Travel behaviour across suburban areas in the province of Zuid-Holland: A comparative study on built environments and travel behaviour

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Abstract

Introduction: Car ownership in the province of Zuid-Holland increased in the past decades. This increase is visible in suburban and rural areas. Suburban areas are areas between the urban and rural clusters, however, a suburban area is not uniformly defined. Therefore it is interesting to investigate what types of travel behaviour can be identified and to what extent they are explained by (suburban) built environments.

Methods: To answer this question the built environment data is categorised using a latent class cluster analysis (LCCA). This method is used to identify suburban and other built environments. Subsequently the travel behaviour is also clustered using a LCCA, this results in possibilities to compare travel behaviour and built environments. Using detailed travel behaviour data based on the ODiN travel behaviour survey on 29721 respondents, differences in travel behaviour could be compared across different suburban environments.

Results: Despite the relatively high proximity to facilities, suburban areas show a high use of cars. It becomes clear that suburban areas have differences in travel behaviour, they are between rural and urban clusters. However in some suburban areas the model split for cars is almost comparable to rural areas, even in suburban station areas. In terms of car use on work-related trips, the model split for cars in suburban areas is up to 3 times higher compared to urban areas, even for shorter distances. This research provides a methodology to define suburban area types. Differences between various suburban areas could be compared resulting to insights in suburban travel behaviour in the province of Zuid-Holland.

Conclusion: Despite the relative good proximity to facilities like supermarkets, shops and train stations, suburban areas reveal a much higher car use compared to urban regions. Within different types of suburban areas differences occur. Moreover, there are opportunities for other (more sustainable) travel behaviour in suburban station areas, due to the availability of jobs and PT alternatives.

Keywords: Travel behaviour, Built environment, Suburbs, Latent Class Cluster Analysis

1 Introduction

Over the past decades, the province of Zuid-Holland has experienced a significant increase in car ownership (Provincie Zuid-Holland, 2023d). This increase causes issues like congestion, challenges in housing developments, the use of limited public space for parking and decline in the availability of public transport. Suburban municipalities experienced a high increase in car ownership, sometimes comparable to rural areas. This is surprising, given the fact that these municipalities have a closer proximity to facilities compared to rural areas. These suburban areas contribute substantially to traffic problems due to their transport relationship with the urban cores. In the future, the negative effects of rising car ownership are expected to intensify, as car ownership is projected to further increase (KiM, 2022).

This policy is reflected in recent coalition agreements (Provincie Zuid-Holland, 2023a,c, 2011) where the coalition partners intended to promote walking, cycling and public transport (PT) usage among residents. Examples of the policy implementations are prioritizing active modes and PT in new developments, minimizing fare increases in PT and developing new PT connections. Local governments share the same ambitions to promote active modes and PT.

Despite policies promoting non-car modes of transport, car ownership has increased, particularly in suburban and rural areas of Zuid-Holland (Provincie Zuid-Holland, 2023d). This province could be described as a polycentric urban region with a mix of suburban and rural areas in-between. Most areas in the province are connected by national and provincial roads as well as PT connections. Since provincial roads (N-roads) are mainly located in suburban and rural areas, the increase of car ownership in these regions is likely to result in higher usage of these roads. This is relevant for the province, as it is responsible for daily operation and maintenance of these roads.

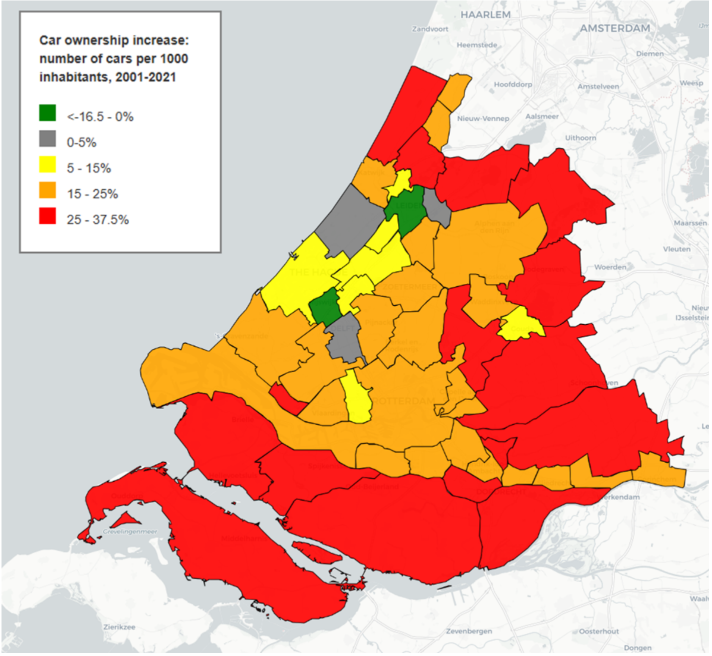

Figure 1: Increase in car ownership in the province of Zuid-Holland. (Provincie Zuid-Holland, 2023d)

The increase in car ownership causes several issues such as increased traffic congestion, challenges for housing developments, use of limited public space and decline in the availability of PT.

The negative effects of increasing car use are likely to intensify in the future. Because car ownership per capita is expected to increase with 5% by 2040 (KiM, 2022). Based on an estimated population growth of approximately 10% in Zuid-Holland (CBS, 2022b), the total number of cars is expected to grow with 15.5%.

Suburban and rural areas contribute substantially to the rise of car ownership in Zuid-Holland (Figure 1). The traffic generated in suburban areas is primarily concentrated between suburban and urban regions, because more activities, like work take place in urban regions (VNG, 2024). This makes it interesting to conduct travel behaviour comparisons between different types of built environment areas, however currently there is no uniform definition of a suburban area (Boomkens et al., 1997; Forsyth, 2012).

In literature it could be seen that there are various types of suburban areas, distant suburban areas or suburban areas adjacent to the city. Sometimes these various types of suburban areas are resulting from historical urban developments like growth cities or Vinex wijken (Kubeš and Ouředníček, 2022). However, in travel behaviour research, suburban areas are described as one type of area (Kockelman, 1997; Ewing and Cervero, 2001). There is no clear literature that examines the relationships between different types of suburban areas and travel behaviour. This definition is interesting for analysis of the specific travel behaviour as well as the built environment indicators influencing the travel behaviour.

In conclusion, literature provides knowledge on the influence of general mechanisms on travel behaviour. The main gap is the unclear role of various types of suburbs on travel behaviour. Therefore it is interesting to identify different area types and conduct travel behaviour comparisons across different area types in order to improve policymaking for 'suburban' areas with a high car ownership increase despite their proximity to urban cores.

The main question in this paper is: How does travel behaviour vary across different types of suburban areas and in comparison to other built environment types?

Given the patterns in travel behaviour data and the built environment defined as area type based on multiple indicators, Latent Class Cluster Analysis (LCCA) was employed to identify subgroups within the data. LCCA allows to identify hidden subgroups within a dataset. Each subgroup may have unique travel behaviour or distinct built environment characteristics. Applying LCCA gives better understanding of the complex relationships between travel behaviour and the built environment clusters across different segments of the population.

The method for clustering is LCCA as it outperforms other clustering methods like K-means (Magidson and Vermunt, 2002). LCCA is a useful method that identifies clusters which are homogeneous within the cluster and as heterogeneous as possible across clusters.

