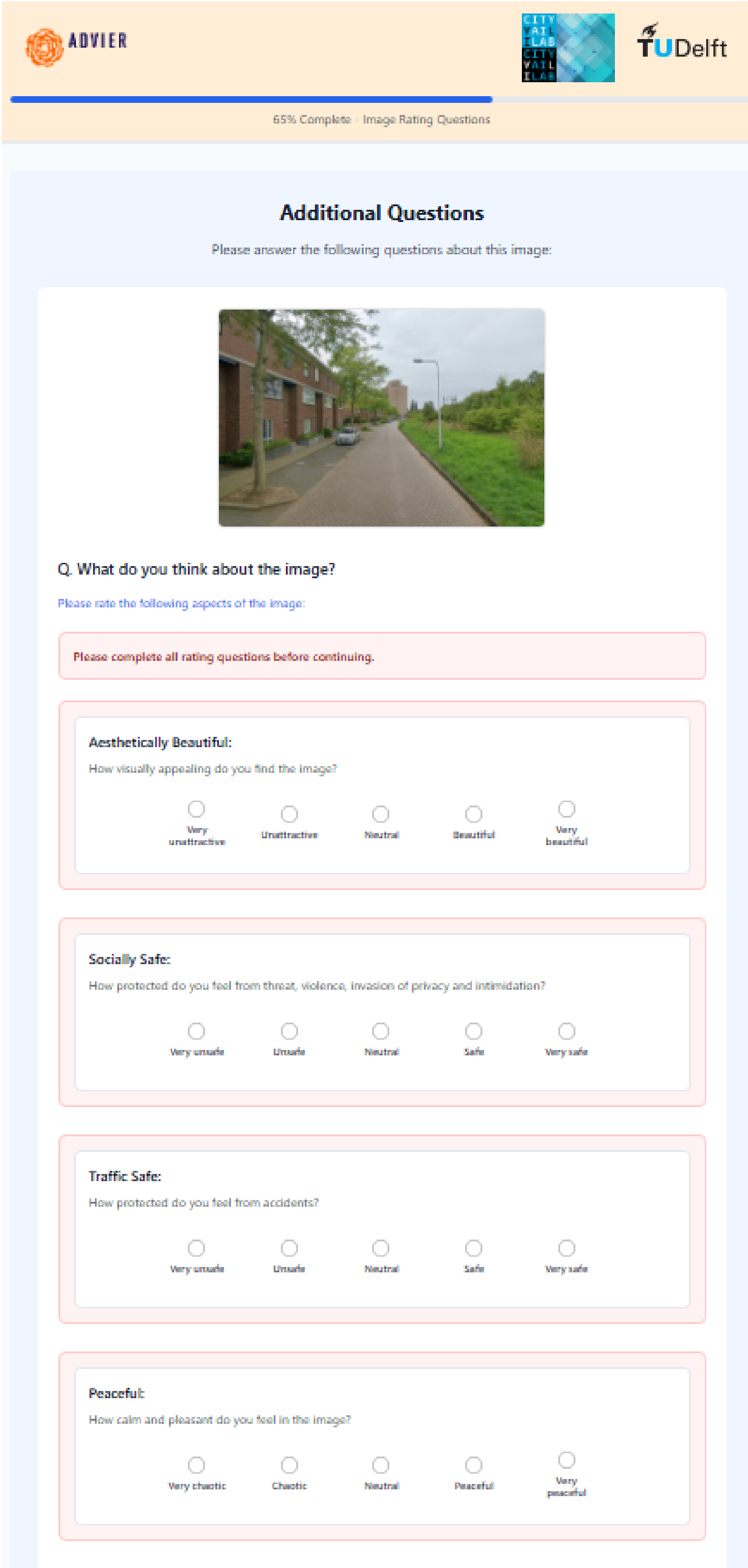
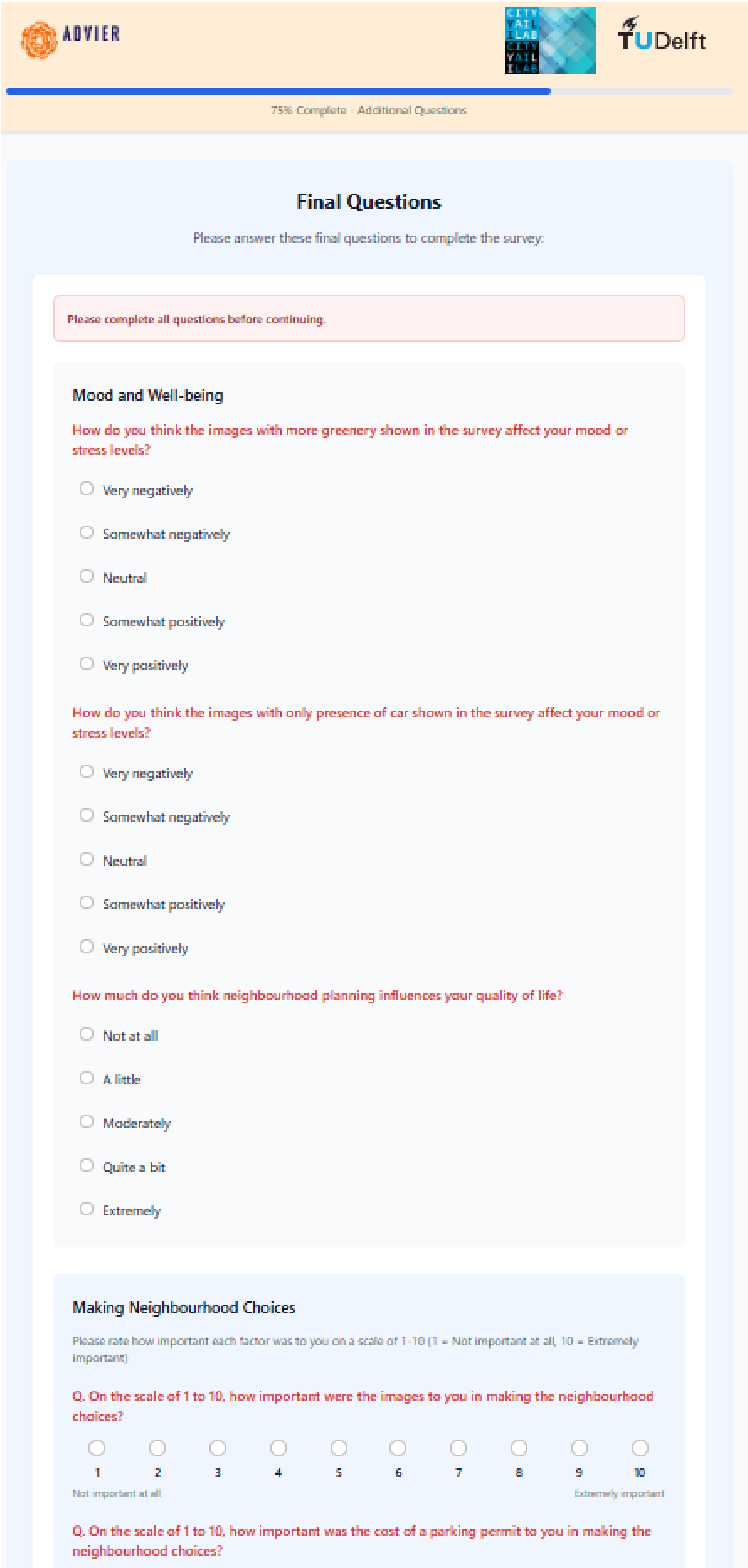


Figure B.3: Survey Part III - Image Rating



75% Complete · Additional Questions

Final Questions

Please answer these final questions to complete the survey:

Please complete all questions before continuing.

Mood and Well-being

How do you think the images with more greenery shown in the survey affect your mood or stress levels?

- Very negatively
- Somewhat negatively
- Neutral
- Somewhat positively
- Very positively

How do you think the images with only presence of car shown in the survey affect your mood or stress levels?

- Very negatively
- Somewhat negatively
- Neutral
- Somewhat positively
- Very positively

How much do you think neighbourhood planning influences your quality of life?

- Not at all
- A little
- Moderately
- Quite a bit
- Extremely

Making Neighbourhood Choices

Please rate how important each factor was to you on a scale of 1-10 (1 = Not important at all, 10 = Extremely important)

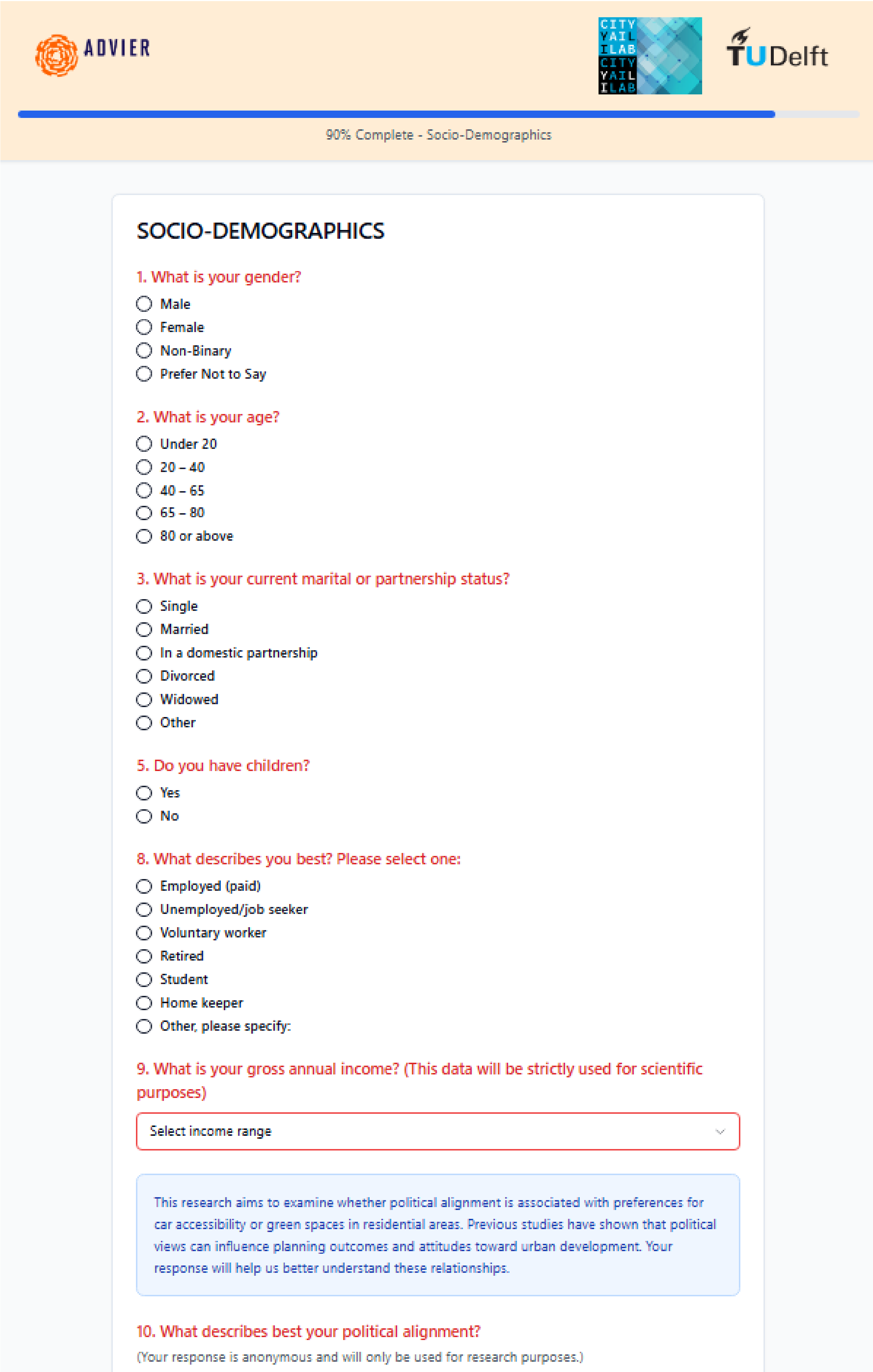
Q. On the scale of 1 to 10, how important were the images to you in making the neighbourhood choices?

