Evaluating the 15-Minute city: A comparative analysis of travel behaviours ,urban accessibility and sustainability within the Netherlands

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Foreword:

This thesis represents the coming together of my passion for sustainability and urban planning. I have always been interested in ways cities could help reduce Carbon emissions whilst simultaneously creating places where people like to live. I personally believe the 15 minute city as proposed by Monreal comes very close to this ideal, where cities focus back on to human scale. So when the opportunity presented itself for me to make my end thesis about this topic I took it.

During this process the help of my supervisor Dr. Tanhua Jin throughout the making of this thesis and the help of Dr. Eric Koomen during the setup phase was immensely appreciated, with both giving valuable feedback and always responding in a timely fashion.

Furthermore, I would like to thank Knap et al., whose paper 'A composite X-minute city cycling accessibility metric and its role in assessing spatial and socioeconomic inequalities – A case study in Utrecht, the Netherlands,' was of considerable importance for this thesis, as without their findings I would have no 15 minute city to test.

I hope my thesis has contributed to the current discussion at hand and shed light on previous unexplored questions regarding the current state of 15 minute cities and the travel patterns they influence.

Sincerely,

Floris de Wagt

Abstract: The 15-minute city concept aims for all citizens to reach daily necessities within a 15-minute trip by walking, cycling, or using public transit. Although this urban philosophy is largely theoretical, recent accessibility analyses suggest some cities could meet these criteria. However, it's unclear if this accessibility translates to actual travel behaviour. This research investigates this by analysing the travel behaviour of citizens in three proposed 15-minute cities and comparing them to similar cities within the Netherlands. Using the ODiN dataset, we examined travel time, mode of transport, socio-economic characteristics, and calculated CO_2 emissions for different trip purposes. The results indicate that many trips exceed the 15-minute threshold and are often made by car. Nonetheless, 15-minute cities generally perform better than their counterparts, suggesting that while the concept is effective, it is not yet fully realised on the expected scale.

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1. Introduction

With an increasing proportion of the global population residing in urban areas, the need for sustainable city development has grown exponentially. Urban centres are major contributors to greenhouse gas (GHG) emissions (Mitchell et al., 2022), and their transformation holds immense promise in combating climate change. A recent and significant concept in urban planning is the "15-minute city," first popularised by urbanist Carlos Moreno. This idea envisions a city where every citizen can reach all their daily needs (such as work, shopping, education, and recreation) within a 15-minute walk or bike ride.

The potential impact of the 15-minute city on climate change is substantial. By reducing car trips, transport emissions can be significantly lowered. Additionally, there are numerous other benefits, including increased accessibility for citizens with limited mobility, reduced traffic congestion and collisions, and improved public health due to decreased air pollution and the promotion of more active transport modes (Bopp et al., 2018). While the principles behind the 15-minute city are not entirely new (many pre-car cities were designed with similar concepts) the COVID-19 pandemic has reignited interest in these ideas. During lockdowns, road closures to motor vehicles led to improved air quality in surrounding neighbourhoods (Albayati et al., 2021), providing a glimpse into the potential benefits of such urban planning.

Cities like Paris, Melbourne, and Utrecht have started to adopt the 15-minute city model, aiming to enhance the quality of life for their residents. However, despite its promise, the 15-minute city remains largely theoretical, with few real-world examples currently in existence. This raises important questions: does the 15-minute city model have the desired effect on travel behaviour? Specifically, do people actually travel shorter distances and choose more sustainable modes of transport when all their needs are accessible nearby?

This thesis aims to analyse the travel behaviour of citizens within 15-minute cities to determine if they indeed travel shorter distances and choose more sustainable transport options compared to other cities. Building upon the research by Knap et al. (2023), which demonstrated that the accessibility in Utrecht and its surrounding municipalities already aligns with the expectations of a 15-minute city by bike, this study will compare their results with the ODiN dataset (a comprehensive collection of travel patterns of Dutch citizens). By integrating socioeconomic factors, this study will also assess the equity and inclusivity of the 15-minute city model, contributing to broader themes of sustainability set out by the sustainable development goals.

Research question: To what extent do travel times in Utrecht reflect the 15-minute city model, and how does this contribute to mitigating carbon emissions from transportation?

Sub Questions:

1. What is the average travel time and mode of transport for citizens living in a 15-minute city (Utrecht, Houten, IJsselstein) for each of the 4 categories (working, commerce, education, and entertainment)?
2. What is the average travel time and mode of transport for citizens living in a comparable city (Eindhoven, Waalwijk, Uithoorn) for each of the 4 categories (working, commerce, education, and entertainment)?
3. What percentage of trips is made within 15 minutes with sustainable transport?
4. How do travel times vary among different socioeconomic groups within Cities?
5. What is the difference in transport CO_2 emissions for each of the 4 categories between the 15-minute cities and the comparison cities?

In addressing these questions, the study will focus on four main categories of daily activities: work, commerce, education, and entertainment. By examining the travel times and modes of transport for these activities, and considering various socioeconomic factors, this research seeks to provide a comprehensive assessment of the effectiveness of the 15-minute city model. Ultimately, this study aims to contribute valuable insights into urban planning strategies that can help mitigate climate change, promote sustainable economic development, and improve urban living conditions.

2 Study areas and data

2.1 The ODiN data set.

The ODiN dataset (On the road in the Netherlands) is an extensive dataset from the Dutch Central Bureau of Statistics (CBS) that provides detailed information on the daily mobility of Dutch citizens. It includes data on various aspects of travel behaviour, such as mode of transport, trip purpose, and travel time, alongside socio-economic characteristics like age, sex, income, and education. This dataset's comprehensive nature makes it ideal for analysing travel patterns and socio-economic characteristics.

2.2 Explaining which cities are used and why

In their paper, Knap et al. (2023) demonstrated that Utrecht and its surrounding municipalities qualify as 15-minute cities, where residents can reach all main amenities within a 15-minute bike ride. For this study, Utrecht and two of its surrounding municipalities were selected and compared to similar cities within the Netherlands. All selected cities share the same urbanity and population class within the ODiN dataset as their 15-minute city counterparts, minimising variable influence on the results. Additionally, size and population density were closely matched. Below is an explanation for the chosen cities:

Utrecht vs Eindhoven.
Finding a suitable comparison for Utrecht was challenging due to its unique characteristics. Utrecht is one of the largest cities in the Netherlands, yet it shares some characteristics with smaller cities like Haarlem and Leiden. After thorough consideration, Eindhoven was chosen for comparison. Both cities are similar in population and area and serve as central points in metropolitan areas consisting of multiple municipalities. Additionally, both are university cities. Despite Eindhoven's classification being the same in terms of population and urbanity within the ODiN dataset, it is a smaller city and includes sparsely populated areas such as Eindhoven Airport and several forests. While acknowledging these limitations, comparing Utrecht with Eindhoven offers valuable insights.
Houten vs Waalwijk
Houten is a relatively new city designed with a bicycle-centric philosophy (Jaffe, 2015). Waalwijk was chosen for comparison due to its similar population, size, and urbanity. Additionally, Waalwijk is a car-centric city with limited public transit and significant road infrastructure, including the A59 highway running through the municipality. This comparison will help assess the impact of Houten's bicycle-friendly design.
IJsselstein vs Uithoorn
IJsselstein is located relatively far from Utrecht and relies more on its own amenities. Uithoorn, in contrast, has minimal local entertainment and low accessibility to higher education. This comparison aims to explore how these differences impact travel time in a similarly sized 15-minute city versus a non-15-minute city.

Table 1: Municipality population, Urbanity and size.

Gemeente	Utrecht	Eindhoven	Houten	Waalwijk	Ijsselstein	Uithoorn
Population	374238	246443	50847	50302	33421	31685
Address density/km2 (urbanity)	3588	2831	1586	1587	1881	1503
Size Km2	93,8	88,0	59,0	39,0	21,7	19,3

based on data from CBS

2.3 Explaining which trip purposes were chosen.

Table 2: Daily activities

Daily Activity	Trip Purpose (ODiN Dataset)	Reasoning
Commerce	Shopping/grocery shopping	Shopping, especially grocery shopping, is essential for people as they need to constantly stock up on food and other necessities. It's important that these amenities are close by.
Working	To and from work	Although the ODiN dataset includes other work-related destinations (e.g., business visits), I focused on daily activities only. Commuting to and from work is a routine daily activity for most people.
Entertainment	Sports/hobbies, Other leisure activities	Leisure activities help us relax, socialise, and meet new people. I omitted touring/walking because the research focuses on travel time differences, and these activities are purposefully travel-oriented.
Education	Taking education/course	Education, especially for younger children, is a daily activity that benefits from shorter trips due to their limited transportation options.

Healthcare
While healthcare isn't a daily activity for most people it is very necessary for some, especially the elderly. Furthermore it's often included within other peoples definition of a 15 minute city. Despite this the choice was made to omit healthcare from this study, as its goal is to strictly focus on daily activities. Furthermore the ODiN dataset categories healthcare broadly under services in general, which would obscure the results.