Using datasets from the built environment (2020, 2022) and travel behaviour (2018,2019 and 2023), containing approximately 30.000 individuals and 512 postcodes, it is possible to make a built environment and travel behaviour cluster model. The two estimated cluster models could be linked trough the postal code which serves as a connection between the built environment and individual travel behaviour clusters. This approach allows for analysis on the relationships between these clusters and different covariates.

2 Literature

2.1 Definition suburban areas

Various terminologies are used to define the types of built environments. For example, CBS categorises areas into 5 area types, ranging from highly urban to non-urban, based on address density (CBS, 2024b). Others classifications have a more qualitative approach (ruimtemettoekomst.nl, 2013).

Internationally, three distinct types of built environments are mostly distinguished: urban, suburban and rural areas (Forsyth, 2012; Harris and Larkham, 2004). However, there is no uniform definition of suburban areas (Forsyth, 2012). Hamers (2003) defines suburban areas by what they are not, they are neither urban or rural. Furthermore suburban areas show variation across themselves, some are more rural-suburban while others show a more urban-suburban character (Boomkens et al., 1997).

Besides the challenge in definition of suburban areas, the history of suburban areas also play an important role. For instance, Dutch areas that can be defined as suburb have a diverse history. In the past there have been 'Groeikernen', 'Bloemkoolwijken' (cauliflower neighbourhoods), Vinex neighbourhoods and Transit-Oriented Developments (TOD developments) in the Netherlands. These developments are the result of specific policy measures (Abrahamse, 2019). Due to the unique character, these developments are not always directly comparable to other countries.

In the US, urban development of some areas experienced a phenomenon known as 'urban sprawl', characterised by residential areas only having residential functions without other amenities. This low function mix leads to a increased need to travel long distances, often by car. In response a counter movement started to emerge, called 'smart growth' or 'traditional neighbourhood development' (TND). Smart growth and TND prioritize a higher function mix in the neighbourhood leading to less car use and shorter travel distances (Khattak and Rodriguez, 2004; Cervero and Radisch, 1996).

The lack of a clear definition of suburban areas combined with the fact that there are different types of suburban areas (with possibly different travel behaviour), complicates the identification of suburban. Especially since there are international variations in suburban area characteristics. This poses challenges for conducting research on suburban areas. (Hamers, 2003). Therefore, it is desirable to analytically identify different types of suburban areas.

2.2 Travel behaviour in suburban areas

In terms of travel behaviour in suburban areas, differences are notable. Internationally, suburban areas are generally characterised by higher car usage compared to cities, while the use of active modes of transport, such as walking and cycling are lower (Liu and Alain, 2014; Friedman et al., 1994). In addition, studies indicate a correlation between distance from a major urban centre and car use: the further an area is from the urban centre, the higher the car usage (Vega and Reynolds-Feighan, 2009; Dandy, 1997).

Some of the studies mentioned earlier were not conducted in the Netherlands, so specific Dutch context is missing. In the Netherlands, unique factors such as high bicycle use (Pucher and Buehler, 2017), the compact urban form of Zuid-Holland with its close city centres (GHSL - Global Human Settlement Layer, 2016; Batty, 2001) and the polycentric travel behaviour characteristics of the Randstad region(Planbureau voor de Leefomgeving, 2006; Boussauw et al., 2012) influence travel behaviour. This leads to different travel behaviour which makes it difficult to apply findings from international studies directly to the Dutch context (De Vos, 2015). Moreover, there is a lack of suitable literature available that directly compares different area types and travel behaviour within the Netherlands. Most studies focus on a single mode of transport, such as car use, or on specific methods of characterizing areas, such as address density. While a focus on suburban areas is actually interesting.

The challenge of defining suburban areas uniformly, combined with the lack of knowledge about travel behaviour in different types of suburban areas makes it interesting to differentiate between several area types and compare them with the existing travel behaviour.

The built environment is defined as a combination of three elements; urban design, land use and the transportation system (Handy et al., 2002; Brownson et al., 2009). Within the built environment, various activities occur, resulting in the individual need for transportation.

2.3 Influence built environment on travel behaviour

Some research describe that the mode choice is based on reaching maximum utility within budget constraints(Crane, 1995), Boarnet and Crane (2001) expanded on this, by arguing that travel costs are influenced by built environment. While others advocate for attitudes and sociodemograpic factors influencing travel behaviour (Ton et al., 2020; Lenormand et al., 2014). Literature reviews of (Ewing and Cervero, 2010; Stead and Marshall, 2001) introduce different built environment factors as variable in the travel behaviour and mode choice. In this field, it can be seen that several factors influence travel behaviour.

Address density is often used as an indicator of the built environment (Kockelman, 1997; Cervero and Radisch, 1996). However, this indicator does not always provide a complete representation. For example, in the Netherlands, some areas are classified as urban based on address density, have facilities located at a considerable distance. (Martensen and Arendsen, 2024a), Therefore, it is desirable to develop an alternative indicator that combines density with proximity to facilities.

The land use mix/job housing balance is regularly used to define the built environment. A high job-housing mix can create opportunities for work close to the residential location, resulting in short travel times for residents (Stoker and Ewing, 2014; Cervero and Duncan, 2006). However, this effect applies in a greater extent to more divergent job/housing balance ratios, according to Peng (1997).

The distance/or travel time to a transit stop is also regularly included as a factor to examine the built environment (Ewing and Cervero, 2010). This factor serves as an explanatory factor in choice to travel behaviour (Krygsman et al., 2004; Lunke and Engebretsen, 2023).

Car ownership in a neighbourhood has also been used as an indicator in this study, similar to previous research by (Martensen and Arendsen, 2024b). Where car ownership serves as a class indicator. The number of parking spaces influences the travel behaviour of individuals in the neighbourhood (Christiansen et al., 2017; Gruyter et al., 2024). In individual car ownership there is a difference between area types. Although this variation has not been extensively documented in the Dutch context in current literature (Ewing and Cervero, 2001; Gruyter et al., 2024). Car ownership influences the travel behaviour, individuals owning a car are using the car for more trips compared to those who do not own a car (Dieleman et al., 2002; Van Acker and Witlox, 2009).

Various social variables influence travel behaviour. Variables such as age, household size, car ownership and income have impact travel behaviour (Dieleman et al., 2002; Stead and Marshall, 2001; Van Acker and Witlox, 2010). For example a higher age is associated with fewer (car)trips and shorter trip distances (Schwanen et al., 2004; Van Acker and Witlox, 2010). Larger households tend to make more car trips on household level although less trips per person (Son et al., 2013). Car ownership correlates with more car trips and longer distances travelled (Van Acker and Witlox, 2009). Income also shows a positive effect on the number of car trips while negatively impacting PT and active mode trips (Dargay and Hanly, 2004).

Given the impact of social variables and built environment categories on travel behaviour choices, it is important to include these factors in the study alongside the comparison of travel behaviour and built environments. Specifically, investigating how these variables define different types of built environments is interesting.

2.4 Conceptual Model

A conceptual model has been developed to examine the influence of (suburban) built environment clusters on travel behaviour clusters, as illustrated in Figure 2.

The conceptual model consists of three main components: (1) clusters of the built environment, (2) clusters of travel behaviour, (3) set of variables. These main components are linked in this conceptual model. First, given the built environment the probability of certain travel behaviour is examined. So for each Built environment cluster the travel behaviour probability is examined, this provides insight in the differences in travel behaviour. Secondly each built environment cluster is described based on socio-demographic variables and built environment characteristics. This includes identifying the types of people persons living in a particular built environment type and BE characteristics in each built environment cluster. A similar approach is applied to describe the TB clusters.