1 2 3 4 5 6 7 8 9 10

Not important at all — Extremely important

Q. On the scale of 1 to 10, how important was the cost of a parking permit to you in making the neighbourhood choices?

Figure B.4: Survey Part IV - Well Being and Travel Behaviour



ADVIER

CITY YAIL LAB

TU Delft

90% Complete - Socio-Demographics

SOCIO-DEMOGRAPHICS

1. What is your gender?

- ◯ Male
- ◯ Female
- ◯ Non-Binary
- ◯ Prefer Not to Say

2. What is your age?

- ◯ Under 20
- ◯ 20 – 40
- ◯ 40 – 65
- ◯ 65 – 80
- ◯ 80 or above

3. What is your current marital or partnership status?

- ◯ Single
- ◯ Married
- ◯ In a domestic partnership
- ◯ Divorced
- ◯ Widowed
- ◯ Other

5. Do you have children?

- ◯ Yes
- ◯ No

8. What describes you best? Please select one:

- ◯ Employed (paid)
- ◯ Unemployed/job seeker
- ◯ Voluntary worker
- ◯ Retired
- ◯ Student
- ◯ Home keeper
- ◯ Other, please specify:

9. What is your gross annual income? (This data will be strictly used for scientific purposes)

Select income range

This research aims to examine whether political alignment is associated with preferences for car accessibility or green spaces in residential areas. Previous studies have shown that political views can influence planning outcomes and attitudes toward urban development. Your response will help us better understand these relationships.

10. What describes best your political alignment?

(Your response is anonymous and will only be used for research purposes.)

Figure B.5: Survey Part V - Socio-Demographics

C

Prompt Description for Open AI

Table C.1: Prompt for Image Transformation

Image	Prompt Description
Image 1	”In this image, the street layout should remain unchanged. Modify the scenario so that more cars are parked than in the original image. Keep the original buildings, roads, footpaths, canals, electric poles, benches, dustbins, and cycle stands intact and unaltered. No cars must be on the footpath (Strictly). Keep the width of the road at least this much that a car can pass (Strictly), No Trees on the road (strictly) Important rules to follow: VERY IMPORTANT: THE IMAGES SHOULD BE LOGICAL. NO CARS PARKED ON FOOT PATH All cars must be parked on clearly paved, tiled, or asphalt parking zones. Keep the roads that much wide that a car can pass easily. There must be a distinct visual and physical separation (like a curb, elevation, border, or concrete edge) between parking areas, roads and pedestrian walkways No wheels, bumpers, or shadows of cars should overlap with grass. Pedestrian footpaths must remain clear and unobstructed. No car should be touching or overlapping footpaths. Pedestrian areas should be visually distinct, ideally separated from both cars and grass by paving or borders. VERY IMPORTANT: Maintain the original layout of roads, houses, paths, and other public infrastructure. VERY IMPORTANT: Maintain the width of the road at least that much so that the parked cars can easily pass. VERY IMPORTANT: Do not change or move buildings, roads, or permanent street elements. No green space should be there on the original road. The road should be intact as it is in the original image VERY IMPORTANT: The car parking space should be connected to the main road. Ensure the result looks realistic and urban, suitable for a residential or mixed-use street. Keep shadow directions and object proportions consistent with the original image.”
Image 2	”In this image, the street layout should remain unchanged. Modify the scenario so that fewer cars are parked than in the original image. Keep the original buildings, roads, footpaths, canals, electric poles, benches, dustbins, and cycle stands intact and unaltered. No cars must be on the footpath (Strictly). Keep the width of the road at least this much that a car can pass (Strictly), No Trees on the road (strictly) Important rules to follow: VERY IMPORTANT: THE IMAGES SHOULD BE LOGICAL. NO CARS PARKED ON FOOT PATH All cars must be parked on clearly paved, tiled, or asphalt parking zones. There must be a distinct visual and physical separation (like a curb, elevation, border, or concrete edge)between parking areas, roads and pedestrian walkways. No wheels, bumpers, or shadows of cars should overlap with grass.

Image	Prompt Description
	Pedestrian footpaths must remain clear and unobstructed. No car should be touching or overlapping footpaths. Pedestrian areas should be visually distinct, ideally separated from both cars and grass by paving or borders. VERY IMPORTANT: Maintain the original layout of roads, houses, paths, and other public infrastructure. VERY IMPORTANT: Maintain the width of the road at least that much so that the parked cars can easily pass. VERY IMPORTANT: Do not change or move buildings, roads, or permanent street elements. No green space should be there on the original road. The road should be intact as it is in the original image VERY IMPORTANT: The car parking space should be connected to the main road. Ensure the result looks realistic and urban, suitable for a residential or mixed-use street. Keep shadow directions and object proportions consistent with the original image.”
Image 3	”In this image, the street layout should remain unchanged. Modify the scenario so that 50 Important rules to follow: VERY IMPORTANT: THE IMAGES SHOULD BE LOGICAL. There must be a distinct visual and physical separation (like a curb, elevation, border, or concrete edge) between roads and green areas. Green zones (with dense grass, a high number of trees, and small plants) must remain completely untouched and undisturbed by vehicles. The greenery coverage should be very high, with trees highly represented relative to parked cars. No tree should appear to be growing out of or overlapping any parked car. VERY IMPORTANT: Maintain the width of the road such that at least a car can pass through it easily. Pedestrian footpaths must remain clear and unobstructed. No car should be touching or overlapping footpaths. Pedestrian areas should be visually distinct, ideally separated from both cars and grass by paving or borders. VERY IMPORTANT: Maintain the original layout of roads, houses, paths, and other public infrastructure. VERY IMPORTANT: Do not change or move buildings, roads, or permanent street elements. VERY IMPORTANT: Ensure the result looks realistic and urban, suitable for a residential or mixed-use street. Keep shadow directions and object proportions consistent with the original image.”
Image 4	”In this image, the street layout should remain unchanged. Modify the scenario so that 50% is green. If the original image has trees, remove them. The street, buildings, roads, footpaths, canals, electric poles, benches, dustbins, and cycle stands must remain intact and unaltered. Remove all cars in the image. No change should be made on the road at all. Keep the width of the road at least this much so that a car can pass (Strictly), No Trees on the road (strictly) KEEP THE WIDTH OF THE ROAD SAME AS THE ORIGINAL IMAGE Efficiently use all available non-road, non-footpath space for abundant greenery (such as trees, grass, and small gardens). In addition to greenery, incorporate a variety of urban elements to create a multifunctional and inviting public space. These may include: Seating areas (benches, picnic tables) Small Playgrounds or fitness equipment Community gardens or urban agriculture plots Lighting and shade structures (e.g., pergolas, pavilions) Wide, accessible pedestrian paths or plazas There must be a distinct visual and physical separation (like a curb, elevation, border, or concrete edge) between roads and green areas. Green zones must remain completely untouched and undisturbed by vehicles. The greenery coverage should be very high, with trees highly represented. No tree should appear to be growing out of or overlapping any parked car. Maintain the width of the road such that at least a car can pass through it easily. Pedestrian footpaths must remain clear and unobstructed, and no car should be touching or overlapping footpaths. Pedestrian areas should be visually distinct, ideally separated from both cars and grass by paving or borders. Maintain the original layout of roads, houses, paths, and other public infrastructure. Do not change or move buildings, roads, or permanent street elements. Ensure the result looks realistic and urban, suitable for a residential or mixed-use street. Keep shadow directions and object proportions consistent with the original image”

Image	Prompt Description
Image 5	”In this image, the street layout must remain unchanged. Transform the scenario to 50% green, so that all available non-road, non-footpath areas are efficiently used for abundant greenery, such as dense grass, bioswales, rain gardens, and small gardens. Keep all original buildings, roads, footpaths, canals, electric poles, benches, dustbins, and cycle stands intact and unaltered. Remove all cars from the image. Keep the width of the road at least this much so that a car can pass (Strictly), No Trees on the road (strictly) REMOVE ALL TREES IN THE IMAGE KEEP THE WIDTH OF THE ROAD THE SAME AS THE ORIGINAL IMAGE, AND NOT GRASS SHOULD BE THERE Important rules to follow: VERY IMPORTANT: The image must be logical and realistic, suitable for a residential or mixed-use street. Maintain the original layout of roads, houses, paths, and all permanent street elements. Do not move or alter buildings, roads, or public infrastructure. The street and footpaths must remain intact and unobstructed, with their original width and clear passage for vehicles (at least one car’s width on the road). There must be a distinct, visible, and physical separation (such as a curb, elevation, border, or concrete edge) between roads, footpaths, and green areas. Green zones (with dense grass, a high number of trees, bioswales, rain gardens, and small plants) must remain completely untouched and undisturbed by vehicles. No tree or plant should appear to be growing out of, overlapping, or obstructing any road, footpath, or permanent urban element. Pedestrian areas should be visually distinct, ideally separated from both roads and greenery by paving, borders, or low walls. Integrate green infrastructure elements such as permeable pavements, vegetated curb extensions, or stormwater planters where possible to enhance stormwater management and urban cooling. Ensure the result looks vibrant, urban, and ecologically rich, with greenery as the dominant visual element but all urban infrastructure logically retained. Keep shadow directions and object proportions consistent with the original image. The goal is to showcase a fully greened urban street that exemplifies best practices in green street design, maximising ecological function, stormwater management, and visual appeal, while preserving all original urban infrastructure and ensuring logical, safe, and accessible public space”

D

Predicted Utility Scores for Different Transformation

Figure D.1: Cluster of Transformation 1

Figure D.2: Cluster of Transformation 2

Figure D.3: Cluster of Transformation 3

Figure D.4: Cluster of Transformation 4

Figure D.5: Cluster of Transformation 5

E

Scientific Paper

Navigating the Trade-off Between Green Spaces and Convenient Parking through Computer Vision-Enriched Discrete Choice Model : Insights from the Residential Areas in the Netherlands

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Abstract

The paper investigates the trade-off between car parking accessibility and exposure to green environment in the residential setting. To represent the visual differences in the environment, street level images generated using artificial intelligence are used. The recently developed state of the art method called computer vision-enriched discrete choice model (CV-DCM) combines computer vision with conventional discrete choice models to analyse decision-making scenarios that incorporate both numerical information and visual data. This method is employed using the stated choice experiment, where the respondents had to choose between two different residential setting. Every setting is defined by three attributes constituting parking cost, walking time and the residential environment, the latter depicted using street level images. It is observed that environment is equivalently influential, although higher priority to accessibility is given. Young participants reported a willingness to walk 1.2 minutes further to reach their cars if their neighbourhood environment are enhanced with more greenery. The same measurement is recorded merely 42 seconds for elderlies marking higher sensitivity towards car access. A similar pattern is observed in the Value of Time assessment, with older participants expressing a willingness to pay €13 more than their younger counterparts for an equivalent increase in car accessibility. These findings provide meaningful insights, equipping policymakers with a valuable tool for evaluating and designing residential complexes.

Keywords: *discrete choice models, computer vision, street level imagery, stated choice experiment, car parking accessibility, green environment*

1 Introduction

Cities today inhabit more than 55% of the world's population (Vilar-Compte et al., 2021). Growing wealth in western economies is pushing demand for better quality housing, which translates into an increased preference for suburban environments characterized by peace, tranquillity, and green spaces (Dowling, 2008; van Cranenburgh & Garrido-Valenzuela, 2023). In the Netherlands, this demand is seen in the widespread preference for family homes with gardens or nearby green spaces (Boelhouwer et al., 1998; Coolen & Meesters, 2012). Households with higher incomes are also more likely to prefer having a car, even in countries with comprehensive public transport systems, and despite a rise in active travel preferences (Maltha et al., 2017; Fioreze et al., 2019; Haas & Kolkowski, 2023). Such trends, while reflecting improved quality of life, put pressure on scarce land and infrastructure especially in high-density cities creating a notable mismatch between consumer preferences and government policies focused on compact, mixed-use development due to limited land resources (Scheiner et al., 2020; Götzeand et al., 2024; Coolen & Meesters, 2012).

Against this background, the trade-off residents make between car parking accessibility and green space has become central to residential location decisions, reflecting a broader urban planning dilemma (Boelhouwer et al., 1998). Car-free districts such as the new Utrecht development illustrate the relevance of examining these factors, as distinctive neighbourhood designs that limit vehicle access are increasingly explored for sustainability purposes (*Start bouw autovrije wijk Utrecht, 'parkeerplekken nemen veel ruimte in'*, 2025). Across the globe, many cities have implemented car-restricted zones in historical and commercial areas (Crawford, 2009), and studies show that car-free neighbourhoods can reduce car ownership and usage (Scheiner et al., 2020; Nobis, 2003). Acceptance of these initiatives depends on factors like site quality and place attachment, emphasizing the importance of including residents' perceptions in planning (Marcheschi et al., 2022).