2.4 Socioeconomic characteristics

For the regression analysis, six socioeconomic characteristics were chosen: age class, sex, origin, education level, household income, and the number of household cars. These characteristics were selected to test for inequalities in travel time among different demographic groups and to provide insights into the travel behaviour and accessibility within 15 minute cities.

Age Class: Age is a crucial factor influencing travel behaviour, as mobility needs and preferences change throughout a person's life. Younger individuals may rely more on public transportation or cycling, while older individuals may prefer walking or driving. By including age, it's possible to assess how travel times vary across different age groups and identify potential inequalities.

Sex: Previous research has shown that men and women often have different travel patterns due to varying responsibilities and preferences(Scheiner & Holz-Rau, 2015). Including sex in the analysis allows us to explore gender-based differences in travel time and mode choice, highlighting potential gender inequalities within 15 minute cities.

Origin: Origin, or ethnic background, was chosen based on findings by Knap et al. (2023), which suggest that people from different backgrounds tend to have less accessibility. This characteristic helps us examine whether travel times and accessibility differ among various ethnic groups, providing insights into potential disparities in urban planning.

Education Level: Education level is often linked to socioeconomic status and can influence travel behaviour and access to different transport modes. Higher education levels may correlate with higher income and car ownership, affecting travel times.

Household Income: Household income is a key determinant of travel behaviour, as wealthier individuals may have more access to private vehicles and can afford to live closer to amenities. By examining income, we can assess the impact of economic status on travel time.

Number of Household Cars: The number of household cars is an indicator of car dependency and urban design favouring car travel. If owning more cars significantly reduces travel times, it could suggest that the city's infrastructure prioritises car travel over other modes of transport. This characteristic helps in understanding the extent to which a city supports sustainable transportation options.

3 Methodology

3.1 Data Cleaning and Preparation

All calculations were performed within the Python workspace. The ODiN dataset was first loaded and prepared for analysis. Non-numeric values were converted to numeric values, and rows where travel time was zero were removed. Duplicate entries were deleted, and trips where the destination was the same as the starting point were excluded to avoid miscategorized touring trips. A copy of the filtered dataset was then made. The transport mode column was mapped into their respective modes and split into dummy variables for subsequent analysis. With these steps, the dataset was ready for use.

3.2 Calculating Mean, Mode, and Median Travel Time per Category

This process was identical for all six municipalities. Using Utrecht as an example, the dataset was filtered to include only respondents from Utrecht (WoGem 344). The dataset was further filtered to include only work-related trips, and the mean, mode, and median travel times were calculated for these trips. This process was repeated for trips related to education, commerce, and entertainment, which allows an accurate analyse between the differences to be made.

3.3 Mode of Transport Analysis

Transport modes were defined as follows: Car (passenger car), Cycling (bicycle and e-bike), Walking (on foot), and Public Transit (train, bus, tram, and metro). The dataset was categorised by trip purpose (work, education, commerce, and entertainment), and the percentage of trips taken by each transport mode within each category was calculated. An OLS regression was performed to determine the impact of transport mode on travel time, using the dummy variables created before, with car trips chosen as the reference point. This approach allowed for a detailed understanding of how different transport modes affect travel time.

3.4 Trips within the 15-Minute City Principle

To assess the adherence to the 15-minute city principle, trips within the dataset were examined based on two criteria: travel time and mode of transport. The objective was to identify trips that could be completed within a 15-minute timeframe and were undertaken using sustainable modes of transport.

Travel Time and transport mode filtering

Firstly, trips with a travel time equal to or less than 15 minutes were filtered from the dataset. This criterion was established to align with the principle of the 15-minute city, where residents ideally have convenient access to essential amenities within a short travel duration. The selected trips were evaluated to ensure they were undertaken using appropriate modes of transport. These modes encompass walking, cycling, and public transit, which are sustainable modes of transport.

Trips that met both criteria (having a travel time of 15 minutes or less and being undertaken using one of the identified appropriate modes of transport) were considered as falling within the scope of the 15-minute city principle.

3.5 Socio-Economic Analysis

An OLS regression analysis was conducted for each municipality where travel time was the dependent variable and the socio economic characteristics the independent variables.
The socio-economic characteristics considered were: age class, sex, origin, education level, household income, and the number of household cars. These characteristics were chosen to test for any inequalities between different socio economic groups when it comes to travel time. Furthermore a variance inflation factor (VIF) test was conducted to assess if there were multicollinearity issues between the independent variables.

3.6 CO_2 emissions

The process of calculating the CO_2 emission from car trips was the same for each city and trip purpose. For demonstration purposes work trips for Utrecht will be shown as an example.

This thesis focuses exclusively on emissions from car trips for several reasons.
First, a significant portion of the public transit network in the Netherlands operates on green electricity, with plans to increase this share further (Ministerie van Infrastructuur en Waterstaat, 2021). Additionally, public transit is often categorised as sustainable transport due to its efficiency in transporting many people.
Furthermore one of the primary goals of the 15-minute city concept is to reduce car usage, which is why it will be the focus of the research.

First the average distance travelled by car for work is retrieved, this is converted from Hm to km. This is multiplied by the average CO_2 emissions from a petrol car which is 170 grams per km travelled (Ritchie, 2023). This gives the CO_2 emissions in grams for an average car trip for work. In order to compare the cities with each other a per person number is necessary. This is done by multiply the CO_2 emission from trips by the percentage of trips taken by car which will give the final grams of CO_2 per person for work commute trips

Parameter	Value
Average travel distance hm	318,72
Average travel distance km	31,87
Average CO_2/km in grams	170,00
Percentage of car trips	24,84%
CO_2 Emissions in gram	5418,26

Formula

$CO_2 / \, Person \; = \; \left(Average\ travel\ distance\ km \; * \; Average\ CO_2/km\right) * \; Percentage\ of\ car\ trips$

Example

$1345,9 \; = \; (31,87 \; * \; 170) * \; 24,84\%$

4 Results

4.1 Mean, Mode, and Median Travel Time

This section investigates whether residents in 15-minute cities, as defined by Knap et al. (2023), travel shorter distances compared to residents of other cities. Travel times for work, education, commerce, and entertainment purposes were compared across six municipalities.

Table 4: Mean Travel Times (minutes) for different daily trips

City	Work	Education	Commerce	Entertainment
Utrecht	43,4	26,7	14,1	34,2
Eindhoven	32,5	40,2	13,8	26,4
Houten	30,4	34,7	12,4	26,1
Waalwijk	29,0	17,3	13,5	37,4
IJsselstein	35	18,7	16,0	31,0
Uithoorn	20,1	47,4	12,5	32,8

Utrecht vs Eindhoven

Utrecht has a substantially higher average for work and entertainment related trips than Eindhoven. In terms of education, Utrecht has a significantly lower travel time than Eindhoven.

Houten vs Waalwijk

The biggest differences are observed between education and entertainment, where Houten has an average education travel time of more than twice that of Waalwijk. Houten does have substantially shorter entertainment trips.

IJsselstein vs Uithoorn

Uithoorn has significantly shorter average working commutes than ijsselstein and a decent decrease in commerce related trips, however IJsselsteijn has a major decrease in travel time for education in comparison to Uithoorn.

Overall only commerce fell below the 15 minute goal as most other average travel times were somewhere between 30 and 40 minutes.

Table 5: Mode Travel Times (minutes) for different daily trips

City	Work	Education	Commerce	Entertainment
Utrecht	15	10	5	15
Eindhoven	15	15	5	15
Houten	30	5	10	5
Waalwijk	15	5	10	15
IJsselstein	15	15	5	5
Uithoorn	10	65	5	5

The mode paints a much different picture, showing that most trips do fall within or below the 15 minute timeframe, with a few outliers notably: Houten work commutes and Uithoorn very long education trips.

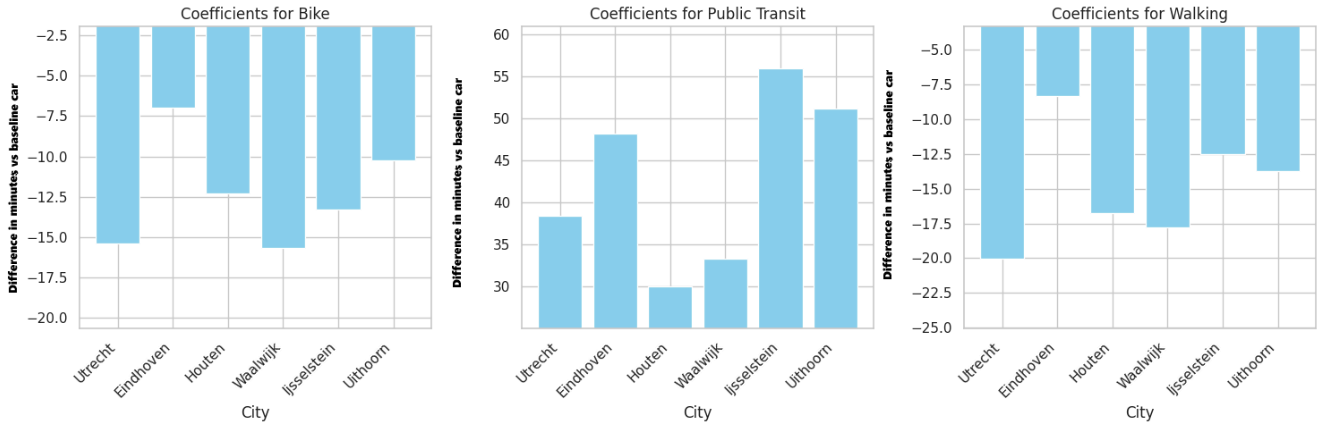
Table 6: Median Travel Times (minutes) for different daily trips

City	Work	Education	Commerce	Entertainment
Utrecht	37,5	20,0	10,0	17,0
Eindhoven	25,0	20,0	10,0	15,0
Houten	30,0	25,0	10,0	15,0
Waalwijk	15,0	10,0	10,0	17,5
IJsselstein	30,0	15,0	10,0	15,0
Uithoorn	15,0	48,0	10,0	25,0

The median shows that a significant portion of trips exceed the 15-minute mark, especially for work commutes, where all 15-minute cities have higher medians than their comparison cities. Commerce is the only category consistently falling below the 15-minute mark.