It is expected that rural cluster show a more car oriented travel pattern compared to the urban clusters. In terms of travel behaviour, suburban clusters are expected to be in-between rural and urban clusters.

This conceptual model forms the basis for this research. section 3 elaborates on the categorization of BE and TB clusters, as well as specific method used to analyse the influence of BE and socio-demographic variables on the probability of TB cluster membership.

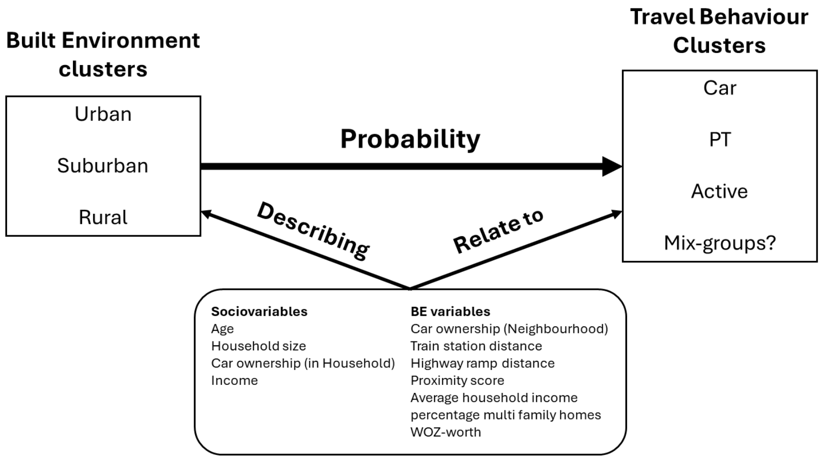

Figure 2: Conceptual model (relation travel behaviour variables and TB clusters are only included in the the thesis from based on this article.)

3 Method

To address the research questions, it is essential to categorize both the built environments and travel behaviour. This requires a methodology to classify the built environment and travel behaviour, followed by an approach to analyse travel behaviour within the identified built environment categories.

3.1 Study Area

The study area of this paper is the province of Zuid-Holland, the most densely populated province in the Netherlands. This region is chosen due to its polycentric travel behaviour (Boussauw et al., 2012), with large cities such as The Hague and Rotterdam as well as suburbs and rural area's in between. For analysis such as proximity to facilities, data beyond the provincial boundaries is considered to avoid inaccurate measurements and unequal weighting of the study area edges.

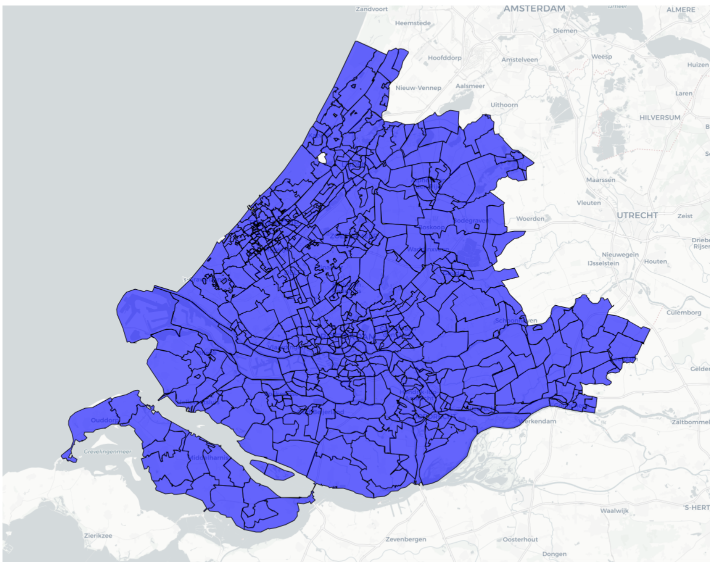

Figure 3: Study area, the province of Zuid-Holland.

3.2 Data

Two types of data are needed in this paper, built environment and travel behaviour data. First built environment data is described followed by the method for gathering and processing travel behaviour data.

3.2.1 General built environment data

Respondents are specified at PC4 level(Postcode-4 level 1234 XX). To ensure comparability with travel behaviour data, the built environment data is collected at PC4 level.

Built environment data, including the accessibility to facilities, population demographics and household characteristics originates from CBS PC4 data (CBS, 2020a, 2022a). This data contains information related to the postcodes. Job data is obtained from processed LISA data (LISA, 2022). LISA is a database with all addresses of jobs in the Netherlands. Car ownership data is also obtained from the CBS (CBS, 2023a).

Postcodes with fewer than 100 households are excluded due to CBS data limitations, as data for areas with fewer than 100 households is anonymised. Additionally, this threshold minimises the influence of outliers making the data more reliable. After these exclusions, 512 from the 537 postcodes in Zuid-Holland are included in the analysis.

Indicators and covariates(n = 512)	**Mean**	**Median**	**SD**	**Minimum**	**Maximum**
OAD	2260	1810	1847	56	8.637
Median construction year	1972	1970	19	1940	2020
Percentage multi-family homes	42,1%	33,5%	29,75%	0%	100%
Mean Household-income	€ 34.070	€ 33.700	€ 7,84	€ 18.200	€ 120.900
WOZ-worth	€ 334.037	€ 322.000	€ 116.590	€ 161.000	€ 1.448.000
Train-station Distance (km)	6.6	3.9	7.41	0.5	42.6
Highway ramp (km)	1.87	1.6	1.07	0.2	6.4
Car ownership per household	0.92	0.97	0.27	0.25	1.6

Table 1: Built environment PC4 data (CBS, 2020a, 2022a). Bold text represents the indicators, rest are covariates

3.2.2 Proximity indicator

A commonly used built environment indicator, the OAD (Address density), only counts the number of addresses in neighbourhood and therefore OAD it is not always represent the availability of facilities in a neighbourhood such as hospitals, shops, supermarkets or restaurants. This results in misinterpretations of some neighbourhoods. Some built environments have a high OAD but a lack of facilities particularly in more residential areas like Vinex-wijken[1] and growth cities such as Zoetermeer. These areas show a high OAD but fewer facilities like shops, restaurants and leisure. Other places such as towns in rural areas appear to have sufficient facilities despite a lower OAD. Therefore an alternative measure is needed to asses the proximity to facilities.

To get a better representation of proximity to facilities, a proximity score is introduced for this paper. This score is calculated using a formula that counts the number of different amenities within a specific range and assigns a weighted value to each amenity. For example a nearby primary school is given a higher weight than a restaurant. The proximity score is scaled to a median of 100 so 50% of the postcodes is below the score of 100 and 50% above.

[1]Vinex-wijken are new urban developments built between 1995 and +-2005. These neighbourhoods were located near (mid-sized) cities to increase the number of customers for existing stores and to reduce travel distances, to encouraging the use of active transportation modes and public transport.