In the Netherlands, growing urbanization and pressure on land resources have led municipalities to target the transformation of underutilized parking spaces into green areas, aligning with sustainability and efficient land use goals (DutchNews.nl, 2025; Leidse Pers, 2025; Nabielek et al., 2013). However, successful urban policy also depends on shaping reforms according to people's preferences (Booth & Richardson, 2001). While the benefits of car-free neighbourhoods extend beyond transportation, fostering social cohesion and cleaner environments for children (Hazel, 1998; Melia et al., 2010; Ornetzeder et al., 2008), little research has addressed how people prioritize car parking accessibility versus exposure to green spaces in residential choices.

Finally, numerous factors affect residential location choice (RLC), ranging from physical and economic to cultural and social dimensions, and these operate at multiple scales from city to neighbourhood to individual homes (Schirmer et al., 2014). Understanding resident perceptions of car-free development is vital for future policies. Preferences often reflect a trade-off between the convenience of accessible parking and the physical and mental benefits provided by green spaces (Hematian & Ranjbar, 2022; Kerimova et al., 2022; Phillips et al., 2023). Variations in these sensitivities across age, income, and lifecycle status highlight the importance of integrating socio-demographic insights into transport and urban planning.

2 Literature Review

The focus of this review is to shed light on the research done in this arena and what gaps still exist to be bridged. The literature review first understands the factors affecting the RLC and then scopes in on the main research question and relevant studies done in this aspect. Moreover, the review also sheds light on the computer vision methods and street-level images. Culminating this, a concise summary compiles the contemporary state of knowledge, emphasising the areas where future research is entailed, and guiding direction for potential future research.

2.1 Factors affecting Residential Location Choices

Residential Location Choice (RLC) refers to the process by which individuals or families evaluate and select a place to reside based on personal preferences and extrinsic factors. In econometric terms, an individual/ a household tries to maximise the utility they gain from the particular residential property to achieve a satisfaction equilibrium. This decision corresponds to the sequential set of choices made on different scales and levels, aligned with the necessities of the resident. Moreover, such decisions on an individual level have a cascading effect on the physical size and spatial configuration of urban economies, which in turn shapes the skeleton of mobility patterns, travel behaviour, energy consumption and travel-induced impacts on the environment and society (Pagliara et al., 2010). Therefore, understanding the dynamics of residential choice and factors affecting it is of great significance (Cockx & Canters, 2020).

Evidence from multiple research suggest age (Willing & Pojani, 2017; Humphreys & Ahern, 2019; Kerstens & Pojani, 2018; Beckers & Boschman, 2019) and income levels (Traoré, 2019; Acheampong, 2018; Wu et al., 2013; Wu et al., 2021) strongly influencing the residential location priorities. Moreover, household size (Hanni & Rao, 2024; Traoré, 2019; Schirmer et al., 2014) and life cycle (Wu et al., 2021; M. Zhang et al., 2024; Kerstens & Pojani, 2018; Willing & Pojani, 2017; Y. Yang et al., 2025) which corresponds to different stages of individual life like marriage, child birth affect their inhabiting decisions. Additionally apart from the above attributes, activity patterns (Frenkel et al., 2013), education levels (Wu et al., 2013), migration background (Wu et al., 2013), car ownership (Hanni & Rao, 2024) and employment status (Schirmer et al., 2014) also is found to shape the location decisions.

Apart from proximity to roads, which has been found preferable in most cases (Acheampong, 2018; Wu et al., 2021; Beckers & Boschman, 2019; Hamersma et al., 2015). Easy access to supporting infrastructure (Acheampong, 2018; Acker et al., 2014; Faber et al., 2021; Humphreys & Ahern, 2019), amenities, and social

(Beckers & Boschman, 2019) and family ties (Frenkel et al., 2013; Kerstens & Pojani, 2018; Willing & Pojani, 2017) is always favourable for people who want to settle down at a location. Preference on the spectrum of urban or countryside lifestyle is subjective to the respondents (Frenkel et al., 2013; Tillema et al., 2010), therefore dual effect can be observed, which is also dependent on socio-demographic factors like age as iterated in van Cranenburgh and Garrido-Valenzuela (2023). A high commute travel time (Wu et al., 2013; Tillema et al., 2010), fuel cost (Tillema et al., 2010) and infrastructure toll cost (Tillema et al., 2010) is always found to have disutility. The propensity to choose a location is highly likely on the mixed land use (Hanni & Rao, 2024; Schirmer et al., 2014), quality of traffic safety (Hamersma et al., 2015), availability of open spaces (Schirmer et al., 2014) and air pollution levels observed in the neighbourhood (Hunt, 2010). Built density has both positive (observed in (Kerstens & Pojani, 2018)) and negative (observed in Willing and Pojani (2017)) effect on the location choice, which majorly is a function of the regional characteristics and personal preferences. It was found in Willing and Pojani (2017) that the foreign student populace specifically from Asia prefer to have a dense built environment over sparse Australian urban planning as most of the Asian cities are highly dense and concentrated urban settlements. Safety and aesthetics are found to have a positive impact on the choice probability (Yuntao & Srinivas, 2020), whereas noise levels observed in the neighbourhood show a negative utility for location choice (Hunt, 2010).

Under the housing amenities, an increase in housing rental cost (Frenkel et al., 2013; Tillema et al., 2010) or housing cost (Y. Yang et al., 2025; Yuntao & Srinivas, 2020) is found to reduce the likelihood of choosing a location, which is also similar for the age of the building (Schirmer et al., 2014). Different strata of populace have affinity to different housing types based on their personal taste and residential attitudes, but they possess an increase in location choice probability with a reasonable increase in housing size or number of bedrooms/bathrooms (Humphreys & Ahern, 2019). Car parking being a subject to car ownership, is preferential for a location choice as observed in Yuntao & Srinivas, 2020, Acker et al., 2014 and Hamersma et al., 2015. Greenery and green frontages are found to increase the likelihood of a location choice, whereas the residential cost associated creates reluctance for the specific location choice (Wiersma & Bertolini, 2024).

Focusing on the Dutch context. A study of the Dutch population above 18 years by van Cranenburgh and Garrido-Valenzuela (2023) analysed residential location choice (RLC) using an imagery-integrated choice modelling approach found that older adults tend to prefer greener environments, while evidence also points to various housing typologies influencing preferences. Faber et al. (2021) identified that individual priorities for mobility access often lead people to settle in denser, transit-accessible areas. Lifecycle stage and household demographics play a significant role in shaping residential choices (Kronenberg & Carree, 2010; Y. Yang et al., 2025). Residents typically seek housing that aligns with their lifestyle, travel behaviour, and personal tolerances even after moving. For instance, Hamersma et al. (2015) showed that moving intentions are affected by tolerance to highway nuisances, balanced against accessibility benefits. Additionally, research on immigrants' RLC found single individuals prioritize house attributes and neighbourhoods with more single inhabitants, while multi-member households emphasize proximity to same-ethnicity residents and educational institutions for children (Beckers & Boschman, 2019). Housing size, income status (Tillema et al., 2010), and factors like place making and neighbourhood greenery (Wiersma & Bertolini, 2024), further influence residential selection.

2.1.1 Green Environment versus Car Parking for residential environment

Car ownership decisions are influenced by a combination of long-term lifestyle preferences, residential location choices, and short-term mobility behaviors, highlighting the interconnectedness of travel and housing decisions (Acker et al., 2014). Parking management requires careful planning due to the significant land resources involved. Wiersma and Bertolini (2024) suggest that parking permit allocation should be based on future spatial needs rather than current availability, recommending the creation of parking hubs on neighbourhood edges where car ownership is high, noting that place-making is hindered when car ownership exceeds 0.8 cars per household. Drivers' willingness to pay for parking depends on factors such as design, payment flexibility, and cleanliness, although residents often prefer parking close to their homes or destinations (Acker et al., 2014; van der Waerden et al., 2013; Kobus et al., 2012; Scheiner et al., 2020). Scheiner et al. (2020) advocate for on-street parking pricing to manage accessibility, while Christiansen, Fearnley, et al. (2017) show that increasing the distance between home and parking reduces car use in dense urban areas, supporting urban development that physically separates parking from residences. This creates a balance where parking hubs can improve neighbourhood place-making and reduce car trips.

Green spaces play a crucial role in urban environments, especially in high-density areas where access can be unequal, affecting mental well-being and social attachment. Jim, 2004; Baur et al., 2013; Zhang et al., 2015; Lauwerijssen et al., 2024 emphasize that individuals' valuation of green spaces is shaped by their personal and social identities, and reduced daily green exposure can harm liveability and well-being. In the Dutch context, there is a strong preference for single-family homes with private gardens, which provide essential space, privacy, and opportunities for outdoor activities (Beumer, 2018). Families with children especially prefer suburban settings, as children's well-being is linked to their exposure to greenery (Coolen & Meesters, 2012; Wu et al., 2021).

2.2 Street View Imagery and Computer Vision

Advances in computer vision, machine learning, and the availability of extensive street imagery datasets have greatly enhanced the ability to analyse urban landscapes and their perceived qualities (Ramírez et al., 2021; Biljecki & Ito, 2021). Street view images (SVI) combined with these techniques have been widely applied in assessing urban health, built environment quality, mobility, climate, transportation, and greenery, demonstrating the versatility of computer vision in urban studies (Kang et al., 2020; S. Li et al., 2021; F. Zhang et al., 2019; Ignatius et al., 2022; Branson et al., 2018).

Specifically in greenery analysis, methods like semantic segmentation and neural networks such as DeepLabv3+ have improved green view indices' accuracy, while novel vegetation indices help monitor changes in urban greenery over time using SVIs (X. Li et al., 2015; Xia et al., 2021; F. Zhang et al., 2019; Yu et al., 2022). Though comprehensive reviews show the strength of SVI in capturing urban fabric elements, there is still limited research on how cars' presence is perceived in urban environments through these computer vision approaches (He & Li, 2021; Lu et al., 2023) .

2.3 Research Gap

A considerable amount of research has explored factors affecting residential location choice (RLC). However, limited research has focused on how individuals trade off amenities such as access to car parking versus green environment, a critical but often overlooked factor that influences residential decisions. Most existing studies rely on stated and revealed preference surveys using text-based descriptions, which may limit respondents' ability to fully visualize choices (Acheampong, 2018; Frenkel et al., 2013; Cherchi & Hensher, 2015). Recent findings suggest that integrating imagery in stated choice experiments improves understanding of preferences for the urban environment (Dongen & Timmermans, 2019; Yang & Tian, 2024), though research explicitly addressing visual perception's effect on RLC remains scarce.

The Computer Vision-Enriched Discrete Choice Model (CV-DCM) developed by van Cranenburgh and Garrido-Valenzuela (2023) advances the field by combining numerical data with imagery through computer vision techniques, allowing for the generation of utility scores reflecting how residential environments are perceived. Despite its potential, the model's interpretability is complex, posing challenges for decision-makers such as municipalities who need clear insights into what influences residential preferences and sensitivities. Understanding the factors that shape these choices and validating the model against real human decision-making are crucial for designing better urban developments that align with residents' needs, while making the model accessible to planners and policymakers for practical applications.

3 Methodology

3.1 Discrete Choice Models

For this study, to predict the residential neighbourhood transformation choice, a computer vision-enriched discrete choice modelling (CV-DCM) method is employed. Furthering the discussion, first, the traditional Multinomial logit discrete choice model based on the random utility maximisation principle (RUM MNL DCM) is discussed.

Discrete choice models are extensively applied to capture individual decision-making across a range of fields, including transportation, energy economics, and agricultural economics (Kim & Bansal, 2024). It has been used for over four decades as a mathematical manifestation of the choices that people make, employing an economic and quantitative framework. It assumes every decision results from a rational decision-making process (Prato, 2009).

Daniel McFadden in his seminal paper McFadden (1974) introduced the widely recognised Random Utility Maximisation (RUM) model, which posits that individuals select the option that yields the highest utility. In this framework, the utility for each alternative is composed of two parts: a component that can be observed—based on measurable attributes influencing the decision—and an unobserved component that captures all other factors affecting choice. The unobserved portion is treated as a random variable, which introduces stochasticity into discrete choice models. This is typically expressed as the utility U for alternative i being the sum of its observed and unobserved utilities (Equation 1).

Maximum likelihood estimation seeks to determine the set of beta parameters that best explain the observed data by maximising the log likelihood (LL) function. This process assigns weights to each observed attribute in the model. The typical linear additive form of the Random Utility Maximisation (RUM) model is shown in Equation 2. With these estimated weights, the probability that a respondent selects a specific alternative can be calculated, most commonly using the multinomial logit (MNL) model. In the MNL framework, the error terms are assumed to be independently and identically distributed as Extreme Value Type I, with a variance of $\pi^2/6$.