4.2 Transport mode

Figure 1. Impact of transport mode on travel time.



Bicycle
In all cities trips taken by bike were shorter than those taken by car. The biggest difference was between Eindhoven and Utrecht. Waalwijk was the only comparison city with lower bike travel times then their 15 minute counterpart.

Public transit
In all cities trips taken with public transit were significantly slower than trips taken by car. Between 30 and 55 minutes extra. Uithoorn was the only non 15 minute city to have lower coefficient then their 15 minute city counterpart.

Walking
Just like cycling trips taken by foot were shorter in all cities, but in general having a higher coefficient. The biggest difference was observed between Utrecht and Eindhoven, -20 vs -8,3.

Figure 2. Mode of transport difference Utrecht vs Eindhoven.

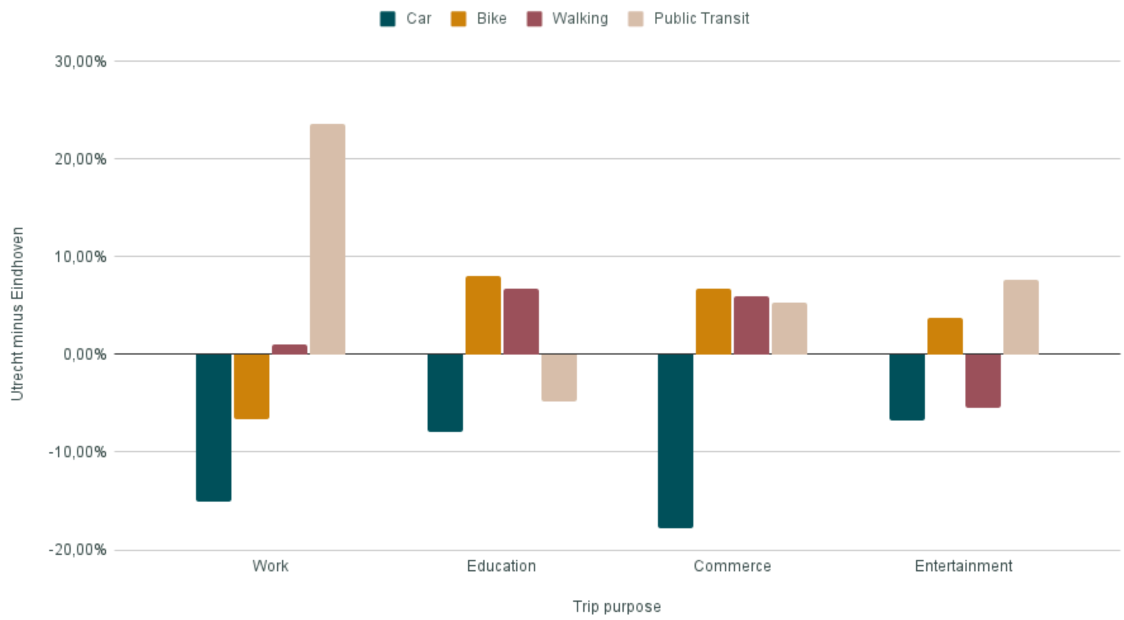


Figure 3. Mode of transport difference Houten vs Waalwijk.

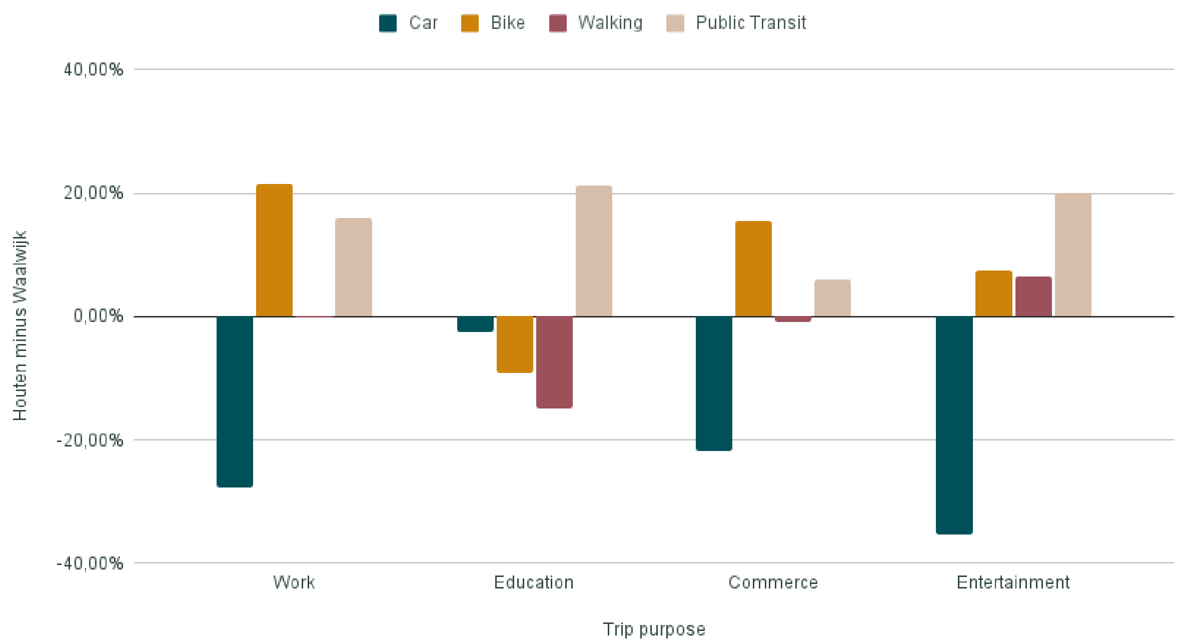
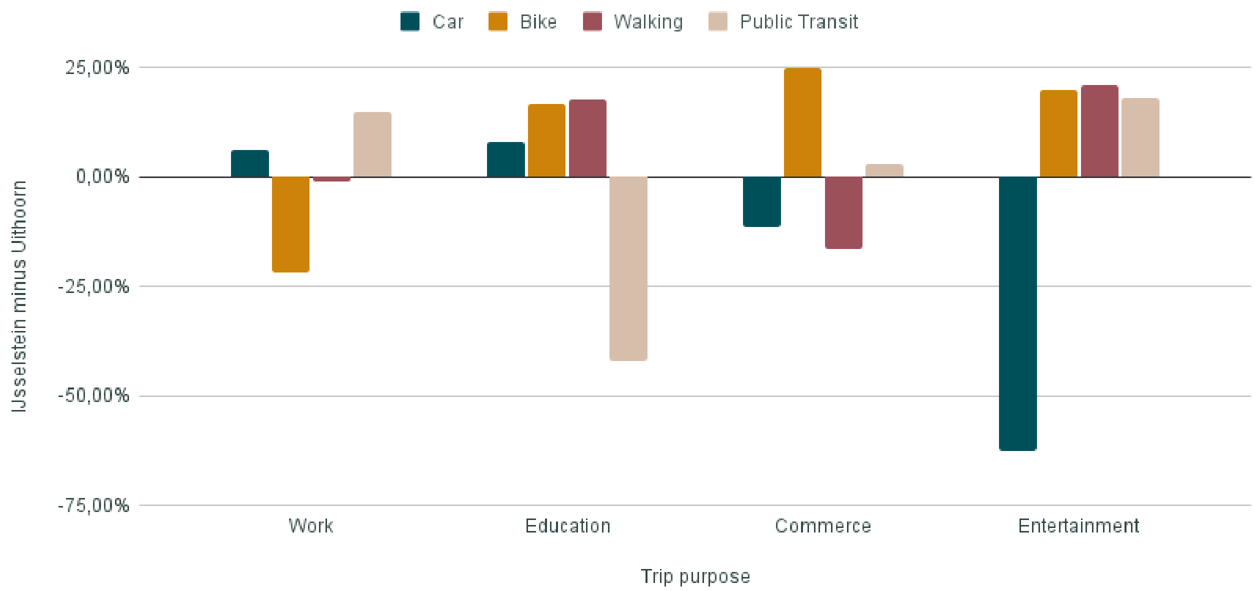


Figure 4. Mode of transport difference IJsselstein vs Uithoorn.