The formula developed for this research to calculate the proximity score is in the equation below.

$$Proximityscore = \sum score_i$$

$$\begin{aligned} \text{n} &= \text{number of facilities} \\ \text{lw} &= \text{number of facilities to start lower weight} \\ \text{median} &= \text{median number of facilities in Zuid-Holland} \\ \text{i} &= \text{Facility like supermarket or primary school} \end{aligned} \tag{1}$$

$$If(n < lw):$$
$$Score_i = \sum \frac{n}{median} \times factor$$

$$Else(n > \text{lw}):$$
$$Score_i = \sum \frac{n[withinlw] + ((n - valuelw) \times lowerweightfactor)}{median} \times factor$$

The developed formula is tested using dummy variables. To prevent outliers due to a more than necessary number of facilities, a "countmax" parameter is introduced. This adjustment is introduced to account for the utility contribution of extra similar facilities in a neighbourhood that already has a sufficient facilities. This utility contribution is lower with already a high number of facilities (Banister and Berechman, 2001). For example, the utility contribution of a 10th supermarket is less than the contribution of the first or second supermarket. This concept is called marginal utility (Vandenbergh, 2024).

The minimum number of different facilities to experience freedom of choice is not clearly defined in literature. Therefore, a survey was conducted among 15 mobility experts at the province of Zuid-Holland to determine the minimum number of facilities for perceived freedom of choice. More details and responses to the survey could be found in Table 2.

To assign appropriate weights to the facilities, the survey conducted among mobility experts also asked for the most and least important facilities. The weights displayed in Table 2 show the adopted weights used in the formula.

The median in the formula was introduced to adjust the score based on the availability of certain facilities. For example, the number of supermarkets is higher compared to the number of hospitals, so dividing by the median helps to correct for this imbalance. In the formula, this is combined with the lower weights (countmax) to account for marginal utility. The combination of the countmax parameter and the inclusion of median scores provides reliable results when using dummy variables.

The count radius is based on values from the CBS dataset (CBS, 2022b). In the dataset the 1, 3, 5 and 10 km radius is included for counting the facilities. For each type of facility a range has been selected, based on kind and frequency of use.

A lower weight factor of 0.1 is applied for all facilities, meaning that after the countmax is reached within the defined range, additional facilities contribute only 10% to the proximity score. Using these parameters the proximity score is calculated. Further research is recommended to define the optimal count radius, weight factor, marginal utility of facilities and lower weight factor.

	Median (number)	Factor	Count radius	Start lower weight (lw)	Lower weight mean from survey (median)
Supermarket	7.1	8	3 km	3	3.9 (3)
Daily groceries	25.9	4	3 km	12	14.1 (11)
Primairy School	1.8	7	1 km	2	2.1 (2)
High School	2.8	4	3 km	3	2.2 (2)
Café	0.8	2	1km	2	1.8 (2)
Cafetaria	2.4	2	1km	2	2.1 (2)
Hotel	3.8	2	5 km	2	2.3 (2)
Restaurant	21.3	2	3 km	4	9.8 (9)
Attraction	3.0	1	10 km	2	2.8 (3)
Cinema	0.9	1	5 km	2	1.6 (2)
Musea	1.1	1	5 km	2	2.7 (2)
Hospital (with beds)	0.9	5	5 km	1	1.5 (1)

Table 2: Weights, start of lower weight factors compared to expert survey results. Used in the proximity formula.

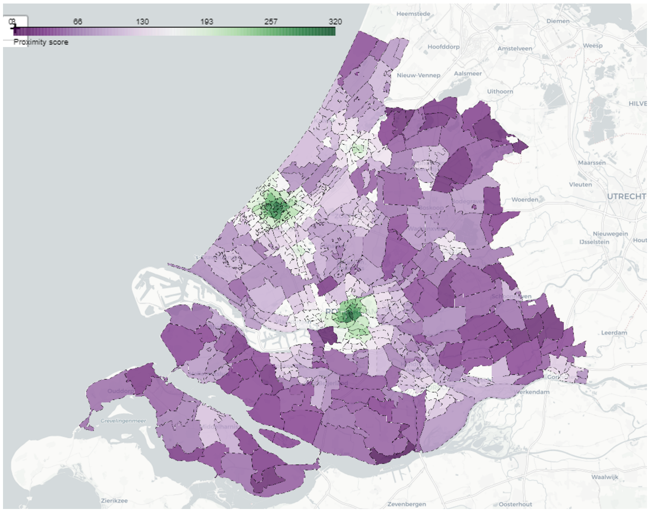

Figure 4: Proximity score in Zuid-Holland.

3.2.3 Function mix-indicator

The function mix indicator, indicates the probability of finding a job within a given area and the ratio of inbound to outbound trips. A high ratio means that the number of jobs does not match the number of households so in theory more incoming trips are needed to fullfill all jobs. An average ratio indicates that the number of jobs and households is well-balanced. This score is based on the job-housing balance, which is a commonly used indicator to measure the land-use mix. (Cropper et al., 2005; Kockelman, 1997; Spears et al., 2014). Table 3 shows the calculated proximity score and function mix indicators.

Indicators and variables (n = 512)	**Mean**	**Median**	**SD**	**Minimum**	**Maximum**
OAD	2260	1810	1847	56	8.637
Proximity Score	116.09	100	77.50	2,42	366.54
Function mix range (All jobs/household in a 3km radius from postcode)	1.18	1.12	0.8	0.38	4.58

Table 3: Built Environment indicators from own calculations. (bold are indicators) (OAD is not from own calculations but included to show difference to proximity score.

The PC4 codes of the individuals respondents, is the link between BE and TB data. This serves as the foundation for the LCCA and further analysis from the LCCA results.

3.3 *Travel behaviour data*

Travel behaviour data originates from the annual CBS travel behaviour research/survey "Onderweg in Nederland" (ODiN) (CBS, 2019, 2020b, 2024a). ODiN data contains data of individual travel behaviour within a 24-hour period, including information on travel mode, distance, trip duration, origin and destination as well as sociodemograpic information about the respondents. The ODiN data is selected due to its number of respondents and possibilities of combining data across multiple years. The unprocessed ODiN datasets for Zuid-Holland of 2018, 2019 and 2023 contains information from 41.856 individuals and 145.537 trips. Some data-adjustments were made to ensure the data gets more reliable and practically applicable.

The first adjustment is exclusion of additional data on regional level known as "ODiN meerwerk". This additional data was performed for the MRDH, a partnership of 23 municipalities in Zuid-Holland, including Rotterdam and The Hague. 'Meerwerk' was excluded to avoid over-representation of the MRDH region, resulting in the exclusion of approximately 11.000 individuals from the ODiN dataset.

Individuals living in small postcode areas are excluded due to the fact CBS built environment data is anonymized for groups smaller than five people, due to privacy regulation. As mentioned earlier, the threshold of 100 households per postcode was applied due to data availability and the prevention of outliers. Consequently, 286 individuals were excluded from the dataset.

Trips made during work-time are reported in ODiN data but were excluded from this analysis. As the focus is on individual travel behaviour. Some examples of work-time trips could be a package deliverer. As a result 4.688 trips are removed. Individuals who did not make other trips during the day are reported as non-travellers, so no respondents are excluded after this step.

Some trips consist a series of trips, sometimes with different modes, such as a train trip where the bike serves as access mode and walking as egress mode. To maintain clear data, only the primary mode of these serie trips are reported in the travel dataset. So the mode used for the largest distance is included, leading to the removal of 18.052 trips. No respondents were excluded since all trips maintain in the dataset with their primary mode.

All adjustments described above are summarised in Figure 5. After these modifications the travel behaviour of 29.721 individuals from the datasets of 2018, 2019, and 2023 is included. Sociodemographic characteristics of these individuals are presented in Table 7.