The associated alternative probabilities are therefore evaluated using the softmax function given in equation 3.

$$U_i = V_i + \varepsilon_i \tag{1}$$

$$U_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{2}$$

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} \tag{3}$$

3.2 Computer Vision enriched Discrete Choice Modelling (CV-DCM)

Visual data provides an important supplementary source of insight for analysing individuals' decision-making processes. In numerous decision-making scenarios, it is difficult to choose without access to visual information. Imagery usage via computer vision has garnered much attention in the recent years towards its utility in urban planning, where a systematic review done by Marasinghe et al. (2024) has thrown light onto this aspect of research. Computer vision (CV) plays a vital role in extracting insights from visual content. Advanced CV models are capable of recognising scenes and objects, with the most complex models utilising over a billion parameters. For the current study, Computer Vision enriched Discrete Choice Models (CV-DCM) introduced and detailed out by van Cranenburgh and Garrido-Valenzuela (2023) is used.

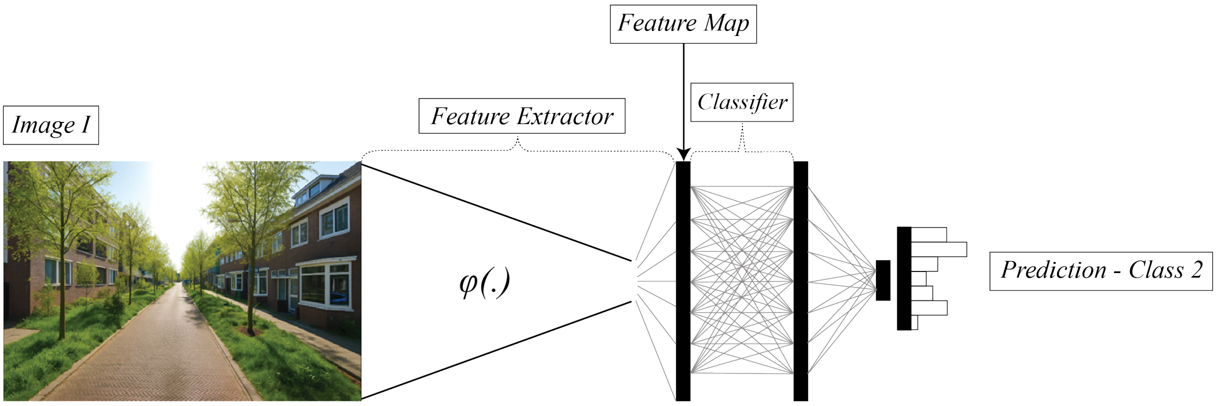


Figure 1: Feature extraction and classification adopted from van Cranenburgh and Garrido-Valenzuela (2023)

For the research, an original baseline situation is given for which a multi-attribute choice task with J mutually exclusive alternatives (in this study, 2 alternatives) is provided to a decision maker, n. Each alternative i is defined by M numeric attributes $X_i = \{x_{i1}, x_{i2}, \cdots, x_{iM}\}$, which can be walking time, cost of amenities and by coloured image I_{in} having a resolution of $H \times W \times C$ (Height, Width, Colour). The image effectively grasps the perceptible attributes like quality, form and shape.

A standard image is made up of millions of pixels, but feeding raw pixel data directly into a computer vision (CV) model is inefficient because of the sheer data volume and the limited value of individual pixels. To address this, the CV model used in this study incorporates both a feature extractor and a classifier. The resulting feature map is a reduced-dimensionality vector representation of the image that encapsulates its most salient characteristics. This feature map condenses the essential visual information from the image into a format that is both machine-readable and computationally manageable. Figure 1 illustrates the structure of the CV model.

The feature map of the image I_{in} is denoted as $Z_i = \{z_{i1}, z_{i2}, \cdots, z_{iK}\}$ where $\varphi(w) : R^{H\times W\times C} \rightarrow R^K$ is a function that transforms the image into its feature map. Here, ϕ refers to the feature extraction process of a computer vision model, and w is referred to as the weights that are its learnable parameters that extract the relevant image attributes.

The assumption that decision-makers act according to the principles of Random Utility Maximisation (RUM) as described by McFadden (1974) and illustrated in Equation 4 are followed. Here, U_{in} represents the total utility that the decision-maker n derives from alternative i. The component V_{in} reflects the utility attributed to observable factors, while an additional error term ε_{in} is included for each alternative to capture influences on utility that are not observed by the analyst (Train, 2009).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{4}$$

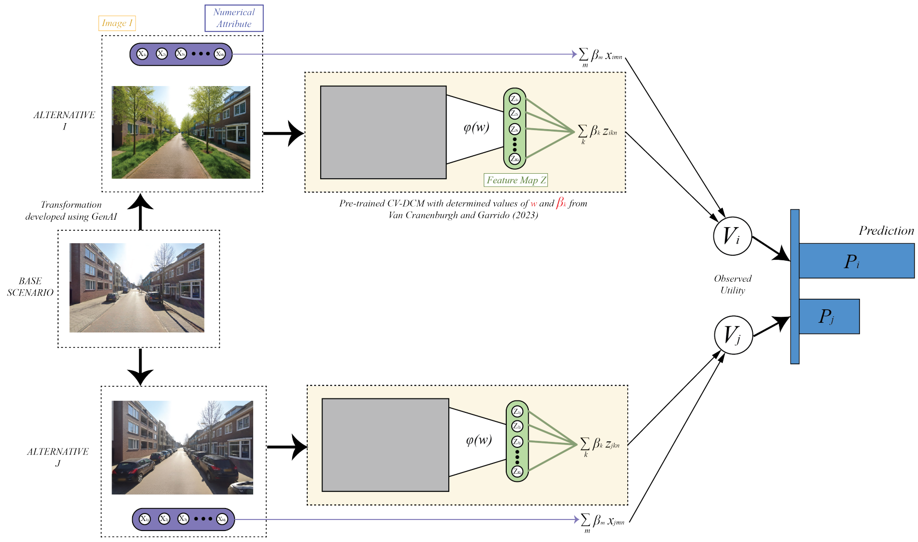


Figure 2: Model Structure for CV-DCM for the study

Additionally, it is also considered that decision-makers derive utility from both the numerical attributes X_{in} and the features represented in the image I_{in}, as shown in Equation 5. Here, ν denotes a preference function that translates both the numeric and image-based attributes of an alternative into utility.

$$U_{\text{in}} \left(X_{\text{in}}, I_{\text{in}}\right) = \nu \left(X_{\text{in}}, I_{\text{in}}\right) + \varepsilon_{\text{in}} \tag{5}$$

The research posits that the contributions to utility from numerical attributes and from image-encoded features are independent and additive within the utility framework, as shown in Equation 6. In this setup, the function f assigns utility to the observed numeric attributes (Equation 7) while the function g does so for the information contained in the images (Equation 8). Since images generally capture several different features, these can be treated collectively as a composite good. Both the numeric attributes X_{in} and the feature map Z_{in} are incorporated into the utility function in a linear and additive way. In this equation, β_m represents the marginal utility of a numeric attribute m; x_{imn} is the value of the numeric attribute m for the alternative i faced by the decision maker n and β_k is the coefficient for the k^{th} component of the feature map Z_{in}.

$$U_{in} \left(X_{in}, F_{in}\right) = f \left(X_{in}\right) + g \left(F_{in}\right) + \varepsilon_{in} \tag{6}$$

$$f \left(X_{in}\right) = \underbrace{\sum_m \beta_m x_{\text{imn}}}_{\substack{\text{Systematic utility} \\ \text{derived from} \\ \text{numeric attributes}}} \tag{7}$$

$$g \left(F_{in}\right) = \underbrace{\sum_k \beta_k z_{ikn}}_{\substack{\text{Systematic utility} \\ \text{derived from attributes} \\ \text{encoded in the image}}} \tag{8}$$

$$\text{where } Z_{\text{in}} = \varphi \left(I_{\text{in}} \mid w\right)$$

Consequently, the outputs at the final layer of the network can be interpreted as utility values. However, while the last layer can be viewed as representing utility, the parameter β_k does not essentially reflect the same meaning as that of β_m. Although β_k can be considered a marginal utility, since it quantifies the change in utility resulting from a unit change in an attribute, its behavioural meaning is ambiguous because the elements of the feature map Z_i are not defined in this context.

An assumption importantly made in this study is that the baseline scenario does not intuitively affect the choice probabilities. It just informs the respondent regarding the changes which the status quo situation undergoes to transform into the new alternatives, but the end choice is made based on the comparative characteristics of the new options.

Figure 2 illustrates the architecture of the applied CV-DCM model, where the network, in the baseline scenario and the other alternatives, is the same. The structure of CV-DCM in this research also upholds the consistency with RUM. The inclusion of a baseline scenario does affect the utility function of the alternatives, but the basic criterion that the utility of one alternative is not affected by another alternative's attributes is retained. Even though the difference in utilities of alternatives and the baseline scenario is taken, yet the ordinality of the whole system is maintained, as discussed in van Cranenburgh and Garrido-Valenzuela (2023).

4 Stated Choice Experiment(SC)

The study follows a stated choice experimental approach described in the book "Stated Choice Methods: Analysis and Application" (Louviere et al., 2000). Designing the survey involves several challenges. One of the primary difficulties in stated choice (SC) experiments is developing choice scenarios that realistically reflect actual decision-making situations. This requires careful examination and evaluation of the relevant attributes and their possible values. With the objective to ensure that the utility functions can be accurately estimated, resulting in reliable parameters with low standard errors, a variation in the choice scenario is essential. For this kind of optimality in the analysis, the selection of an appropriate experimental design is quite significant (Bliemer & Rose, 2011). Moreover, balancing this, it is essential to maintain the number of choice tasks which are paratactically doable by the respondents and do not overwhelm them.

4.1 Selection of Attributes and respective Levels

An appropriate set of attributes is essential not only for guiding policy and design but also for addressing the specific needs and conditions of individuals (Nielsen et al., 2021). Identifying these attributes involves literature review and extensive expert discussions. Research highlights the critical role of accessible parking availability at both workplaces and residences in shaping long-term car usage (Nielsen et al., 2021; Z. Guo, 2013; Millard-Ball et al., 2022). Convenience in parking significantly increases car use, though high costs can deter ownership (Ostermeijer et al., 2019; van der Waerden et al., 2013). Access to greenery is also highly valued, especially by families, and proximity to green spaces is linked to higher property values (Beumer, 2018; J. Li et al., 2024; Chen et al., 2022). The residential environment's appeal includes aesthetics, greenery, parking, open spaces, and built environment features, all influenced by image attributes (van Cranenburgh & Garrido-Valenzuela, 2023). Subjective perceptions such as aesthetics, safety, and peacefulness are captured through participant ratings, as these cannot be directly extracted from images (Aziabah et al., 2025; Henderson et al., 2016). Socio-demographic factors, including age, gender, income, partnership status, and children, also shape residential preferences, with political alignment recognized as an influencing factor in urban planning attitudes (J. Guo & Bhat, 2001; Cockx & Canters, 2020; Freemark, 2024; Clegg, 2021). For this study parking cost and walking time to the car are taken into consideration.

Specifying attribute levels requires careful consideration, as images alone cannot be assigned levels critical for experimental design. Following van Cranenburgh (2024), the entire image database is utilized, with transformations focusing on car presence and greenery. A wider range of attribute levels (e.g., 1–5 minutes walking time) enhances statistical power but risks dominant alternatives, so discrete time intervals were chosen to capture expected non-linear effects (Bliemer & Rose, 2024; Christiansen, Engebretsen, et al., 2017; Ostermeijer et al., 2019). Time-based accessibility measures from "In Front of House", "30 seconds away", "1 minute away", "2 minutes away" and "3 minutes away" were defined, as time is more intuitive than distance (Pot et al., 2021), while vague categories like "more than 3 minutes" were excluded. Parking permit fee variations across locations led to a pivot design tailored to respondents' context for realistic decision-making (Rose & Hess, 2009). Because most residents do not pay parking fees, the cost question was simplified to a yes/no format, with attribute levels finalized to range from -100 €, -50 €, -25 €, -10 €, 10 €, 25 €, 50 €, 100 €, balancing relevance and complexity for respondents.