Car usage was down for almost all categories in all 15 minute cities, exception being work and education for Uithoorn. This reduction was substituted on average by an increase in predominantly cycling and public transit with a reasonable increase of walking as well. Biggest decrease in car usage was seen for entertainment between Uithoorn and Ijsselstein.

4.3 percentage of 15 minute trips

Figure 5. Percent of 15 minute trips taken by walking, cycling and public transit.

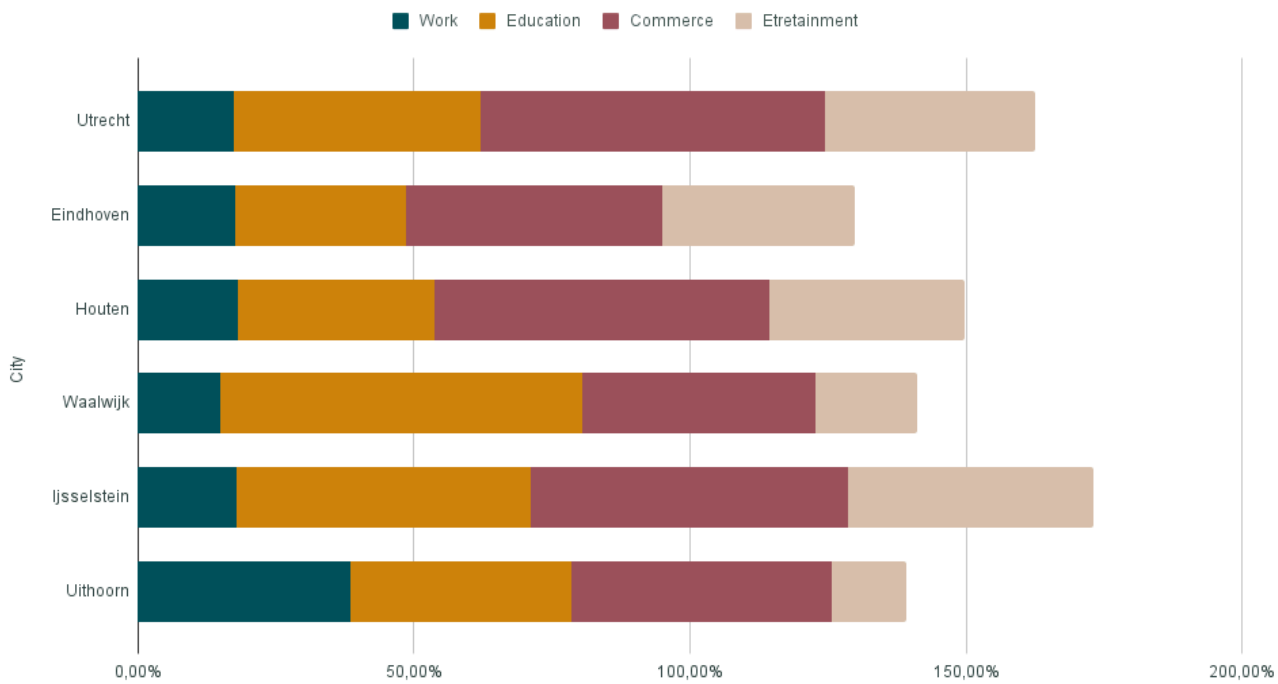
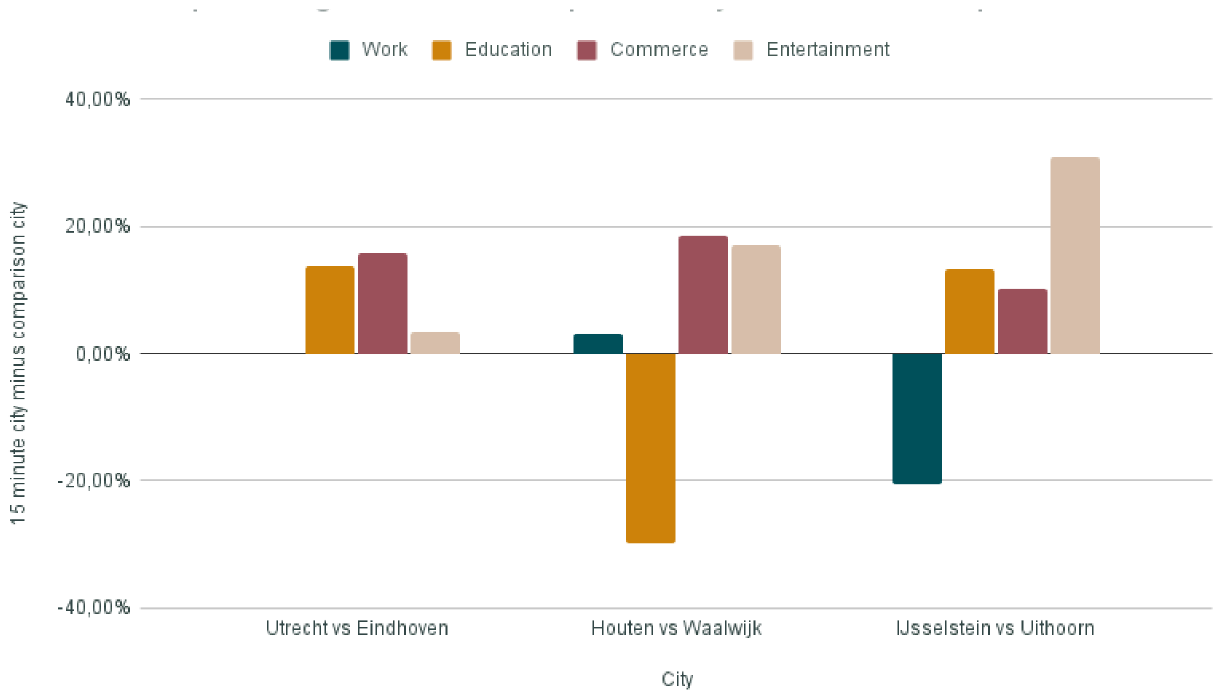


Figure 6. Difference in percent of 15 minute trips taken by walking, cycling and public transit.



Utrecht vs Eindhoven
In terms of work-related trips, there was no significant difference between Eindhoven and Utrecht, with both cities showing comparable percentages. However, for education and commerce, Utrecht demonstrated notably higher percentages, with increases of 13,7% and 15,8% respectively. The margin for entertainment was marginal, with Utrecht showing a modest increase of 3,4% over Eindhoven.

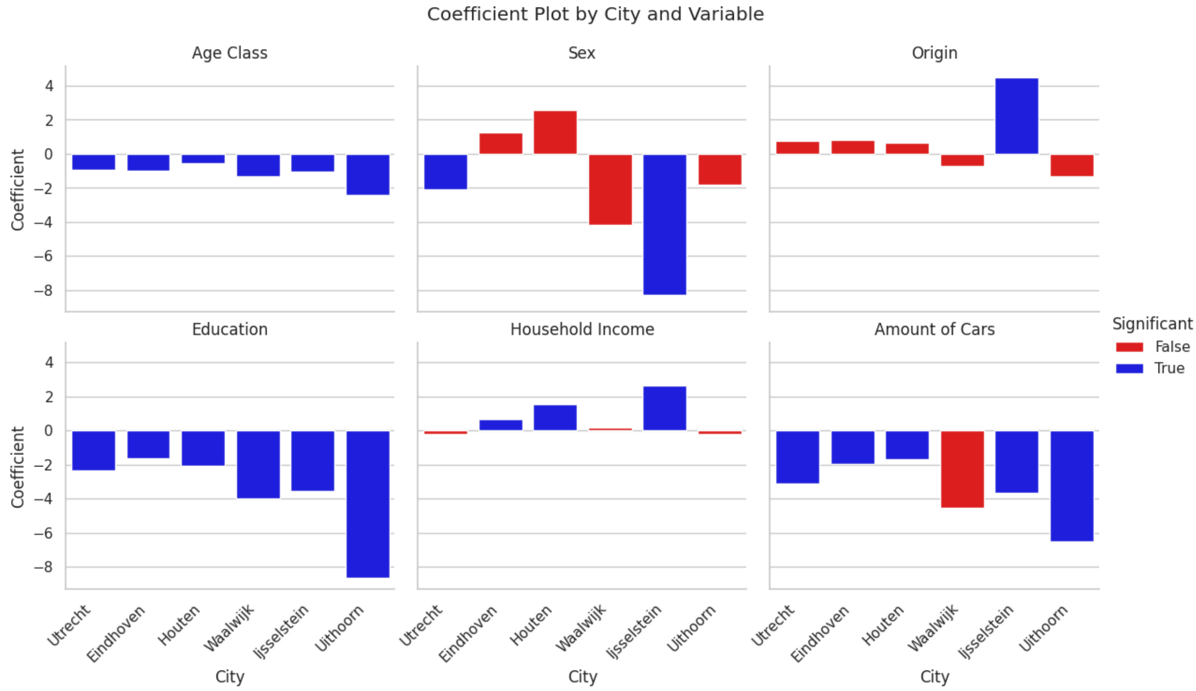
Houten vs Waalwijk
Houten exhibited a slightly higher percentage of work-related trips within 15 minutes compared to Waalwijk, with a difference of 3,2%. However, for education, Houten lagged significantly behind Waalwijk, showing a decrease of 30,0% in trips taken within 15 minutes using sustainable transport. Conversely, Houten outperformed Waalwijk in both commerce and entertainment, with increases of 18,4% and 17,0% respectively.