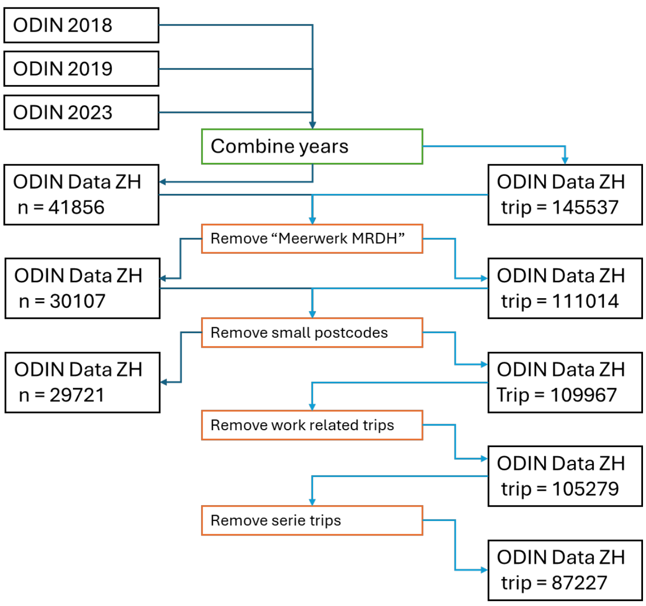

Figure 5: Data processing steps, number of respondents (n) and number of trips (verpl).

The trip data in ODiN contains 21 different travel modes. For this research and comparability these modes are categorised into four groups; Car, Public transport, Active modes and Other. The assignment of each ODiN mode to its respective group is visible in Table 4.

Motorcycles are placed under to the car mode category due to their speed and place on the road which is comparable to cars. Mopeds are grouped with the active mode group because their usage, position on road and lower

Mode (in this Report)	Mode (ODiN dataset) NL and EN translation
Car	personenauto, bestelwagen, motor (car, delivery van, motorcycle)
public transport (PT)	Bus, Tram, Metro, Taxi (bus, tram, subway, taxi)
Active	speedpedelec, elektrische fiets, niet elektrische fiets, te voet, skates/step, anders zonder motor (speed pedelec, electric bike, non-electric bike, On foot, Skates/scooter, Other without motor, moped, light moped)
other	other

Table 4: Grouping of Travel modes in this report and ODiN travel modes.

speed are more comparable with active modes. The other category includes modes such as boats and tractors, which do not fit with one of the other groups.

Since the "other" mode accounts for only 0.05 trips per person per day, the "other" mode is excluded from the dataset. This adjustment effects the data of 193 respondents where 83 respondents did not make any trip other than a trip with the mode categorised as "other". These respondents were therefore excluded from the dataset.

Indicator (n = 29721)	Mean	Median	SD	Minimum	Maximum
Car trips	1.21	0	1.65	0	16.0
PT trips	0.22	0	0.63	0	5.0
Active trips	1.33	1.0	1.73	0	17.0
Distance car	21.74	0	45.45	0	560.0
Distance PT	5.76	0	24.4	0	517.1
Distance Active	4.01	0	7.69	0	205.9
Distance total	31.53	13.0	49.04	0	560.0
% agenda-setting	26.3	0	38.29	0	100
% Non-agenda-setting	57.32	66.7	44.43	0	100
% Peak hour trip	30.26	25.0	32.07	0	100
% Car less 2km	4.27	0	17.26	0	100

Table 5: ODiN Travel Behaviour Data. Trips, distances and some other information reported.

Representativeness tests on socio-demographic variables (gender, age, household size, household income and car ownership) revealed differences between the dataset and the average of the population in the Province of Zuid-Holland. (Provincie Zuid-Holland, 2023b,c; CBS, 2023b) All socio-demographic variables were found to be significant different compared to the population. The average age is higher in the sample, The household size and car ownership is higher compared to the population average. This could be due to the under-representation of lower income classes in the ODiN data. More info on the sample is presented in Table 6

CBS uses stratification on national level to correct for this kind of errors, this CBS stratification values could not be used on regional level (CBS, 2023b). It was decided to not correct for this by using the stratification of the CBS in order to maintain unmodified travel behaviour data.

3.4 Latent Class Cluster Analysis

Given the diverse nature of travel and built environment data, it is necessary to group the data. By applying a cluster analysis we can better understand the complex relationships in travel behaviour and built environment clusters across different segments of the population. This leads to meaningful insights in clusters.

Indicator (n = 29721)	Mean	Median	SD	Minimum	Maximum
Age	43.84	44.0	22.23	6.0	99.0
Household size	2.78	2.0	1.41	1.0	10.0
Income Class	6.69	7.0	2.69	1.0	10.0
Car ownership per household	1.24	1.0	0.91	0.0	9.0

Table 6: Sociodemograpics of all ODiN Respondents. (Provincie Zuid-Holland, 2023b,c; CBS, 2023b)

Sociodemograpic	Sample mean	Population PZH mean	Test of significance
Age (from 6-older)	43.84	43.52	t = 2,469 df = 29721 p = 0,014
Household size	2.78	2.1	t = 83,084 df = 29721 p = 0,000
Income Class (10% class)	6.69	*	t = 76,264 df = 29721 p = 0,000
Male (%)	51.1	49.4	
Female (%)	48.9	50.6	
Car ownership per household	1.24	1.03	t = 40,172 df = 29721 p = 0,000

Table 7: Sociodemograpic data (Whole population) and ODiN sample data compared, (PZH income class mean for the population is estimated as the median of 5.5)

Various methods for conducting a cluster analysis exist in the literature. Latent Class Cluster Analysis (LCCA) is selected as the preferred method, as it outperforms other clustering methods like the k-means clustering method (Magidson and Vermunt, 2002). For the LCCA we use the software package Latent Gold 6.0 developed by (Magidson and Vermunt, 2002). LCCA offers flexibility with nominal and continuous variables (Kaplan, 2004). Another advantage of the LCCA is its probabilistic approach, instead of the deterministic approach employed in k-means. leading to insight in cluster membership probabilities (Lee et al., 2019). Furthermore, the data did not require standardisation when using Latent Gold(Vermunt and Magidson, 2016). The step-3 method is employed, as it is the most suitable LCCA approach for modelling the associations between classes and external variables or class indicators (Vermunt and Magidson, 2020). The step 3 method consists of 3 steps. Step 1: Define classes: Class membership probability for 1-10 classes is generated using the indicators described in the data section. The number of classes is chosen based on statistical indicators like stabilization in BIC (Flynt and Dean, 2016), BVR prefearble below below 3.84 (Kroesen, 2019), interpretability of classes and minimum class size of +- 3%. Step 2: Assign individuals to classes: Based on the class membership probability, individuals are assigned to a class. In this research the BCH assignment method is used as state-of-the-art method for assignment with continuous variables (Vermunt, 2010). Step 3: Relationship between class membership and indicators: In this step, the class membership variable will be used to examine the relationship between built environment data and class membership. This analysis is conducted using multi-nominal logistic regression analysis (Vermunt and Magidson, 2016), which will identify predictors of class membership. External covariates are included to examine the cluster membership probabilities.

Class membership estimation and the inclusion of external variables are performed across several variables. First the relationship between BE cluster membership and TB cluster membership is examined. Next the relationship between TB covariates and TB clusters are examined. Followed by evaluating BE indicators in relation to TB clusters. Subsequently the relationship between BE covariates and TB clusters is examined. Finally, the relationship among all variables and TB clusters are analysed. All mentioned steps are illustrated in Figure 6. Using these values from the estimates enables the possibility of calculating the probability of belonging to a cluster.