4.2 Development of Efficient Design

In stated choice (SC) studies, various experimental design options exist, including full factorial, random fractional factorial, orthogonal, and efficient designs. While full factorial designs generate extensive choice tasks, orthogonal designs improve reliability by minimizing correlations between attribute levels, thereby reducing standard errors (Rose & Hess, 2009). However, orthogonal designs may include dominant alternatives—options clearly superior or inferior—that do not reveal trade-offs and must be removed, which can decrease design efficiency (Hensher et al., 2015). Efficient designs overcome this by excluding dominant alternatives and balancing utilities within choice sets, maximizing trade-off information and minimizing parameter estimate errors. Despite these advantages, efficient designs are infeasible here due to the image data's non-ordinal, non-categorical nature; thus, a random experimental design similar to that used by van Cranenburgh and Garrido-Valenzuela (2023) is employed. This design sets a baseline scenario based on car parking permit and accessibility, guiding the logical flow and survey structure (see Figure 3).

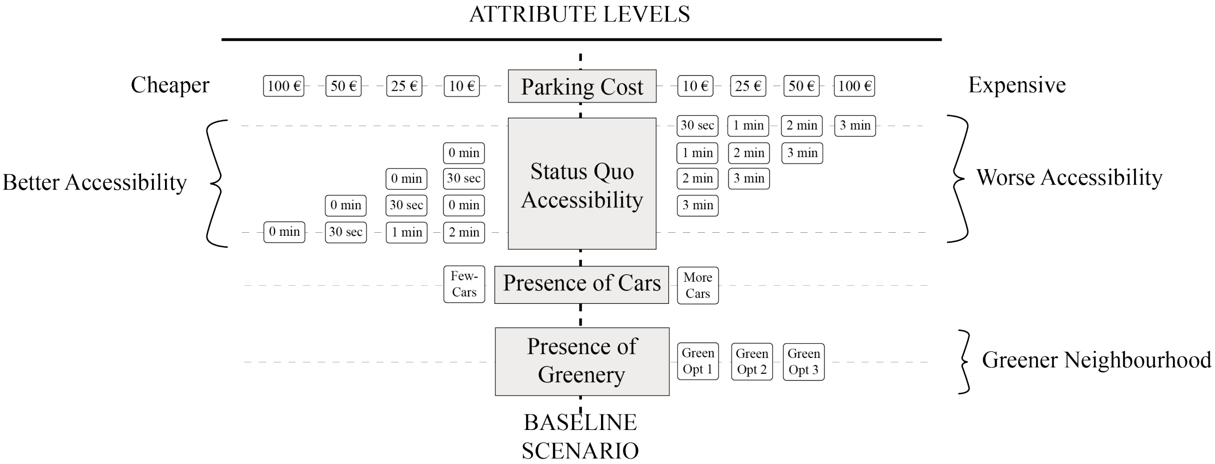


Figure 3: Alternative Schema

4.2.1 Leg 1

This leg of the survey is made for those respondents who assign "Yes" for parking cost and have to walk some distance to access their cars. Under such condition, they are required to trade-off accessibility to car with greenery and parking permit costs. As illustrated in 4, the option of status quo = "in front of house" is blocked. For a random base image, its transformation with the presence of a car is pulled and combined with an increase in cost and decrease in accessibility and in case of greenery the vice versa is done. Example of alternative 1 describes that if a respondent reports 1 minute as the current walking time. Alternative 1 envelops transformation with car (any of the two), an increase in the parking cost (25 €) and increase in accessibility (Walking Time = 0 minute/ " In front of House"). Similarly, alternative 2 combines a random green transformation (out of 3 transformations) with worse accessibility measure (Walking Time = 3 minutes) but a decrease in parking cost (50 €). In this algorithm, other alternatives are made in same manner and then paired to form one choice task.

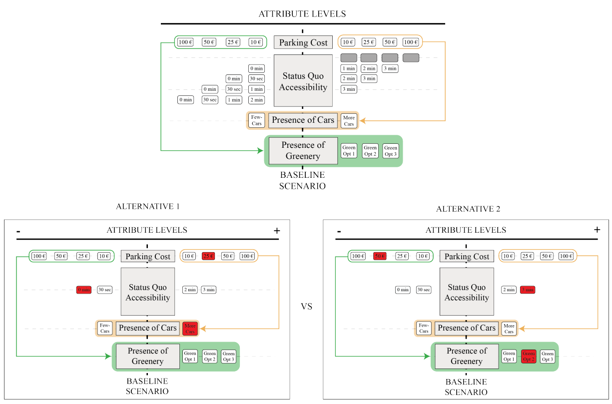


Figure 4: Alternative Development: Leg 1

4.2.2 Leg 2

This leg corresponds to respondents who pay some parking cost, and parking their cars in front of the house. It is pertinent to mention that in such context, the trade-off is between parking permit costs reduction, increase in walking time, and greenery. The example for this leg is shown in Figure 5. For a respondent who pays something and parks their car in front of house. Either they are provided with option 1, with 10 € reduction in parking cost complemented with increase in greenery and walking time by 1 minute, or 100 € reduction with 2 minute accessibility and other green transformation. The alternatives are developed in such a manner that there is no repetition of same attribute level for any chosen attribute, therefore a trade-off always exists.

4.2.3 Leg 3

Those respondents for whom the status quo is defined by not paying any parking cost, but have to walk certain distance to access car. The trade-off for them is of car accessibility against their willingness to pay for such access. Therefore the alternatives always have an increase in parking permit price coupled with higher accessibility time

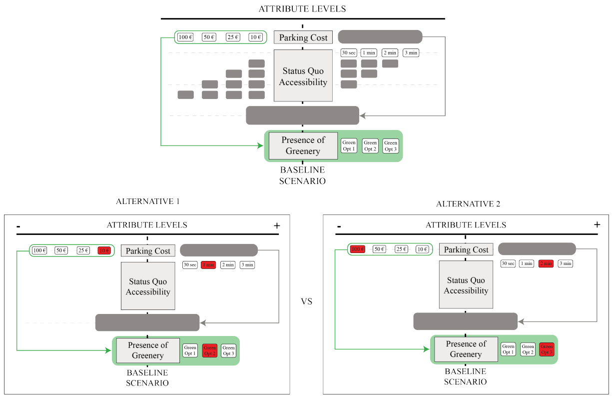


Figure 5: Alternative Development: Leg 2

than status quo, and image with presence of car. This intuitively indicates how the situation would be if the respondents wants to priorities their car over anything else. As shown in Figure 6, with a current walking time of 2 minutes, alternative 1 subjugates an increase in parking cost (25 €) and a walking time reduction of 1 minute and alternative 2, with a hike of 100 € but no walking time.

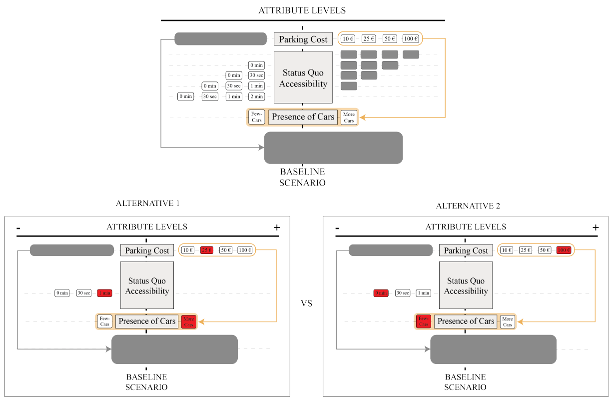


Figure 6: Alternative Development: Leg 3

4.2.4 Leg 4

This last leg of survey addresses those respondents who neither pay a parking permit, nor have a walking time. Therefore, the trade-off is only between greenery and accessibility to their cars. It records their willingness to keep their cars away if they get a greener environment in front of their house. Figure 7 gives this example where alternative 1, increases the walking time by 3 minutes but in return provides a greener environment. Similar is done with Alternative 2.

These four legs attempt to cater to the logical dynamics of all kinds of respondents and generally understand the variation in trade-offs. Following the guidelines of van Cranenburgh and Garrido-Valenzuela (2023), the study calibrates all the choice tasks such that

1. All the developed alternatives in any leg are different to each other (varied attribute levels), so that there always is a trade-off in the generated choice tasks.
2. All dominant choice tasks are removed since the study relies on strong prior assumptions about the expected signs of the preference parameters for parking cost and walking time.
3. All the choice task where involved alternatives have one or more equal attribute levels are removed, which ensures that every choice situation has a mandatory trade-off involved.

4.3 Information flow and implementation of Survey

Based on the initial baseline image, the respondents are asked to compare the two different transformations and associated numerical attributes. During the Decision-making process, they are asked to consider the following situation:

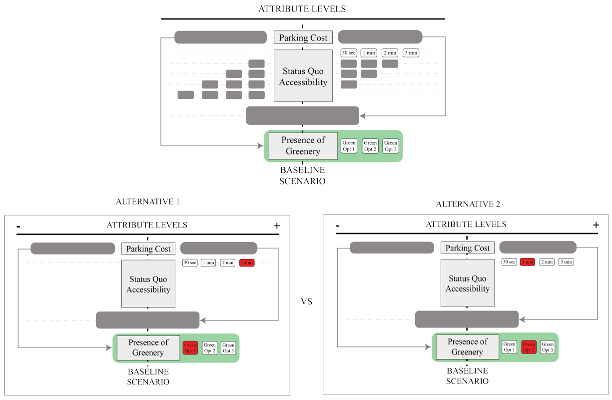


Figure 7: Alternative Development: Leg 4

- Imagine that you live in the neighbourhood shown in the current situation, which is going to get transformed into 2 alternative neighbourhoods.
- With the transformation, there is a new cost for a parking permit, a new walking time to access your car and a new neighbourhood environment, which is shown in the image.
- All other aspects of the house, locality, and accessibility to different facilities remain the same.
- **Which transformation would you choose?**
- The following assumptions are made:
  - You are taking this decision, seeing the requirements of your household.
  - The photo gives a good idea of what the transformation would look like.
  - Since the alternatives are generated using Artificial Intelligence, there is a chance that some images may contain logical inconsistencies. Therefore, please prioritise the relevance of the image to the topic rather than focusing solely on its accuracy.

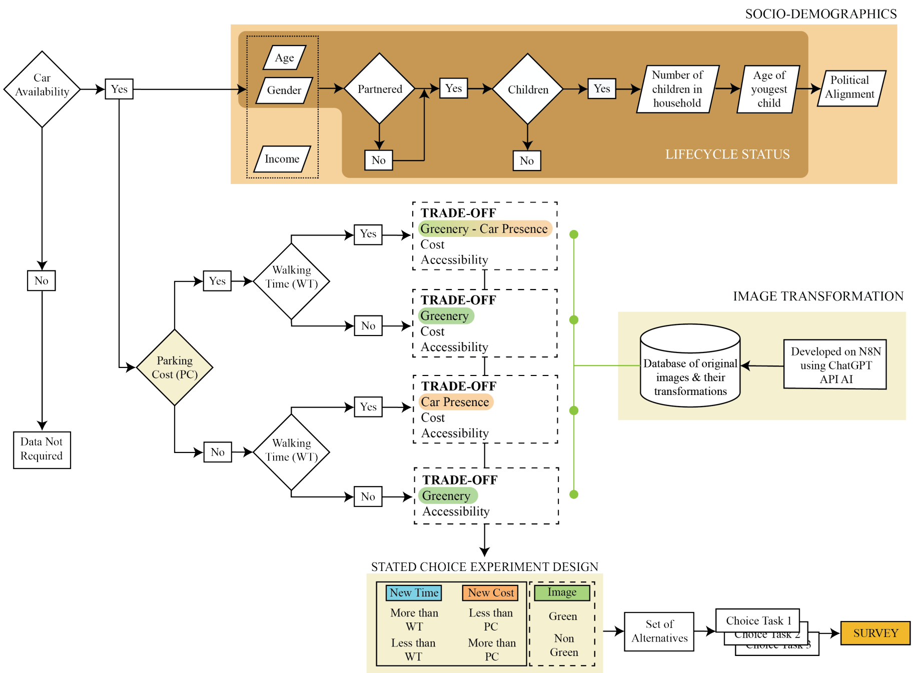


Figure 8: Survey Information Flow Design

The survey is designed into different phases to understand the characteristics of respondents, capture their preferences, and collate perceptions associated with imagery. Figure 8 describes the logical flow of the survey design.