IJsselstein vs Uithoorn
IJsselstein showed a marked decrease of 20,6% in the percentage of trips taken within 15 minutes compared to Uithoorn for work-related purposes. However, Ijsselstein outperformed Uithoorn in all other categories, with increases of 13,3% for education, 10,2% for commerce, and a substantial 30,8% increase for entertainment.

Overall Comparison
On average, the 15-minute cities demonstrated better performance in terms of trips taken within 15 minutes using sustainable transport modes compared to their respective comparison cities. However, notable exceptions were observed, particularly in the case of work-related trips.

4.4 Differences between socio economic groups

Figure 7. Impact of socio economic characteristics on travel time in minutes.



Variance inflation factor test
For all the cities the VIF for the socio economic characteristics lay between 1 and 1,8, which are all low VIF values, in general a VIF above 5 is cause for concern when talking about multicollinearity, but the results for this test shows that this is no concern for the variables chosen in this study.

Age class
Age significantly influences travel time across all cities with higher aged individuals having shorter travel times, with a statistically significant impact noted everywhere. However, a notable distinction emerges between the 15-minute cities and their comparison counterparts: age has a greater influence on travel time in the comparison cities. This is particularly evident in the differences between Houten and Waalwijk (-0,554 vs -1,298) and IJsselstein and Uithoorn (-1,069 vs -2,434). These differences suggest that age is less influential in reducing travel time in 15-minute cities compared to their comparison cities.

Sex
Sex was only statistically significant for Utrecht and IJsselstein, where being female had a negative impact on travel time.

Origin
Origin was only statistically significant for IJsselstein where it had a positive impact on travel time.

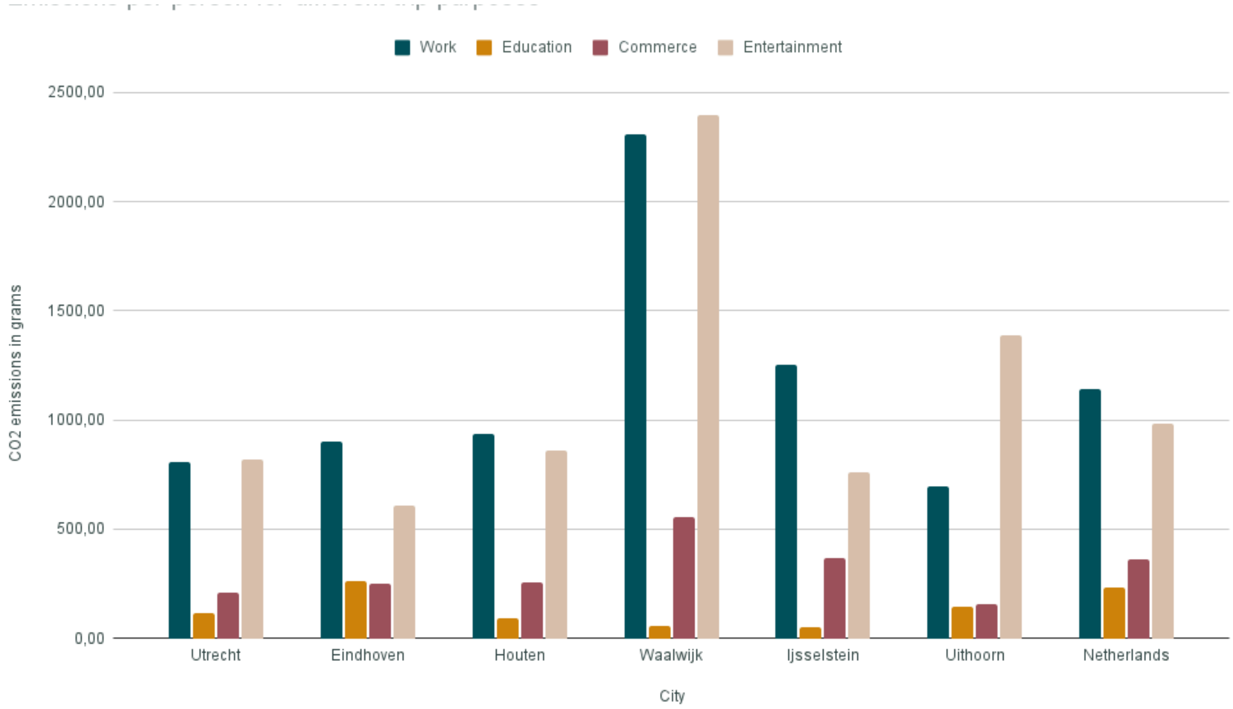
Education
Education was the only other socio economic characteristic that was statistically significant for all cities. It has a negative impact on travel time for all cities. For Waalwijk and Uithoorn the impact education had on travel time was much higher then their 15 minute city counterpart, -2,065 vs -3,964 for Houte nand Waalwijk and -3,558 and -8,641 for IJsselstein and Uithoorn.

Household income
Household income was significant for Eindhoven, Houten and IJsselsteijn where wealthier families had higher travel times on average.

Amount of cars
The amount of cars was only insignificant for Waalwijk, for all other cities the more cars a household owned the shorter their travel times were. For IJsselstein and Uithoorn the amount of cars had less impact on travel time for the 15 minute city, while for Eindhoven and Utrecht this was the other way around.

4.5 Differences between emissions

Figure 8. CO_2 emissions per person for different trip purposes.



Utrecht vs Eindhoven
The differences between Utrecht and Eindhoven in terms of emissions were not too pronounced, overall Utrecht had slightly less emission for work and commerce, –149,2 and -73,0 grams per person respectively. Education had a more pronounced difference in emissions with -250,0 grams per person. Overall Utrecht produced less emissions per person on average, only emitting more for entertainment where it emitted 356,8 grams more.

Houten vs Waalwijk
The largest differences in emissions are observed between Houten and Waalwijk, primarily due to Waalwijk's overall high emissions. Specifically, for work and entertainment purposes, Houten produces significantly less CO_2, with reductions of 2,279.5 grams and 2,552.0 grams, respectively, compared to Waalwijk. Commerce also shows a notable difference, with Houten emitting 490.3 grams less. The only category where Houten produces more emissions is education, with an increase of 67 grams.

IJsselstein vs Uithoorn
The differences between IJsselstein and Uithoorn were more varied, with IJsselsteijn emitting less for education -156,2 grams and especially entertainment -1045,9 grams and more for work and commerce 934,2 and 353,5 grams. Showing a clear correlation between Uithoorn lack of access for entertainment and education and emitted CO_2 for those purposes.

Overall Comparison
In general the 15 minute cities produced less CO_2 than their comparison cities with differences ranging from rather small (70 gram difference) to very large (more than 2500 grams difference).

5 Discussion:

5.1 interpreting results

The average travel time analysis reveals that the 15-minute cities did not significantly outperform their comparison cities. Most cities had average travel times for daily activities around 30 minutes, with only commerce achieving the desired travel time of 15 minutes. One possible explanation for this is that commerce, especially grocery shopping, is less heterogeneous than other categories. For instance, someone who prefers relaxing in a park for entertainment cannot fulfil this need in a busy bar, whereas most supermarkets can equally meet the need for groceries. This suggests that citizens may not always choose the closest location since not all locations can equally satisfy individual needs.

However, the mode and median travel times for other activities showed that most fell within the 15-minute mark, indicating that a large portion of the city's inhabitants are living a 15-minute lifestyle. This is further supported by the data on the percentage of 15-minute city trips, where a significant proportion of the population's trips fell within the 15-minute time frame using sustainable transport. In this regard, the 15-minute cities performed significantly better than their comparison cities, showing a higher overall percentage of 15-minute trips. The one category where they did not perform particularly well was work, with all 15-minute cities falling short of even 20%. This could further support the idea that heterogeneous locations play a role, as jobs can vary greatly from person to person.

In terms of emissions, the difference was not substantial between most cities, with Waalwijk being a notable exception. The trip purposes with the highest carbon footprints were work and entertainment, which also tended to have the lowest percentage of 15-minute trips. This correlation suggests that these activities are less likely to fall within the 15-minute city framework, leading to higher emissions. This means that the biggest improvements in terms of CO_2 reduction can be made for these trip purposes and should gain priority for cities trying to improve their carbon footprint.

The results of this study provided no strong evidence that the origin of individuals played a major role in their travel time, as concluded in Knap et al. (2023). This might indicate that their lower accessibility does not translate into longer trips.

The observed difference in the decrease in travel time for older citizens between the 15-minute cities and their comparison cities suggests that younger people have higher accessibility in 15-minute cities. This aligns with the fact that younger people tend to rely more on bicycles, walking, and public transportation, as most do not own a car. Therefore, the increased mobility provided by these types of transport in 15-minute cities could explain the difference in the impact of age on travel time.

The impact of education on travel time may be attributed to the fact that higher-educated individuals have more options when choosing a job, allowing them more flexibility in picking a job that is closeby.