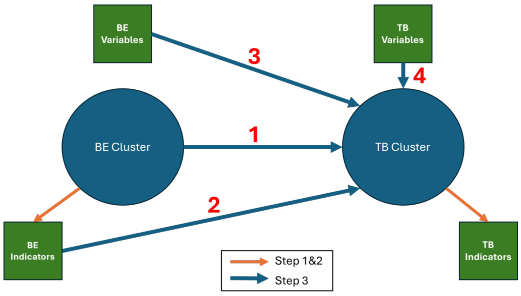

Figure 6: Visualisation of the analysis steps in the Step-3 LCCA. Red numbers represent the steps of the step-3 method. Blue lines are calculated in the third step and the orange lines in the first en second step of the step-3 LCCA.

4 Results

4.1 LCCA results

4.1.1 Travel behaviour LCCA

The LCCA was conducted using travel behaviour data. Various indicators described in the data section were tested, but the LCCA solely on trips made, yielded the best statistical outcome. These results include the highest decrease in BIC, identification of logical classes and low BVR values. 7-clusters model was chosen based on stabilization of decrease in model fit, low BVR values (less interaction effects) and interpretability for further analysis.

7 clusters could be identified based on the trip indicators. (1) Active only, (2) Car only, (3) Car+Active, (4) No trips, (5) Public transport + active, (6) PT only, (7) Mix PT, Car and Active. The number of trips per cluster, social variables per cluster and cluster sizes are visualised in Table 9.

	LL	**BIC(LL)**	**Npar**	**Max. BVR**	**Class.Err.**	**Entropy R^2**	**Smallest class size**
1-Cluster	-139135	278311	4	7970.5	0	1.000	1.000
2-Cluster	-123548	247189.2	9	10998.3	0.018	0.904	0.469
3-Cluster	-111080	222304.2	14	3349.7	0.027	0.919	0.166
4-Cluster	-106747	213690.6	19	27.4	0.041	0.893	0.122
5-Cluster	-103992	208231.7	24	24.3	0.066	0.859	0.121
6-Cluster	-103504	207307	29	32.3	0.076	0.839	0.034
7-Cluster	**-103226**	**206803.5**	**34**	**13.0**	**0.086**	**0.829**	**0.033**
8-Cluster	-103143	206689.1	39	16.3	0.093	0.820	0.006
9-Cluster	-103062	206577.1	44	16.5	0.096	0.817	0.004

Table 8: Travel behaviour latent class statistics with different number of clusters.

	active modes only	**car only**	**car+ active**	**no trips**	**PT + Active**	**PT only**	**Mix PT, Car,Active**	**Overall**
Cluster Size	0.256	0.235	0.209	0.166	0.062	0.038	0.033	
Car trip	0	2.86	2.33	0	0.01	0	1.62	1.2122
PT trip	0	0	0.01	0	1.51	2.01	1.26	0.2138
Active trip	3.09	0	1.98	0	1.72	0	0.52	1.3294
made trip	1	1	1	0	1	1	1	0.8339
no trip	0	0	0	1	0	0	0	0.1661
Age	39.9	46.6	43.2	52.3	36.7	36.4	38.6	43.84
Income class	6.6	7.2	7.2	5.7	6.2	6.2	6.8	6.69
HH car	1.1	1.6	1.5	1.0	0.8	0.8	1.2	1.25
HH size	2.92	2.77	2.93	2.51	2.63	2.65	2.77	2.79

Table 9: Indicators for cluster membership used in the LCCA with their mean in each cluster.

4.1.2 Built environment LCCA

With a LCCA using 4 indicators: proximity score, distance to train stations, neighbourhood car ownership and job/household mix 7 Clusters ranging from 1 to 9 were generated. This LCCA results in statistics presented in Table 4.5. The 7-clusters model was chosen based on stabilization of decrease in model fit, low BVR values (less interaction effects) and interpretability of built environment areas. Despite some interaction effects the 7 clusters model has the lowest number of indicator interaction effect, compared to a 6 or 8 cluster model.

Table 11 shows how all socialvariables and indicators applied in the BE LCCA differ per cluster. The clusters are grouped from large to small, with the percentage of respondents in the sample and actual population reported. From the 7 identified clusters 4 could be characterized as suburban although some are more or less a mix of suburbs and rural or urban areas. The 7 clusters could be identified as follow:

Cluster 1: Suburban 1 | Suburban train
Suburban areas between major cities with average proximity to train stations (3 km). Cluster has a high car ownership and above-average income. Functions as suburban residential areas.
Cluster 2: Suburban 2/City 1 | Midsized cities/TOD urbanization
This cluster is close to train stations and contains midsized cities like Dordrecht and Delft or is situated adjacent to large cities. Lower car ownership, younger population with a lower income. A mix of urban and suburban characteristics, but could be characterized as suburban area.
Cluster 3: Suburban 3/Rural 1 | Greenports and distant residential area
Located further from train stations, sometimes connected by light rail or metro (not recorded in data). Higher car ownership, older population, above-average income. Mix of suburban areas and rural characteristics, such as agricultural zones nearby.
Cluster 4: Rural 2 | Distant cultural landscape
Rural areas with low proximity to facilities and a high distance to train stations, high car ownership, and older, wealthier population. Cluster contains mainly agricultural landscapes distant from urban cores, however some small towns could be found in these areas.
Cluster 5: Rural 3 | Logistics and ribbon development
Smallest postcode in terms of population, contains rural areas with some job intensive logistical hubs (Bleiswijk, Westland) and ribbon developments alongside dikes. Cluster has a high job-to-household ratio, large household sizes, and high car ownership. Income levels are above average.
Cluster 6: City 2 | Large cities
This cluster is found in major cities like Rotterdam, The Hague, and Leiden. Areas with a high proximity to facilities, train stations nearby, a job/household ratio above average and the lowest car ownership. The population is younger and has the lowest average income with the smallest average household size.
Cluster 7: Suburban 4 | Residential urban sprawl
Smallest cluster in terms of postcodes, contains suburban sprawl near large cities but further from train stations compared to cluster 2. Lower car ownership and income, with average age and slightly smaller households. mainly residential areas but high proximity score due to nearby city.

	LL	**BIC(LL)**	**Npar**	**Max. BVR**	**Class.Err.**	**Entropy R^2**	**Smallest class size**
1-Cluster	-5009	10069	8	369.9	0	1	1
2-Cluster	-4425	8957	17	152.1	0.065	0.797	0.481
3-Cluster	-4247	8655	26	56.5	0.072	0.834	0.238
4-Cluster	-4147	8513	35	48.2	0.124	0.787	0.177
5-Cluster	-4090	8454	44	29.4	0.145	0.775	0.121
6-Cluster	-4038	8406	53	13.8	0.141	0.795	0.0998
7-Cluster	**-3993**	**8373**	**62**	**13.6**	**0.144**	**0.803**	**0.091**
8-Cluster	-3964	8370	71	12	0.115	0.834	0.039
9-Cluster	-3934	8367	80	7.3	0.118	0.841	0.053

Table 10: Latent class statistics with a variable number of clusters.