- The survey is initialized with questions regarding to the ownership or possession of car. Those respondents are not furthered who do not own the cars, as this study focuses on the residents who might experience or are experiencing the trade-off for greenery and car parking accessibility.
- All the Socio-demographic dataset is collated through the questions. This resembles the 1^{st} phase of the survey.
- One the basis of the questions regarding parking permit payment and current walking time, four legs for the survey are designed.
- With an appropriate images combined with set of attribute levels, alternatives are generated, which are then bundled as choice tasks. Oehlmann et al. (2017) recommend administering between 10 and 15 choice tasks per respondent, as this range strikes a balance between obtaining sufficient data and avoiding excessive cognitive burden. Therefore, 15 choice tasks are set in the survey.
- The survey culminates with basic questions associated to current travel behaviour, self-reported importance of images and other numerical attributes.

5 Collection of Imagery Dataset

For the stated choice model, street-level images are incorporated to illustrate the residential neighbourhoods and their respective changes. To capture the preference for greenery and accessibility to cars, a street-level image of the residential neighbourhood and its surrounding settings is required. Following the method in Garrido-Valenzuela et al. (2023), Google Street View (GSV) are handled with IDs, and then the images are used (Google, 2023). The images are selected based on the suitability for transformation, clarity and variation. Of all angles, the most suitable angle is selected where the image captures the characteristics of the residential neighbourhood.

5.1 Image Collection

This study focuses on high-density residential regions of the Netherlands, defined through spatial data translation since population density thresholds are not directly available. Using Statistics Netherlands (CBS) data, areas with 2,500 or more addresses per square kilometre were identified, corresponding to at least 25 addresses per 100 x 100 meter grid cells, with population ranging from 500 to 146,500 per square kilometre and a median of 8,000 people per square kilometre set as the high-density threshold. Images were collected from these regions and categorized according to residential neighbourhood types from the *Klimaateffectatlas Kaartviewer* (2025). The geographic information system QGIS was used to collate residential neighbourhood data with imagery. Out of 14 neighbourhood categories, two with minimal residential presence were excluded. Out of 14 neighbourhoods, two, Villawijk and Bedrijven, are not considered in the data collection. This is due to the lesser presence of residential neighbourhoods in these categorizations. From the clipped areas, 480 images captured in 2022 were randomly selected—40 per neighbourhood—ensuring clarity, variation, and suitability for transformation. The images, originally 360º panoramas, were split into four 90º photos, with unique images representing the highest residential characteristics chosen for analysis.

Figure 9: Spatial Distribution of selected images for the study

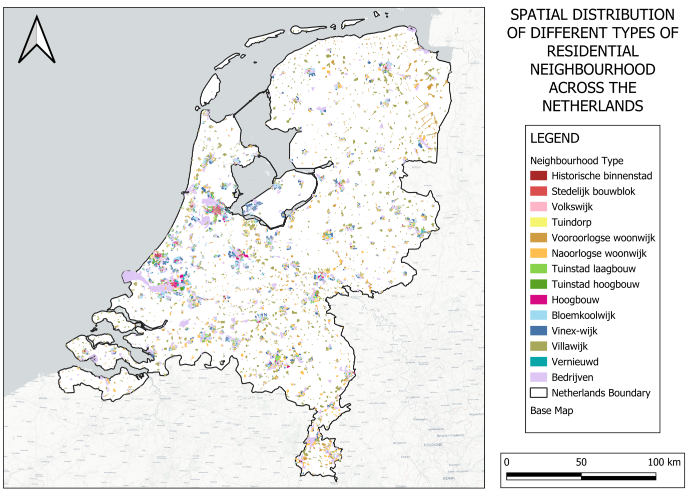


Figure 10: Spatial Distribution of Different Types of Residential Neighbourhoods across the Netherlands

5.2 Image Transformation using Generative Artificial Intelligence

Many platforms now enable rapid, real-time visualizations that help stakeholders and citizens actively participate in the design process by previewing potential street transformations and expressing their preferences. This makes dataset development faster and more cost-effective. For this study, which required a large imagery dataset for the CV-DCM model, generative AI was used to create different image transformations. Out of the initial 480 database images, blank photos discovered during testing were removed using a Python script. The clean images were then processed using the N8N v1.99.1 workflow (*N8N: Workflow Automation Tool*, 2025) integrated with the API of CHAT GPT-4o (OpenAI, 2025), resulting in five variations per image, each differing in the attributes of car presence, greenery, landscaping, and tree quantity (see Table 2).

Table 1: Transformation Information

Transformation	Car Presence	Greenery	Landscaping	Trees
Transformation 1	More	0%	0%	Same
Transformation 2	Less	0%	0%	Same
Transformation 3	0%	50% More	0%	More
Transformation 4	0%	50% More	50% More	More
Transformation 5	0%	50% More	0%	Less

All values are with respect to status quo situation. As the transformations are modelled on the original image, if the original images have trees, then they are also illustrated in transformations.

Figure 11: N8N Work Flow

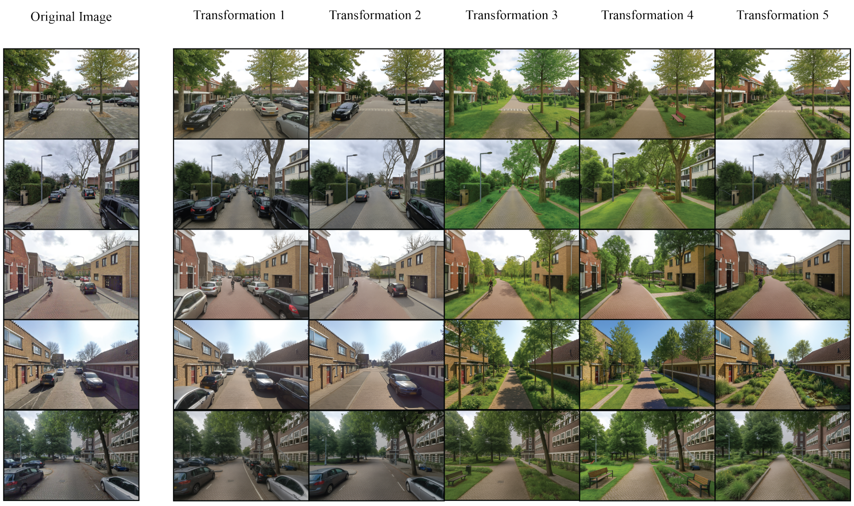


Figure 12: Original Images and their Transformations

Transformation 1 included more cars and no greenery or landscaping, while the number of trees matched the original. Transformation 2 featured fewer cars with attribute levels otherwise identical to the first. Transformation 3 depicted a no-car scenario, 50% more greenery, and increased tree presence; Transformation 4 added 50% more greenery and landscaping (such as benches and gardens) but also had no cars. Transformation 5 involved no cars, 50% more greenery, no landscaping, and fewer trees. The process aimed to retain the base image wherever possible to minimize bias. As illustrated in Figure 11, the workflow sequentially generated and stored each transformation, assigning URLs for each image. Most images took 4–5 minutes to transform; images that failed due to logical inconsistencies were dropped. Ultimately, the final database included 449 images and their five respective transformations, resulting in a data retention rate of 93.54%. Examples of original and transformed images are shown in Figure 12.

6 Results

In totality, the survey was fully completed by 101 individuals between end of June and beginning of august, 2025. Convenience sampling was used to gather the appropriate dataset where the survey was circulated on different social media platforms like LinkedIn, Reddit, Facebook and also shared among the 1^{st} and 2^{nd} degree acquaintances. Apart from this, the survey was posted on open survey groups like survey swap (Surveyswap, 2025) and survey circle (Surveycircle, 2025) for more response inputs.

6.1 Descriptive Statistics

Table 2: Descriptive Statistics

Variable	Categories	Distribution
Gender	Male	67.32 %
	Female	30.69 %
	Prefer not to say	1.99 %
Age Range	Under 20	3.96 %
	20 - 40	66.33 %
	40 - 60	23.76 %
	60 - 80	4.95 %
	Above 80	0.99 %
Income	Less than 10000	37.62 %
	10000 - 20000	6.93 %
	20000 - 30000	23.76 %
	30000 - 50000	11.88 %
	50000 - 100000	0.00 %
	100000 - 200000	1.98 %
	Prefer not to say	10.89 %
Political Alignment	Left	14.85 %
	Centre-Left	27.72 %
	Centre	15.84 %
	Centre-Right	24.75 %
	Right	8.91 %
	Prefer not to say	7.92 %
Lifecycle	Stage 0	37.62 %
	Stage 1	23.76 %
	Stage 2	11.88 %
	Stage 3	6.93 %
	Stage 4	4.95 %
	Stage 5	14.85 %

Maximal efforts were made to gather a pan-Netherlands dataset, but due to the sampling method used, the majority of respondents share similar age, educational background, and socio-demographic characteristics. Most respondents were male (72.7%) and predominantly aged 20–40 (62.3%). This skew towards younger respondents likely results from the survey's distribution within the author's professional and personal networks, which mainly consist of people in this age range. Supporting this, 2019 statistics from CBS (Statistics Netherlands (CBS), 2019) show that adults aged 18–40 hold a majority of issued driving licenses, partially explaining this demographic's dominance in the survey sample. Regarding preferences for car accessibility and green space, life cycle status has been shown to exert a strong influence (Kronenberg & Carree, 2010; Beckers & Boschman, 2019 Y. Yang et al., 2025), as changing household size, age, and maturity shape evolving household needs and priorities, which manifest in trade-offs between greenery and car accessibility.

Since the 1950s, various life cycle models have been developed and widely applied; early models such as those by (Gilly & Enis, 1982; Murphy & Staples, 1979; Glick, 1955) examined hierarchical household stages sequentially, while recent studies (Zhao & Yuan, 2023, Larouche et al., 2020) explore family structure impacts on contemporary travel behavior. This classification helps contextualize respondents' current statuses and enables analysis of how these affect their preferences and choice priorities. Logical hypotheses arise, for example, that elderly respondents would prioritize both car parking accessibility and greenery, while solitary couples might be less concerned with proximity to parking. Incorporating life cycle status into the model allows these hypotheses to be tested and better understood.

6.2 Images Applied in the Survey

The choice situation is developed for specific legs of survey, with logical combination of attribute levels and transformation images. The distribution of unique and appropriate numerical choice situations. Furthermore, 446 different image and their transformation are used. As the images are randomly deployed in the survey by the developed algorithm, the distribution is homogenous. One of the image has been shown more than 16 times, representing the highest frequency.

6.3 Employing the CV-DCM

It is pertinent to mention that for current study, pre-trained CV-DCM from van Cranenburgh and Garrido-Valenzuela (2023) was taken. This was done majorly for the following two reasons.

1. The present study leverages GenAI to generate various image transformations using tailored prompts. However, due to certain inherent limitations, not all outputs maintain logical coherence across every generated scenario. Therefore, training the model on defective training dataset not only lets the fault creep into the model, but also leads to inconclusive results.
2. The CV-DCM model in study is trained on real residential neighbourhood image dataset. As the weights and taste parameters rendered in the model are in resonance to what is required in the study. This can be directly used for extracting the utility values for images.