The influence of car ownership on travel time supports the philosophy that Houten was designed with the bicycle in mind, as the impact of car ownership is the lowest in Houten. This design likely encourages the use of bicycles and other forms of sustainable transport, reducing overall travel times and emissions.

5.2 implication of results

The Methodology of this study could be repeated in the future when Utrecht reaches its goal of a 10 minute city with the ODiN dataset of that year to see if there are any major changes. It could also be used to test how far along a city currently is in terms of reaching a 15 minute city goal in addition to an accessibility analysis.

Utrecht generally outperformed the other two 15 minute cities, aligning with Knap et al.(2023) work that showed Utrecht to have the highest accessibility out of the cities they looked at. This combined with the lower access for education and entertainment in Uithoorn translating into both longer trips and higher CO_2 emissions shows there is a potential correlation between higher accessibility and improved sustainability. This combined with commerce being able to be gnarly reachable for the population could point towards Knap et al.(2023) accessibility score for the other categories to be too generous, due to not taking quality and capacity of services into account for their analysis.

Given these results, classifying Utrecht and its surrounding municipalities as a 15-minute city might be premature, as many trips still exceed the 15-minute timeframe. While these cities perform better in terms of CO_2 emissions and car usage compared to their counterparts, they still have significant room for improvement before achieving true 15-minute city status. In particular, work and entertainment trips represent the biggest areas for improvement, both in reducing transport emissions and increasing accessibility.

5.3 limitation and recommendation for future research

Data Limitations
While the ODiN dataset is extensive, only a small portion was ultimately used. This was particularly true for some smaller cities, where only about 1% of the population was analysed, potentially leading to overgeneralization. Future research should aim to gather more comprehensive data, especially for these smaller cities, to ensure more representative and reliable results.

Limited CO_2 calculations
In this study, CO_2 emissions were calculated exclusively for car trips, with public transit emissions omitted. Additionally, all cars were generalised as petrol cars, without differentiation based on fuel type. These simplifications were made due to the scope of this research. For future research, a more detailed CO2 calculation that includes public transit emissions and differentiates between various car fuel types (such as petrol, diesel, electric, and hybrid) would provide more nuanced and accurate insights.

Further Analysis of Daily Activities in Utrecht
A follow-up study to Knap et al. 's research could provide valuable insights, particularly through a more detailed analysis of Utrecht that accounts for the heterogeneity of daily activities such as job types and education forms. While Knap et al. analysed different forms of entertainment, they treated jobs and education as overarching categories. Examining these in more detail could reveal disparities in travel behaviours, such as whether higher education is less accessible to residents in the west of the city, or if office jobs are more concentrated in the city centre.

Residential Self-Selection
The phenomenon of residential self-selection, where individuals who prefer walking or biking may choose to live in 15-minute cities, was not accounted for in this study. This could significantly impact travel behaviour findings. Future research should explore this aspect to understand its influence on the effectiveness of the 15-minute city model.

Applicability to Other Countries
This study focused exclusively on cities within the Netherlands, where cycling is already a prevalent mode of transport. In countries where cycling is less common, such as the USA where 87% of daily trips are by car (Bureau of Transport Statistics, 2017) the 15-minute city model could have a more substantial impact on CO_2 emissions. Future research should consider international comparisons to assess the model's effectiveness in different countries.

Verification of Comparison Cities
The comparison cities were chosen for their similarities to the 15-minute cities. However, it is possible that these cities may already exhibit characteristics of 15-minute cities, which could explain their sometimes better performance. Conducting a similar accessibility analysis as Knap et al. (2023) for these comparison cities could provide deeper insights into their suitability as control cases.

6 Conclusion

This study aimed to assess the effectiveness of the 15-minute city concept through a comparative analysis of travel times, transportation modes, and CO_2 emissions in three designated 15-minute cities and their respective counterparts across the Netherlands. Utilising data from the ODiN dataset, the analysis categorised trips into four primary activities: work, education, commerce, and entertainment.

Overall, results indicate that the three 15-minute cities generally outperform their counterparts in terms of reducing car usage, lowering CO_2 emissions, and promoting sustainable transportation modes. The study highlighted the potential of the 15-minute city concept in contributing to CO_2 emission reduction, particularly notable in the comparison between Houten and Waalwijk, which showed a drastic difference in CO_2 emissions. Additionally, there was a noticeable increase in trips completed within 15 minutes using sustainable transport modes in the designated 15-minute cities. This, combined with decreased inequality in travel times across socio-economic characteristics such as age and education, reinforces the proposed benefits 15-minute cities could offer.

However, the study identifies areas for improvement. Despite the increase in 15-minute trips, overall travel times did not significantly decrease. A substantial portion of trips still did not adhere to the 15-minute city principles, particularly work-related trips, which were predominantly taken by car and often had longer travel times. This suggests that categorising Utrecht and the other cities studied as true 15-minute cities may be premature. Reducing travel times and car dependency in these areas will be crucial to fully realising the benefits of the 15-minute city model.

In conclusion, this research demonstrates that the 15-minute city concept can positively influence urban travel patterns, even in a country with high levels of bicycle usage like the Netherlands. However, there is still room for improvement. Achieving the goal of a 15-minute city may require not only increasing accessibility but also reducing car infrastructure and enhancing public transit and cycling networks to further discourage car usage. Continued research in this area can provide deeper insights into the key factors that contribute to successfully implementing the 15-minute city concept, drawing lessons from Utrecht and its surrounding municipalities.

References

- Albayati, N., Waisi, B., Al-Furaiji, M., Kadhom, M., & Alalwan, H. (2021). Effect of COVID-19 on air quality and pollution in different countries. Journal of Transport & Health, 21, 101061. https://doi.org/10.1016/j.jth.2021.101061
- Bopp, M., Sims, D., & Piatkowski, D. (2018). Benefits and Risks of Bicycling. In Elsevier eBooks (pp. 21–44). https://doi.org/10.1016/b978-0-12-812642-4.00002-7
- Centraal Bureau voor de Statistiek. (2024, March 14). Kerncijfers wijken en buurten 2023. Centraal Bureau Voor De Statistiek. https://www.cbs.nl/nl-nl/maatwerk/2024/11/kerncijfers-wijken-en-buurten-2023
- Jaffe, E. (2015, June 17). A case study in Bike-Friendly Suburban Planning. https://www.bloomberg.com/news/articles/2015-06-17/the-dutch-town-of-houten-is-a-case-study-in-bike-friendly-suburban-planning
- Knap, E., Ulak, M. B., Geurs, K. T., Mulders, A., & Van Der Drift, S. (2023). A composite X-minute city cycling accessibility metric and its role in assessing spatial and socioeconomic inequalities – A case study in Utrecht, the Netherlands. Journal of Urban Mobility, 3, 100043. https://doi.org/10.1016/j.urbmob.2022.100043
- Ministerie van Infrastructuur en Waterstaat. (2021, July 19). Duurzaam openbaar vervoer. Openbaar Vervoer (Ov) | Rijksoverheid.nl. https://www.rijksoverheid.nl/onderwerpen/openbaar-vervoer/duurzaam-openbaar-vervoer
- Mitchell, L. E., Lin, J. C., Hutyra, L. R., Bowling, D. R., Cohen, R. C., Davis, K. J., DiGangi, E., Duren, R. M., Ehleringer, J. R., Fain, C., Falk, M., Guha, A., Karion, A., Keeling, R. F., Kim, J., Miles, N. L., Miller, C. E., Newman, S., Pataki, D. E., . . . Wofsy, S. C. (2022). A multi-city urban atmospheric greenhouse gas measurement data synthesis. Scientific Data, 9(1). https://doi.org/10.1038/s41597-022-01467-3
- National Household Travel Survey Daily Travel Quick Facts. (2017, May 31). Bureau of Transportation Statistics. https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-daily-travel-quick-facts
- Ritchie, H., & Roser, M. (2024, March 18). Which form of transport has the smallest carbon footprint? Our World in Data. https://ourworldindata.org/travel-carbon-footprint

- Scheiner, J., & Holz-Rau, C. (2015). Women's complex daily lives: a gendered look at trip chaining and activity pattern entropy in Germany. Transportation, 44(1), 117–138. https://doi.org/10.1007/s11116-015-9627-9

Annexes

CO_2 Calculations

City	Percentage car	Average travel distance hm	Average travel distance km	Average CO2/km	CO2 Emissions gram	CO2/person
Utrecht	24,84%	318,72	31,87	170,00	5418,26	1345,90
Houten	38,34%	239,30	23,93	170,00	4068,05	1559,69
Ijsselstein	54,74%	224,62	22,46	170,00	3818,46	2090,22
Eindhoven	39,94%	220,20	22,02	170,00	3743,32	1495,08
Waalwijk	65,96%	342,38	34,24	170,00	5820,46	3839,18
Uithoorn	48,72%	139,58	13,96	170,00	2372,83	1156,04
Nederland	45,38%	246,03	24,60	170,00	4182,43	1897,98