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Overall
	Suburban train	Midsized cities TOD urbanization	Greenports and distant residential area	Distant cultural landscape	Logistics and ribbon development	Large cities	Residential urban sprawl	
	Suburban 1	Suburban 2/City 1	Suburban 3/Rural 1	Rural 2	Rural 3	City 2	Suburban 4	
Cluster Size (% of all postcodes)	0.254	0.150	0.147	0.133	0.130	0.095	0.091	
Score	103.85	158.53	89.35	49.93	43.34	252.46	162.40	114.23
Train station distance	3.07	1.62	9.54	19.85	7.38	1.80	4.36	6.60
Car owenership	1.00	0.66	0.99	1.19	1.20	0.44	0.66	0.92
Functionmix in range	1.18	1.29	0.94	0.96	1.54	1.48	1.00	1.19
Age	44.99	42.19	45.25	47.16	44.61	37.42	45.2	43.84
Income class	7.14	6.06	6.99	7.14	7.34	5.65	6.13	6.69
Cars in HH	1.41	0.92	1.45	1.61	1.62	0.7	1.01	1.25
Size HH	2.94	2.46	2.95	2.89	3.08	2.41	2.63	2.79
ODiN Respondents percentage	34.8%	18.4%	14.5%	5.7%	7.5%	10.4%	8.7%	
Actual population percentage	32.2%	18.3%	14.7%	5.9%	7.1%	12.5%	9.2%	

Table 11: Indicators and sociovariables for cluster membership with their mean in each cluster

Using the LCCA methodology it becomes possible to identify subgroups in the Built environment and travel behaviour datasets, these subgroups allow for further analysis of travel behaviour and the built environment while focussing on suburban travel behaviour. The identified clusters are visible in Figure 7.

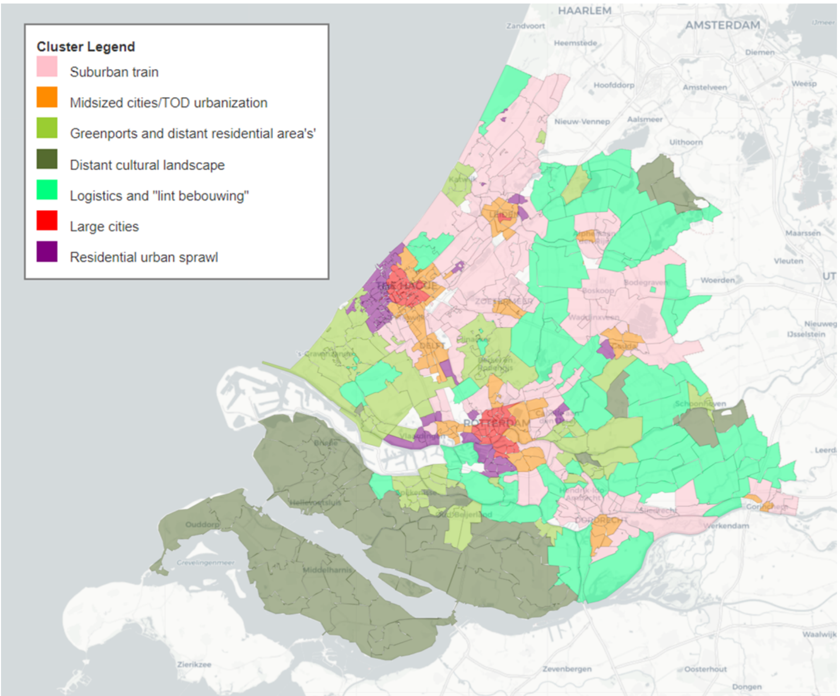

Figure 7: Built environment clusters

4.2 *Estimation travel behaviour Cluster membership*

The membership of the travel behaviour clusters is reflected on residential location of individuals. Table 12 shows the distribution of people living in a specific built environment class across all travel behaviour clusters. Each column represents 100% of the travel behaviour categories for a particular BE cluster.

In the "suburban train" cluster, 30% of individuals belong to the "car-only" group, higher than the 23% average, while public transport use remains low despite nearby train station access. Across all clusters, at least 20% use "only active modes" with midsized cities, large cities, and urban sprawl showing the highest shares, though even rural clusters like "distant cultural landscape" reach 20% active mode use.

Car use is most visible in the "distant cultural landscape" (38%) and "logistics and ribbon development" (34%) clusters, compared to just 14% in large cities. The "no trips made" group is slightly higher in rural and residential sprawl clusters, while public transport use is almost absent in rural clusters while most prevalent in large cities.

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
	Suburban train	Midsized cities /TOD urbanisation	Greenports and distant residential area's	Distant cultural landscape	Logistics and "ribbon development"	Large cities	Residential Urban sprawl
	Suburban 1	Suburban 2/City 1	Suburban 3/Rural 1	Rural 2	Rural 3	City 2	Suburban 4
Only active modes	27% (2834)	34% (1837)	27% (1145)	21% (350)	24% (535)	34% (1055)	33% (846)
Only car	30% (3149)	20% (1085)	30% (1315)	38% (640)	34% (755)	14% (438)	22% (559)
Car + Active	18% (1901)	14% (756)	19% (828)	18% (306)	19% (418)	10% (312)	13% (348)
No trip	16% (1617)	17% (909)	16% (695)	19% (316)	17% (374)	17% (541)	19% (479)
PT + Active	3% (261)	6% (352)	3% (110)	1% (25)	1% (30)	11% (330)	4% (116)
PT	4% (389)	7% (393)	3% (147)	2% (38)	3% (65)	11% (335)	7% (188)
Mix PT, Active and car	2% (199)	2% (131)	2% (73)	1% (19)	2% (38)	3% (88)	2% (51)

Table 12: Travel behaviour cluster membership given the built environment cluster, this is based on where the ODiN respondents live. (So each column is 100%)

4.3 Travel behaviour commuter trips

As visible in the last section the share of car-related travel behaviour is relatively high. Therefore more in depth analysis is needed on trip level. So all trips made in suburban areas are analysed for commuting trips[2] on of the most frequent in number (18% of all trips) but also at an interesting time, often in the morning or evening peak hours. First commuting trips are differentiated on distances between all clusters Table 13, secondly the share of car on each distance group is analysed Table 14.

Commuter trips reveal specific TB across clusters based on distance and mode of transport. Up to 2 km, there is some variation in the share of trips, this distance is ideal for walking/cycling. Within 5 km, 30-50% more people in urban clusters live close to their work compared to suburban and rural clusters, with 36% of trips in cities occurring at a maximum of 5 kilometer compared to 25% in other clusters. The distance of 5 km to work makes cycling a practical option. Trips in the range of 5-15 km account for 30% of suburban trips and 21% of urban trips. Notably, 60% of commuter trips in suburban and urban clusters occur within 0-15 km, with rural clusters also showing 45% of trips within this range, making e-bikes a possible alternative for this 0-15 and 5-15 km trips.

Car use varies significantly between clusters. From 2-5 kilometer suburban clusters have a car use of 18.9-41.7%, urban areas 11% and rural areas 52.1%, the largest suburban cluster 1, (32.2% of population) has a car use percentage of 36.1% in the 2-5 km range and 18.3% in the 0-2 km range. In suburban areas, 43% of commuter trips under 15 km are made by car, compared to 21% in urban areas and 50% in rural areas. For trips between 5-15 km, car use is the highest in rural clusters (62-75%) and lowest in urban areas (35%), with suburban clusters in-between (34-62.5%). Active modes of transportation are present across all clusters, with urban areas and urban-sprawl cluster showing the highest share. However, suburban and rural areas also have active modes, although less: the percentage is lower. For instance, 81.5% of trips under 2 km in suburban area 1 is active, compared to 93% in urban areas.