6.4 Cross-Entropy Loss Function

For this pre-trained model, the most suitable beta parameters for the 1000 elements of the feature map are found where the respective cross-entropy loss is minimised. The cross-entropy loss function seeks to minimise the difference between the true and predicted results (Mao et al., 2023), where a lower cross-entropy value signifies better model accuracy. Minimizing this loss is essentially the same as maximizing the log-likelihood (LL). Equation 9 shows the cross-entropy loss function, where the second term represents L2 regularization. L2 regularization is used to prevent over fitting by adding a penalty based on the magnitude of the model's weights, with the penalty's strength determined by the parameter γ. This regularization is applied only to the feature extractor weights w, and not to the preference parameters β_k and β_m, since regularizing these could introduce unwanted bias into the model (van Cranenburgh & Garrido-Valenzuela, 2023).

$$w, \beta = \arg\min_{w,\beta}(\underbrace{\frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{J} y_{nj}\log\left(P_{nj} \mid X_{nj}, S_{jn}, \beta\right)}_{\text{Cross-entropy loss}} + \underbrace{\gamma\sum_{r=1}^{R} w_r^2}_{\text{L2 regularisation}}) \tag{9}$$

6.5 Estimate of Parameters

Model 1 estimates the likelihood of data using just the information from parking cost and walking time. This model acts as an benchmark to understand the improvement in the models and predict precision of CV-DCM. Model 2 is an extension of Model 1 but it also takes the image type into consideration. For this purpose, the 5 transformations are encoded into 2 set, one for car intensive neighbourhood transformations (Transformation 1 and 2) and two for green neighbourhood transformations (Transformation 3, 4 and 5). This helps in estimating a numerical understanding towards the type of residential neighbourhood environment preferred by respondents. Model 3 estimates the data using predicted utility scores rendered by CV-DCM for each image, where the interaction of age with the utility score is taken into consideration. This emphasises on the varied sensitivity across different age groups. The age grouping is done in accordance with van Cranenburgh and Garrido-Valenzuela (2023) [Young : 18 - 40 years; Middle: 41 - 60 Years and Old: Above 60 years]. This establishes a threshold on how better CV-DCM is able to explain the data over other traditional discrete choice models. Subsequently, Model 4 is estimated by incorporating the CV-DCM scores as well as the interaction of age group with walking time. This is done to understand and therefore find the age specific marginal rate of substitution for environment over walking time. The estimates are elucidated in Table 3

Model Equations

$$\text{Model 1}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility for walking time}} + \varepsilon_{in} \tag{10}$$

$$\text{Model 2}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility for walking time}} + \underbrace{\beta_{Car\ Green}\cdot(Img)_{in}}_{\text{Utility for type of image}} + \varepsilon_{in} \tag{11}$$

$$\text{Model 3}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\beta_{wt}\, wt_{in}}_{\text{Utility from walking time}} + \underbrace{\sum_{age}\beta_s^{age}\cdot S_{in}\cdot age}_{\text{Utility from predicted utility score}} + \varepsilon_{in} \tag{12}$$

$$\text{Model 4}: U_{in} = \underbrace{\beta_{pc}\, pc_{in}}_{\text{Utility for parking cost}} + \underbrace{\sum_{age}\beta_{wt}^{age}\cdot wt_{in}\cdot age}_{\text{Utility from walking time}} + \underbrace{\sum_{age}\beta_s^{age}\cdot S_{in}\cdot age}_{\text{Utility from predicted utility score}} + \varepsilon_{in} \tag{13}$$

Model 1: Walking Time and Parking Costs

Model 1 only takes walking time and parking costs into account which has a ρ^2 value of 0.121. Although it is within acceptable range but this still can be improved to make the model robust. The value of time (VOT = β_{wt}/β_{pc}) in this context is evaluated to be 26.36 Euros, indicative of the fact that means respondents are willing to pay 26.36 euros extra annually to increase their accessibility by 1 minute.

Model 2: Walking Time, Parking Costs with Image Type
The ρ^2 for this model increased to 0.153, relatively higher than Model 1. Therefore, it can be considered that inclusion of type of image as a numerical attribute is able to estimate the data and the type of residential environment does have a significant influence on the choice behaviour. The observed parameters are consistent with expectations, especially concerning the negative effects of walking time and parking costs. The VOT is found to be 54.80 Euros. Here, the marginal rate of substitution (MRS = $-\beta_s/\beta_{wt}$) essentially represents the trade-off between any two attributes while maintaining the same level of utility. It is found to be 2.230 minutes in context of walking time traded off with type of image, implying that respondents are willing to walk for almost 2 minutes in exchange of greener residential neighbourhood.

Model 3: CV-DCM derived Utility
The estimated ρ^2 value of for Model 3 is found to be 0.164 with a BIC value of 1776.15 which is lower than the earlier models. This supports the argument that CV-DCM can reliably estimate the utility of images. Moreover, the visual characteristics of the residential environment play a notable role in shaping individuals' choice behaviour. The VOT is equivalent to 44.93 Euros whereas the segmentation of predicted utility in accordance with the age provides three unique MRS values. Young respondents are willing to walk for almost a minute for balancing greenery against car presence (unitary increase in predicted image score is equal to 1.039 minutes), but elderlies are more sensitive to the accessibility (0.862 minutes). This aligns with the current literature pool which says that elderlies essentially value a proximity to car as this can be helpful in any situation and reduces social isolation (McFeeters-Krone, 2024).

Model 4: CV-DCM derived Utility with Age interaction
Model 4 predicts the data based on the utility scores, parking cost and interaction of walking time with the age categorisation as done for the predicted utility score. The ρ^2 value is found to be highest among all the models that is 0.178 with the lowest BIC value of 1762.50. The utility score and walking time interaction with age substantially predicts the data, which is in accordance with the expectation as the image score encompasses data about the environment. The segmentation of walking time also allows a precise estimation VOT and MRS. The VOT is found to be 36.52 Euros for young respondents whereas this is higher for the elderlies it is 49.63 Euros. This essentially implies that elderlies are willing to pay 13 euros extra for the same accessibility increase, proving their sensitivity and reliance on cars. Similar to Model 3, the MRS value is found to be around 1.2 minutes for young respondents whereas the sensitivity of elderlies is for accessibility shrinks this value to approximately 42 seconds. The estimate for middle-aged people is not found to be statistically significant for both Model 3 and 4.

Table 3: Model Comparison

	Model 1			Model 2			Model 3			Model 4		
Model Type	RUM-MNL			RUM-MNL			CV-DCM derived Utility			CV-DCM derived Utility with Age		
Estimation Method	bgw			bgw			bgw			bgw		
Number of Parameters	2			3			5			7		
Set (N = 1515)												
Log-Likelihood	-914.01			-878.68			-869.79			-855.65		
ρ^2	0.121			0.153			0.164			0.178		
BIC	1842.66			1779.31			1776.15			1762.50		
Parameters	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**	**Est**	**S.E.**	**Sig.**
β_{wt}	-0.495	0.001	0.00	-0.707	0.060	0.00	-0.650	0.065	0.00			
$\beta_{wt\ young}$										-0.536	0.062	0.00
$\beta_{wt\ middle}$										-1.036	0.100	0.00
$\beta_{wt\ old}$										-0.726	0.153	0.00
β_{pc}	-0.018	0.001	0.00	-0.012	0.001	0.00	-0.014	0.001	0.00	-0.014	0.001	0.00
$\beta_{Car-Green}$				1.584	0.192	0.00						
$\beta_{utility\ Young}$							0.626	0.237	0.00	0.649	0.241	0.00
$\beta_{utility\ Middle}$							-0.152	0.245	0.90	-0.157	0.246	0.94
$\beta_{utility\ Old}$							0.561	0.202	0.00	0.505	0.205	0.01
Value of time	26.36			54.80			44.93					
Young										36.52		
Middle										71.41*		
Old										49.63		
Marginal Rate of Substitution				2.230								
Young							1.039			1.225		
Middle							-0.234*			-0.152*		
Old							0.862			0.701		

**not Significant*

6.6 Results from CV-DCM

6.6.1 Descriptives of Image derived Utility scores

CV-DCM is applied to the imagery dataset developed using GenAI consisting 2400 images for 480 original images across different neighbourhoods in the Netherlands. Here, a brief summary will is provided. Initially, in accordance with the definition for high density region, images are enlisted. A set of 40 images each from all 12 kinds of neighbourhood is collated to have variation and heterogeneity in the samples. Then, an N8N base workflow plugged with ChatGPT API AI version is used to create 5 transformation for each image. Subsequently, some set of images are removed due to discrepancies in the development.

For all the transformations and base images, predicted utility score is assigned. While the utility score does not have an absolute scale and is therefore limited in stand-alone value, it is useful for highlighting differences in utility between images. Since knowledge regarding the source neighbourhood image is known, it can also be used in analysis for comparing neighbourhoods and analysing the status quo context of the study. Additionally, analysing utility differences alongside the utility values for walking time and parking costs offers insights into the trade-off involved in residential environment selection.

The utility score for all transformation spans from -1.0 to 1.25, although this model is specific to the Dutch context and might change for any other countries or region. The mean utility score is found to be 0.467. It is pertinent to highlight that a negative utility score does not imply a poor residential environment as the stand-alone value of utility score does not impart much insight.

6.6.2 Transformation based analysis of Utility scores

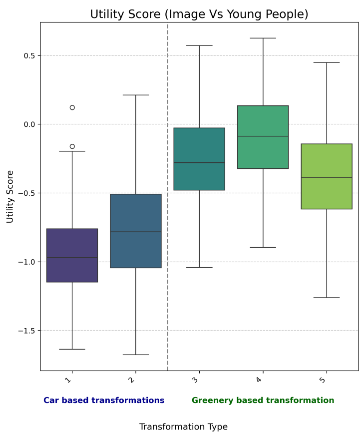


Figure 13: Predicted Utility Score of Images for young people

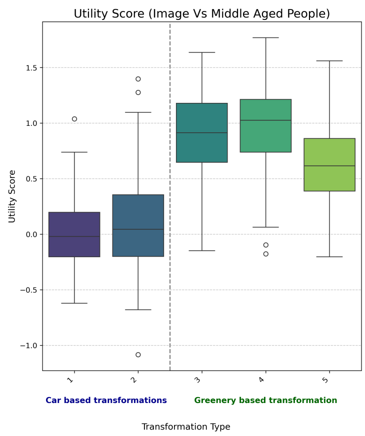


Figure 14: Predicted Utility Score of Images for Middled-Aged people

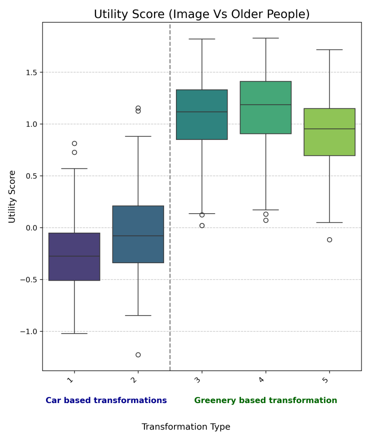


Figure 15: Predicted Utility Score of Images for Old people

The transformation-specific analysis of predicted utility scores by age group provides valuable qualitative insights into how different environments are valued. As shown in Figures 13, 14, 15 transformations characterized by either higher (Transformation 1) or lower (Transformation 2) car presence tend to have negative or near-zero utility scores. This suggests that regardless of car density, these environments receive lower utility assessments. Notably, Transformation 2 shows a slight increase in utility, indicating the model captures some sensitivity to car density, which aligns with existing research and the hypothesis. Xu et al. (2024) found that people prefer neighborhoods with less frequent car use and expected lower utility scores with higher car presence.

Conversely, transformations associated with greenery consistently receive higher utility scores across age groups. Transformation 4, representing a residential environment rich in greenery and amenities, scores the highest, followed by Transformation 3 with simpler green features, and Transformation 5, which lacks trees. Supporting literature by Giannico et al. (2021) and Wolch et al. (2014) links access to green spaces with enhanced happiness, mood, and well-being. The difference between predicted utility scores for baseline and green transformations is positive, contrasting with the negative or near-zero changes for car-related transformations. On average, the utility difference between the lowest and highest scoring transformations is 1.073 points.

Applying the walking time parameter (β_{wt} = -0.495) from Table 3 indicates that individuals are willing to walk nearly 2 minutes longer to move from the car-heavy Transformation 1 to the greenery-rich Transformation 4. The utility increase from Transformation 1 to 2 corresponds to a trade-off of about 20 seconds. Transitioning from car presence to greenery results in a mean utility gain equivalent to around 1.75 minutes of extra walking time. Among green transformations, those with trees and amenities are preferred over greener environments without trees, with residents willing to walk an additional 22 and 34 seconds, respectively, for these improvements. These utility differences are illustrated in Figures 16, 17,18.