City	Percentage car	Average travel distance hm	Average travel distance km	Average CO2/km	CO2 Emissions gram	CO2/person
Utrecht	8,30%	134,28	13,43	170,00	2282,69	189,46
Houten	6,96%	132,38	13,24	170,00	2250,38	156,63
Ijsselstein	16,67%	30,20	3,02	170,00	513,40	85,58
Eindhoven	16,28%	158,80	15,88	170,00	2699,60	439,49
Waalwijk	9,38%	56,00	5,60	170,00	952,00	89,30
Uithoorn	8,89%	160,00	16,00	170,00	2720,00	241,81
Nederland	13,56%	165,73	16,57	170,00	2817,41	382,04

City	Percentage c	Average travel distance hm	Average travel distance km2	Average CO2/km	CO2 Emissions gram	CO2/person
Utrecht	22,93%	88,80	8,88	170,00	1509,60	346,15
Houten	29,59%	85,22	8,52	170,00	1448,71	428,67
Ijsselstein	30,15%	119,27	11,93	170,00	2027,56	611,31
Eindhoven	40,67%	60,63	6,06	170,00	1030,68	419,18
waalwijk	51,32%	105,33	10,53	170,00	1790,61	918,94
Uithoorn	41,51%	36,54	3,65	170,00	621,18	257,85
Nederland	42,82%	82,19	8,22	170,00	1397,23	598,29

City	Percentage c	Average travel distance hm	Average travel distance km2	Average CO2/km	CO2 Emissions gram	CO2/person
Utrecht	28,83%	278,77	27,88	170,00	4739,09	1366,28
Houten	35,81%	235,70	23,57	170,00	4006,82	1434,84
Ijsselstein	23,61%	315,41	31,54	170,00	5362,00	1265,97
Eindhoven	35,57%	166,94	16,69	170,00	2838,05	1009,49
Waalwijk	71,05%	330,07	33,01	170,00	5611,26	3986,80
Uithoorn	86,36%	157,47	15,75	170,00	2677,05	2311,90
Nederland	45,40%	212,12	21,21	170,00	3606,02	1637,13

Mode of transport

Utrecht					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	24,84%	8,30%	22,93%	28,83%	18,69%
Bike	27,45%	49,12%	35,03%	33,33%	37,20%
Walking	3,56%	16,08%	34,79%	19,06%	18,14%
Public Transit	42,05%	25,44%	6,11%	17,91%	24,53%
Houten					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	38,34%	6,96%	29,59%	35,81%	24,96%
Bike	36,27%	40,87%	41,84%	28,38%	39,66%
Walking	4,15%	6,96%	21,43%	14,41%	10,85%
Public Transit	16,06%	40,00%	6,12%	20,09%	20,73%
Ijselstijn					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	54,74%	16,67%	30,15%	23,61%	33,85%
Bike	24,21%	56,60%	41,91%	33,33%	40,91%
Walking	4,21%	20,00%	25,00%	20,83%	16,40%
Public Transit	14,74%	6,67%	2,94%	18,06%	8,12%

Eindhoven					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	39,94%	16,28%	40,67%	35,57%	33,12%
Bike	34,08%	41,09%	28,29%	29,64%	33,28%
Walking	2,51%	9,30%	28,88%	24,51%	16,30%
Public Transit	18,44%	30,23%	0,79%	10,28%	14,94%
Veldhoven					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	65,96%	9,38%	51,32%	71,05%	49,43%
Bike	14,89%	50,00%	26,32%	21,05%	28,07%
Walking	4,26%	21,88%	22,37%	7,89%	14,10%
Public Transit	0,00%	18,75%	0,00%	0,00%	4,69%
Uithoorn					
Trip purpose	Work	Education	Commerce	Entertainment	Average
Car	48,72%	8,89%	41,51%	86,36%	46,37%
Bike	46,15%	40,00%	16,98%	13,64%	29,19%
Walking	5,13%	2,22%	41,51%	0,00%	12,22%
Public Transit	0,00%	48,89%	0,00%	0,00%	12,22%

Python code used

Loading in dataset and making ready for use

```
import pandas as pd

# Loading ODiN dataset into a pandas DataFrame, specifying the encoding
df = pd.read_csv('ODiN.csv', encoding='latin1')
# Convert all columns to numeric
df_numeric = df.apply(pd.to_numeric, errors='coerce')
df_nozero = df_numeric[df_numeric['Reisduur'] != 0]
# Remove duplicate rows
df_dupli = df_nozero.drop_duplicates()
# remove wrong tour responses
df_clear = df_dupli[df_dupli['Toer'] != 1]
df_clear = df_clear.dropna(subset=['Reisduur', 'Leeftijd', 'Geslacht',
'Herkomst', 'Opleiding', 'HHGestInkG', 'HHAuto'])
df_copy = df_clear.copy()
# Map transport mode codes to their respective modes
df_copy['Transport_Mode'] = df_copy['Hvm'].map({
    1: 'Car',
    2: 'Public Transit',
    3: 'Public Transit',
    4: 'Public Transit',
    5: 'Public Transit',
    7: 'Bike',
    8: 'Bike',
    9: 'Walking'
})

# Create dummy variables for each transport mode
df_copy = pd.get_dummies(df_copy, columns=['Transport_Mode'],
prefix='', prefix_sep='')
```

These steps are done for each city and each trip purpose.

```
# filter data to just include people living in Utrecht
df_Utrecht = df_copy[df_copy['WoGem'] == 344]

# Filter rows where 'Trip Purpose' is 1
df_work = df_Utrecht[df_Utrecht['MotiefV'] == 1]


# Calculate the average travel time for trip purpose 1
average_travel_time_work = df_work['Reisduur'].mean()
```

```
mode_travel_time_work = df_work['Reisduur'].mode()
median_travel_time_work = df_work['Reisduur'].median()

print("Average travel time for work:", average_travel_time_work)
print("Mode travel time for work:", mode_travel_time_work)
print("Median travel time for work:", median_travel_time_work)

# Filter the DataFrame for car trips (Hvm == 1)
car_trips = df_work[df_work['Hvm'] == 1]

# Calculate the average distance traveled for car trips
average_distance_car = car_trips['AfstV'].mean()

print("Average distance traveled by car:", average_distance_car)
```

Calculating percentage of 15 minute trips, done for each trip purpose

```
# Filter trips with travel time <= 15 minutes
df_15_minutes = df_work[df_work['Reisduur'] <= 15]

# Filter trips with the right mode of transport
right_modes = [2, 3, 4, 5, 7, 8, 9]
df_15_minutes_right_mode =
df_15_minutes[df_15_minutes['Hvm'].isin(right_modes)]

# Count the number of trips that meet both criteria
num_15_minute_trips = len(df_15_minutes_right_mode)

# Calculate the percentage of 15-minute trips
total_trips = len(df_work)
percentage_15_minute_trips = (num_15_minute_trips / total_trips) * 100

print("Number of trips that fall under the 15-minute city principle:",
num_15_minute_trips)
print("Percentage of trips that fall under the 15-minute city
principle:", percentage_15_minute_trips)
```

Ols regression transport mode on travel time

```
# Verify the mapping to ensure all categories are included
print(df_Utrecht['Transport_Mode'].value_counts())

# Fit the OLS regression model with travel time as the dependent
variable and transport mode as the independent variable
model = smf.ols('Reisduur ~ C(Transport_Mode,
Treatment(reference="Car"))', data=df_Utrecht).fit()
```

```
# Print the summary of the regression model
print(model.summary())
```

Transport mode calculations

```
# Define the transport modes
transport_modes = {
    'Car': [1],
    'Bike': [7, 8],
    'Walking': [9],
    'Public Transit': [2, 3, 4, 5]
}

# Define the trip purposes
trip_purposes = {
    'Work': 1,
    'Education': 6,
    'Commerce': 7,
    'Entertainment': [11, 12]
}

# Initialise an empty dictionary to store the results
results = {}

# Calculate the percentage of trips for each transport mode and trip
purpose
for purpose, purpose_value in trip_purposes.items():
    if isinstance(purpose_value, list):
        purpose_mask = df_Utrecht['MotiefV'].isin(purpose_value)
    else:
        purpose_mask = df_Utrecht['MotiefV'] == purpose_value

    # Filter the dataframe for the current trip purpose
    df_purpose = df_Utrecht[purpose_mask]

    # Initialise a dictionary to store percentages for the current
purpose
    mode_percentages = {}

    # Calculate the percentage for each transport mode
    for mode, mode_values in transport_modes.items():
        mode_mask = df_purpose['Hvm'].isin(mode_values)
        percentage = (mode_mask.sum() / len(df_purpose)) * 100
        mode_percentages[mode] = percentage
```

```
    # Store the percentages for the current purpose in the results
dictionary
    results[purpose] = mode_percentages

# Print the results
for purpose, mode_percentages in results.items():
    print(f"Trip Purpose: {purpose}")
    for mode, percentage in mode_percentages.items():
        print(f"  {mode}: {percentage:.2f}%")
    print()
```

Socio economic OLS regression and VIF test

```
import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import
variance_inflation_factor

# Define the dependent variable
y = df_Utrecht['Reisduur']

# Define the independent variables
X = df_Utrecht[['KLeeft', 'Geslacht', 'Herkomst', 'Opleiding',
'HHGestInkG', 'HHAuto']]

# Add a constant to the model (intercept)
X = sm.add_constant(X)

# Fit the regression model
model = sm.OLS(y, X).fit()

# Print the regression results
print(model.summary())

# Calculate VIF for each explanatory variable
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in
range(X.shape[1])]

print(vif_data)
```