Commuter trips cumulative	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
0 - 2 km	10.7%	12%	14.2%	14.5%	11.8%	14.2%	10.7%
0 - 5 km	27.4%	32.9%	27.7%	24.9%	21.6%	36.2%	33.4%
0 - 15 km	58%	56.4%	57.1%	45.1%	54.9%	57.9%	66.5%
Total	100%	100%	100%	100%	100%	100%	100%

Table 13: Distance of work related trips per cluster: suburban train. distant cultural landscape and large cities. Note: This are trip distances. (CBS, 2019, 2020b, 2024a)

4.3.1 Travel behaviour and filtering on station distance in suburban areas

Cluster 1 with train stations nearby, show a high use of cars, even for shorter distances, the use of public transport is relatively low in these areas. The mean distance to stations is 3.1 km, for comparison with urban clusters suburban

[2]Dashboard on website shows data for all trip motives: maxkl.nl, for access-token mail: m.r.klootwijk@gmail.com

Commuter trips cumulative	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
0 - 2 km	18.3% (n = 105)	8.8% (n = 32)	15.9% (n = 52)	15.9% (n = 21)	19.1% (n = 26)	5.2% (n = 14)	13.4% (n = 19)
2 - 5 km	36.1% (n = 324)	18.9% (n = 119)	41.7% (n = 130)	52.1% (n = 49)	37.2% (n = 42)	11.0% (n = 46)	23.4% (n = 71)
5 - 15 km	55.2% (n = 907)	43.9% (n = 311)	62.5% (n = 423)	74.9% (n = 137)	62.4% (n = 239)	34.6% (n = 143)	34.0% (n = 150)
Total	55.8% (n = 2995)	38.3% (n = 1152)	58.5% (n = 1348)	69.5% (n = 631)	65.2% (n = 749)	24.4% (n = 466)	37.9% (n = 505)

Table 14: Car share within each cluster and distance category.

train areas have been filtered on the same station distance compared to the urban cluster. So only postcodes within a 1.8 km distance from train stations have been included.

This filtering is shown in Table 16, where the modal split for BE cluster 1 is visible. Despite the proximity to stations, the modal split in filtered areas is almost comparable to the entire suburban cluster shown in Table 15. PT usage is 4 percentage points higher in the filtered areas however, this is not a result of a reduction in car usage but rather a consequence of the decrease in active modes of transportation.

For shorter distance the use of car is interesting in suburban areas with a proximity to train stations (and to other facilities). Do the residents use the car while there are alternatives to car use or do the have to use the car due to their inaccessible work location, time of work or simply a car minded attitude? For the scope of this research this isn't investigated. However the higher car use in suburban clusters, even for short distances and with possibilities for other modes of transport, is an interesting topic for further research.

	Car	PT	Active
2km	18% (n = 105)	0% (n = 1)	82% (n = 468)
5km	29% (n = 429)	2% (n = 32)	69% (n = 1010)
15km	43% (n = 1336)	8% (n = 237)	49% (n = 1536)
total	56% (n = 2977)	14% (n = 745)	30% (n = 1595)

Table 15: Suburban train cluster modal split (cumulative)

	Car	PT	Active
2km	26% (n = 45)	0% (n = 0)	74% (n = 125)
5km	33% (n = 142)	3% (n = 12)	64% (n = 272)
15km	44% (n = 389)	10% (n = 91)	46% (n = 402)
Total	55% (n = 859)	18% (n = 274)	27% (n = 418)

Table 16: Suburban train (cumulative): only postcodes within a distance of 1.8 km or less from train stations are included.

5 Discussion

This study explores travel behaviour across different built environments, with a specific focus on suburban areas, areas that can't be classified as rural or urban areas. The main question in this study is: Which mobility patterns can be identified and to what extent are they influenced by built environment?

The travel behaviour of individuals was only measured over a 24-hour period, which means that the results at individual level could differ, as travel behaviour can vary from one day to the other. The study would be more robust if travel behaviour was analysed over several days. However, there's currently no data available for the province of Zuid-Holland that provides this information with a usable sample size.

A limitation of this study is that the CBS data did not include light rail, metro and tram lines in the calculation of distance to train stations. This may affect the classification of towns such as Spijkenisse, Hoek van Holland and Pijnacker. These areas are adjacent to light rail or metro lines , which are similar to sprinter stations, which are included in the station distance dataset. These sprinter stations are mainly present in the suburban areas. This may lead to local errors in classification.

Another important point to consider is the influence of residential self-selection on the difference in travel behaviour between the BE clusters. Residential self-selection means that people choose their residential location based on their travel behaviour. For example, individuals who travel a lot by car are more likely to choose a residential location that is easily accessible by car. These individuals are less likely to live in a car-free city centre (van Wee, 2009).

Residential self-selection might contribute to the higher car use in suburban clusters. Those who prefer travelling by car are more likely to live in regions that support car usage, such as suburban or rural areas. Area types that typically implement fewer car-oriented policies, such as limiting parking spaces or introducing paid parking. However other factors like social, economical and geographical factors also play important a role in residential selection (van Ham, 2012)

Besides residential self-selection, attitude may also play a role in higher car use in suburban areas. Residents of suburban areas may have a certain preference in the use of cars, influenced by several factors (van Wee et al., 2019). The same attitude may conversely apply to public transport and active forms of transport in urban areas. In addition to residential self-selection, a car-minded attitude in suburban areas may be a factor behind their higher levels of car use.

6 Conclusion

Several clusters of the built environment can be identified in the province of Zuid-Holland. Seven clusters have been identified based on homogeneity within clusters and heterogeneity between clusters. Four clusters show suburban characteristics. These suburban clusters differ from each other on the basis of the indicators used, This is consistent with the theory of suburban areas (Forsyth, 2012; Hamers, 2003). However, their characteristics remain between those of urban and rural clusters. The remaining clusters show rural or urban characteristics, making them suitable for comparison with suburban areas.

The comparison of BE (built environment) cluster membership with the probability of belonging to a particular TB (travel behaviour) cluster shows that in suburban and rural areas the probability of belonging to a car cluster is higher, while the probability of belonging to a public transport cluster is lower. In urban areas the opposite is observed. It can be observed that active clusters are present everywhere, although the probability of belonging to an active cluster is higher in urban clusters.

Comparing suburban areas with other area types provides valuable insights into differences in travel behaviour. Data analysis shows that car use is much higher in suburban areas, even for short distances. The suburban areas in Cluster 2 and 7) with a higher proximity score reveal the lowest car use of suburban areas. While in the suburban train cluster (cluster 1), the distance to stations does not play a visible role. The filtering of cluster 1 at the same or lower distance from stations compared to urban clusters, results in similar travel behaviour compared to the unfiltered cluster 1. It could be concluded that in the urban clusters travel behaviour is less car oriented and in the rural clusters travel behaviour is more car oriented. In terms of travel behaviour, the share of work trips made by car is 24% in urban clusters, 70% in rural clusters, and between 38% and 58% in the 4 suburban clusters. Travel behaviour differs across suburban clusters, where some areas are more similar to rural regions, while others tend toward urban patterns. The car use of in suburban areas is in-between rural and urban cluster. Travel behaviour differences across clusters even occur in different distance classes like the 0-2, 2-5 and 5-15 km distance classes. In some suburban clusters, especially in station areas, the higher use of car is interesting. Despite relative good proximity to facilities like supermarkets, shops and train stations, these suburban areas reveal a much higher car use compared to urban regions.

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