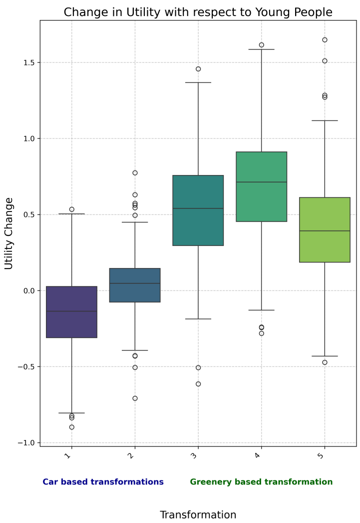


Figure 16: Utility Difference with respect to Base Image for young respondent

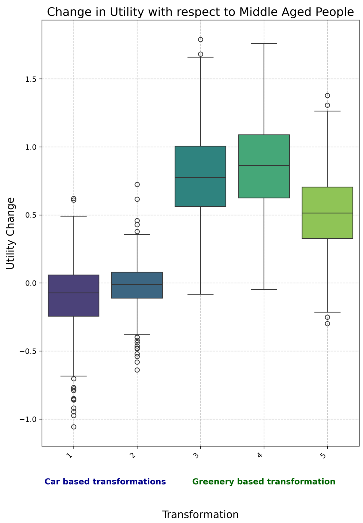


Figure 17: Utility Difference with respect to Base Image for Mid-Aged respondent

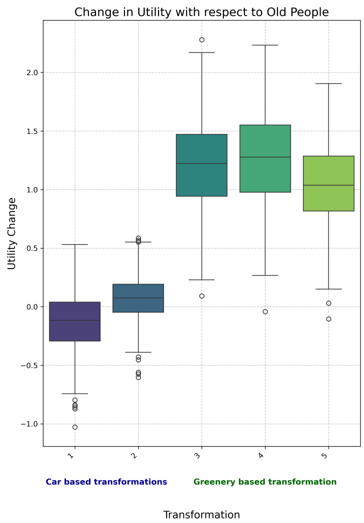
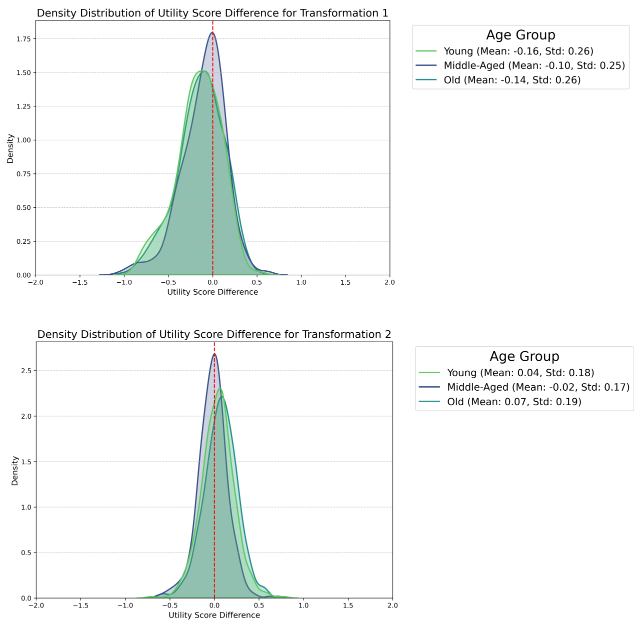


Figure 18: Utility Difference with respect to Base Image for Old respondent

6.6.3 Age based analysis of Utility scores Difference



To have a deeper understanding with respect to the age based distribution of utility score difference for the images, Figure 19 illustrates a kernel density distribution. An increase in the utility score measurement recorded between base image and image transformation is a strong indicator towards the how the image is perceived and preferred. As observed in the figure, the impact of these transformations is perceived differently based on age. It could be due to varying needs, preferences and lifestyle requirements. The density plot for transformation 1 is observed to have small yet negative mean values for all age group, indicating that compared to the status quo, car intensive environment are unattractive. For transformation 2 as well, this trend is observed but with 0 mean value for all the age groups. The density plots for transformation 3 record highest mean score difference for elderlies (1.21) followed by middled-aged (0.79) and youngsters (0.53). This indicates a higher attractiveness of environment with greenery over the status quo situation. The same trend is followed for transformation 4 (Mean difference for youngster = 0.69; Mean difference for Middle-Aged = 0.86; Mean difference for Elderlies = 1.27) and transformation 5 (Mean difference for youngster = 0.41; Mean difference for Middle-Aged = 0.52; Mean difference for Elderlies = 1.04). It is therefore evident that the sensitivity towards the transition from a car-based to a greenery intensive environment is very strong, especially for elderlies. The average utility score for elderlies has a substantial improvement by almost 1 utility unit, indicating that elderlies are highly sensitive to the greenification.

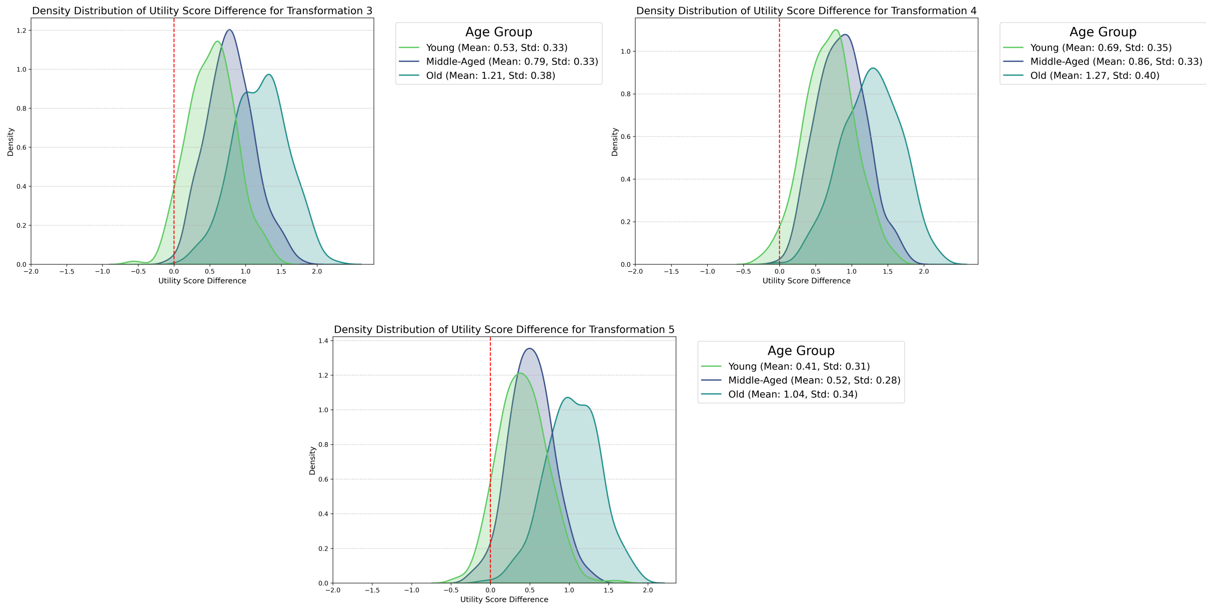


Figure 19: Density Plots for different Transformation with respect to Age

7 Conclusion

7.1 Scientific Contributions

This study advances the integration of image analysis into discrete choice models by applying computer vision through the recently developed CV-DCM model by van Cranenburgh and Garrido-Valenzuela (2023). It examines preferences between residential environments characterized by high car presence or greenery, combining quantitative and visual data to capture the trade-offs people make. This approach deepens understanding of contemporary preferences for greener neighborhoods and sensitivity to car accessibility, shedding light on people's willingness to walk for greener settings. The research innovatively employs generative AI (GenAI) to create diverse image transformations used in a logically structured experimental design, enhancing realism and precision in choice measurement. By building on foundational work with three key innovations—GenAI-driven image transformations, efficient survey design, and comprehensive data collection—the study establishes a robust framework that reduces statistical errors and enriches insights into residential location decision-making.

The CV-DCM's neural network foundation presents interpretability challenges, which this study addresses by validating GenAI's utility and bridging neural networks with classical discrete choice modeling within the specific context of stated choice experiments. The careful calibration of image analysis and experimental design enables nuanced understanding of how comprehensible attributes influence residential preferences. Overall, the findings provide valuable scientific contributions and practical implications, offering policymakers actionable insights into how different individuals balance cost, accessibility, and environmental attributes in their residential choices, thereby supporting sustainable urban planning and car-free neighborhood initiatives.

7.2 Conclusion regarding Residential Setting Preference

The study utilized a CV-DCM model to capture the influence of residential environment characteristics on preferences, demonstrating a strong explanatory power with a high ρ^2 value of 0.178 and a low BIC of 1762.50. The analysis revealed that the value of time (VOT) for young residents is €36.52 for each additional minute of car accessibility, while elderlies are willing to pay nearly €13 more, showing greater sensitivity to accessibility as age increases. Middle-aged residents did not show statistically significant VOT. Additionally, the marginal rate of substitution (MRS) indicated younger residents would trade 72 seconds of walking time for improved accessibility, compared to 42 seconds for elderlies, reflecting reluctance—especially among older residents—to sacrifice car accessibility for greener environments. The utility analysis also showed elderlies derive more satisfaction from greenery than other age groups, with residents willing to walk extra seconds to trade high car presence for greener, landscaped settings.

8 Discussions

The results of this study highlight that the quality of the residential neighbourhood environment is as important as traditional factors like walking time and parking cost in influencing residential location choices. This emphasis on the environment may partly arise from the way information was presented—visual images for the environment versus numerical values for walking time and parking cost—which can lead to cognitive bias as images tend to attract more attention than numbers (Dikgang, 2022,van Cranenburgh & Garrido-Valenzuela, 2023). However, this heightened attention to imagery might not fully translate into actual behaviour. The study did not incorporate the time spent cruising for parking, an influential factor discussed in prior research (van Ommeren et al., 2012), to avoid making the survey overly complex. Also, factors related to cruising, such as extra fuel consumption and lost time, were not directly considered, potentially leading to an underestimation of parking cost impact. Acknowledging limitations of stated choice experiments, the study recognizes that respondents' stated preferences may not perfectly reflect their real behaviour, and suggests combining revealed preferences for a more comprehensive understanding.

The street-level image collection had some limitations: some neighbourhood images were blank due to changes in Google imagery databases and thus removed entirely. The images used were from the year 2022, and variables such as image quality, weather, and lighting differences were not controlled, although the paired comparison between base and transformed images assumed these factors did not bias choices. Seasonal changes in neighbourhood characteristics, like greenery or street activities, were also not considered. Additionally, the data collection reflected sampling bias, with respondents largely from the researcher's own age group, limiting population representativeness. Future studies could address this by including residents planning to purchase cars to provide insights into future ownership trends.

The use of generative artificial intelligence (GenAI) to create image transformations introduced some limitations as well. Despite iterative improvements to prompt specificity, some generated images contained logical inconsistencies, which respondents were asked to overlook and instead base their choices on overall appearances. This may introduce minor systematic errors into the data, which future research could mitigate by training the model on carefully curated, logically consistent images. The CV-DCM model itself also poses interpretability challenges; unlike traditional discrete choice models with clear parameter estimates, the CV-DCM relies on deep neural network image embeddings, reducing accessibility of results to decision-makers who prefer straightforward interpretations. Despite this, the model demonstrated improved estimation performance with a high ρ^2 value, reflecting its effectiveness in capturing residential environment preferences.

9 Recommendations

This study identifies several promising directions for future research to deepen our understanding of residential environment preferences and the capabilities of the CV-DCM model. One key area is analysing how perceptions of neighbourhood aesthetics, traffic safety, social safety, and peacefulness influence residential choice, including which physical features most effectively promote safety and well-being. Improving the quality and precision of artificial intelligence-generated image transformations by calibrating them could reduce data inconsistencies and enhance interpretability. Furthermore, complementing stated choice data with revealed preference information, such as real estate prices and actual residential selections, would help validate findings and provide a more comprehensive picture of how environmental features like greenery and car presence actually influence behaviour. Exploring machine learning methods such as semantic and panoptic segmentation could make the CV-DCM's image-based utility scores more transparent by pinpointing the exact elements driving preferences. Additionally, incorporating demographic heterogeneity into model training—such as differences in sensitivity to greenery or parking by age groups—could yield more tailored insights, while immersive technologies like virtual reality could further enhance realism in choice experiments by simulating sensory-rich urban experiences.

The research also recognizes the potential to extend this methodology and the CV-DCM approach to other countries, provided sufficient street-level imagery is accessible from sources like Google Street View or open-source databases such as Mapillary. Since housing typologies vary widely across regions, models may require retraining to reflect local characteristics accurately. However, challenges remain with integrating large image datasets into survey platforms, often demanding advanced programming skills. Beyond residential location choices, the CV-DCM framework shows promise in other domains where visual cues are critical, such as investigating perceptions of safety along walking routes or studying urban disorder indicators like graffiti and lighting. These applications could substantially enrich research on urban safety, social dynamics, and urban planning. Overall, this work offers a scalable and nuanced tool to better capture how visual environmental attributes shape human preferences in varied contexts.

From a policy perspective, the study's findings offer actionable guidance to support sustainable urban development. Notably, they suggest designing car-free neighbourhoods with accessible parking within approximately one minute's walking distance, reflecting residents' stated willingness to walk for greener environments and reduced car dependency. This threshold can inform planners aiming to nudge sustainable travel behaviours and improve neighbourhood livability, acknowledging that acceptance of car-free interventions may increase over time. The CV-DCM approach also enables systematic quantification of the trade-offs between greenery and car accessibility, translating preferences into monetary values useful for infrastructure planning decisions such as locating parking zones. Integrating these insights into advanced residential location choice models can enhance their realism and predictive accuracy, though validation with real-world data remains important to reconcile stated and actual preferences. Ultimately, this research contributes both scientifically and practically by providing deeper understanding and effective tools for shaping healthier, greener, and more sustainable urban neighbourhoods.

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