Socioeconomic OLS regression results

Utrecht

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.023
Model:                            OLS   Adj. R-squared:                  0.022
Method:                 Least Squares   F-statistic:                     28.61
Date:                Mon, 10 Jun 2024   Prob (F-statistic):           5.11e-34
Time:                        15:14:32   Log-Likelihood:                -36193.
No. Observations:                7300   AIC:                         7.240e+04
Df Residuals:                    7293   BIC:                         7.245e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         53.2887      2.854     18.673      0.000      47.695      58.883
KLeeft        -0.9328      0.126     -7.410      0.000      -1.180      -0.686
Geslacht      -2.0713      0.811     -2.554      0.011      -3.661      -0.481
Herkomst       0.7472      0.544      1.374      0.169      -0.319       1.813
Opleiding     -2.3602      0.385     -6.128      0.000      -3.115      -1.605
HHGestInkG    -0.1822      0.135     -1.350      0.177      -0.447       0.082
HHAuto        -3.0974      0.375     -8.249      0.000      -3.833      -2.361
==============================================================================
Omnibus:                     5457.646   Durbin-Watson:                   0.836
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           130554.452
Skew:                           3.377   Prob(JB):                         0.00
Kurtosis:                      22.585   Cond. No.                         88.6
==============================================================================
```

```
      Feature        VIF
0       const  50.089163
1      KLeeft   1.268659
2    Geslacht   1.010592
3    Herkomst   1.028073
4   Opleiding   1.287391
5  HHGestInkG   1.110332
6      HHAuto   1.064810
```

Eindhoven

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.023
Model:                            OLS   Adj. R-squared:                  0.020
Method:                 Least Squares   F-statistic:                     7.316
Date:                Mon, 10 Jun 2024   Prob (F-statistic):           9.56e-08
Time:                        15:14:52   Log-Likelihood:                -9193.4
No. Observations:                1886   AIC:                         1.840e+04
Df Residuals:                    1879   BIC:                         1.844e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         35.9439      4.871      7.379      0.000      26.391      45.497
KLeeft        -1.0134      0.204     -4.970      0.000      -1.413      -0.614
Geslacht       1.2727      1.471      0.865      0.387      -1.612       4.157
Herkomst       0.8031      0.984      0.816      0.415      -1.128       2.734
Opleiding     -1.6527      0.688     -2.402      0.016      -3.002      -0.304
HHGestInkG     0.6554      0.248      2.643      0.008       0.169       1.142
HHAuto        -1.9472      0.838     -2.322      0.020      -3.592      -0.303
==============================================================================
Omnibus:                     1969.022   Durbin-Watson:                   0.960
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           164065.084
Skew:                           4.995   Prob(JB):                         0.00
Kurtosis:                      47.587   Cond. No.                         88.3
==============================================================================
```

	Feature	VIF
0	const	44.429269
1	KLeeft	1.299341
2	Geslacht	1.004378
3	Herkomst	1.057889
4	Opleiding	1.284399
5	HHGestInkG	1.070708
6	HHAuto	1.052022

Houten

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.034
Model:                            OLS   Adj. R-squared:                  0.029
Method:                 Least Squares   F-statistic:                     7.521
Date:                Mon, 10 Jun 2024   Prob (F-statistic):           6.09e-08
Time:                        15:14:12   Log-Likelihood:                -5924.2
No. Observations:                1299   AIC:                         1.186e+04
Df Residuals:                    1292   BIC:                         1.190e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         23.4085      4.589      5.101      0.000      14.406      32.411
KLeeft        -0.5431      0.173     -3.131      0.002      -0.883      -0.203
Geslacht       2.5481      1.302      1.958      0.050      -0.005       5.101
Herkomst       0.6609      1.179      0.561      0.575      -1.651       2.973
Opleiding     -2.0645      0.547     -3.775      0.000      -3.138      -0.992
HHGestInkG     1.5349      0.283      5.414      0.000       0.979       2.091
HHAuto        -1.6940      0.694     -2.440      0.015      -3.056      -0.332
==============================================================================
Omnibus:                      444.136   Durbin-Watson:                   0.889
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1252.783
Skew:                           1.781   Prob(JB):                    9.15e-273
Kurtosis:                       6.235   Cond. No.                         98.2
==============================================================================
```

	Feature	VIF
0	const	50.803437
1	KLeeft	1.344390
2	Geslacht	1.021210
3	Herkomst	1.022650
4	Opleiding	1.344521
5	HHGestInkG	1.134323
6	HHAuto	1.124822

Waalwijk

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.049
Model:                            OLS   Adj. R-squared:                  0.030
Method:                 Least Squares   F-statistic:                     2.591
Date:                Mon, 10 Jun 2024   Prob (F-statistic):             0.0183
Time:                        15:22:34   Log-Likelihood:                -1450.5
No. Observations:                 311   AIC:                             2915.
Df Residuals:                     304   BIC:                             2941.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         61.8164     10.870      5.687      0.000      40.427      83.206
KLeeft        -1.2982      0.424     -3.062      0.002      -2.132      -0.464
Geslacht      -4.1850      3.082     -1.358      0.176     -10.250       1.880
Herkomst      -0.7357      2.656     -0.277      0.782      -5.962       4.490
Opleiding     -3.9642      1.214     -3.265      0.001      -6.353      -1.575
HHGestInkG     0.1876      0.626      0.300      0.764      -1.043       1.419
HHAuto        -4.5570      2.501     -1.822      0.069      -9.479       0.365
==============================================================================
Omnibus:                      183.468   Durbin-Watson:                   1.331
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1065.806
Skew:                           2.518   Prob(JB):                    3.66e-232
Kurtosis:                      10.542   Cond. No.                         102.
==============================================================================
```

	Feature	VIF
0	const	54.533107
1	KLeeft	1.804377
2	Geslacht	1.053875
3	Herkomst	1.079490
4	Opleiding	1.560258
5	HHGestInkG	1.270978
6	HHAuto	1.397079

IJsselstein

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.119
Model:                            OLS   Adj. R-squared:                  0.108
Method:                 Least Squares   F-statistic:                     11.32
Date:                Mon, 10 Jun 2024   Prob (F-statistic):           6.95e-12
Time:                        15:20:59   Log-Likelihood:                -2371.5
No. Observations:                 512   AIC:                             4757.
Df Residuals:                     505   BIC:                             4787.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         42.6297      7.667      5.560      0.000      27.566      57.693
KLeeft        -1.0694      0.280     -3.820      0.000      -1.619      -0.519
Geslacht      -8.2632      2.240     -3.688      0.000     -12.665      -3.862
Herkomst       4.4986      1.743      2.580      0.010       1.074       7.924
Opleiding     -3.5584      0.919     -3.872      0.000      -5.364      -1.753
HHGestInkG     2.6256      0.477      5.507      0.000       1.689       3.562
HHAuto        -3.6693      1.502     -2.443      0.015      -6.620      -0.718
==============================================================================
Omnibus:                      303.169   Durbin-Watson:                   1.245
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2729.971
Skew:                           2.486   Prob(JB):                         0.00
Kurtosis:                      13.161   Cond. No.                         98.2
==============================================================================
```

```
      Feature        VIF
0       const  48.070897
1      KLeeft   1.336035
2    Geslacht   1.020412
3    Herkomst   1.094435
4   Opleiding   1.319351
5  HHGestInkG   1.221036
6      HHAuto   1.217361
```

Uithoorn

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Reisduur   R-squared:                       0.160
Model:                            OLS   Adj. R-squared:                  0.141
Method:                 Least Squares   F-statistic:                     8.244
Date:                Mon, 10 Jun 2024   Prob (F-statistic):           3.53e-08
Time:                        15:20:02   Log-Likelihood:                -1236.5
No. Observations:                 266   AIC:                             2487.
Df Residuals:                     259   BIC:                             2512.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         99.8486     13.403      7.450      0.000      73.456     126.242
KLeeft        -2.4343      0.415     -5.865      0.000      -3.252      -1.617
Geslacht      -1.8131      3.234     -0.561      0.576      -8.182       4.556
Herkomst      -1.3403      2.251     -0.595      0.552      -5.774       3.093
Opleiding     -8.6415      1.467     -5.892      0.000     -11.529      -5.754
HHGestInkG    -0.2233      0.660     -0.338      0.735      -1.523       1.076
HHAuto        -6.4887      1.886     -3.440      0.001     -10.203      -2.775
==============================================================================
Omnibus:                       70.056   Durbin-Watson:                   0.819
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              136.298
Skew:                           1.353   Prob(JB):                     2.53e-30
Kurtosis:                       5.230   Cond. No.                         120.
==============================================================================
```

```
      Feature        VIF
0       const  72.857654
1      KLeeft   1.729930
2    Geslacht   1.060053
3    Herkomst   1.317276
4   Opleiding   1.872952
5  HHGestInkG   1.102187
6      HHAuto   1.152540
```