Development of 3 'brede welvaart' indicators

Ministerie van Infrastructuur en Waterstaat

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Contents

1 Introduction

In 2023 The Ministry of IenW, Directorate for Innovation and Strategy for Mobility (DG Mobility / DG Aviation and Maritime) and TNO Traffic & Transport started a multi-year collaboration on 'brede welvaart' (BW). This programmatic collaboration (PSBW[1]) created the possibility to cooperate strategically and programmatically to formulate future knowledge questions in relation to BW, to investigate them and to make the results and insights applicable for policy and instrument development. In 2024 this program was continued.

The goal of the PSBW is to develop knowledge and tools, in close cooperation and coordination with each other, to be able to develop data-driven policy and supporting instruments that enable both TNO and IenW to manage transitions in spatial development and mobility (and logistics) policy in a manner in that they contribute to current and future societal goals, such as BW.

TNO joined the development and quantification of the indicators by participating in the IenW ISM indicator working group: transferring insights gained in indicators and collaborating actively in the development of new knowledge about the indicators.

For 2024, TNO and IenW have identified three priority indicators for development in the standardization of a base list of BW indicators. These indicators are relevant to the focus in WP2.1 of the PSBW and align with TNO's expertise. Special attention is given to the requirements for making these indicators operational using model data. The approach is tool-agnostic, meaning it does not rely specifically on TNO models but applies to traffic and simulation tools in general. Additionally, we have examined how distribution effects across different groups can be made available and which characteristics (population group factors) are shared among the three indicators. Furthermore, the indicators in this report rely on (traffic) model data as an input, this is further discussed in 1.1.

1.1 Traffic model data as input for indicators

In 2024, we have focussed our efforts on developing three BW indicators. On the one hand for monitoring purposes, on the other hand for ex-ante insight into the impact of (policy) decisions and interventions. TNO has several models that can be used to assess changes in certain BW indicator values after an intervention. The added value in this is that multiple scenarios, which include (combinations) of policy options, can be simulated to project what the impact is on a range of aspects of BW and distribution effects over different population groups. This is different from calculating indicators using historic data, such as CBS Statline data from previous years as a basis. Using historic data provides a reflection of the historic situation (ex-post) and it does not provide answers of what effects policies might have for current and future situations when several scenarios of policies are simulated (ex-ante).

The scope of this work package is different from other indicator work done elsewhere, such as in the IMA. The IMA includes BW indicators, though these focus on one set time horizon (2040/2050). It outlines the various possible developments regarding passenger mobility

[1] Programmatische samenwerking brede welvaart (PSBW)

and freight transport and sets out further strategic challenges. In contrast to the work in the report before you, the IMA does not focus on providing a tool that allows the projection of multiple scenarios. The indicator setup in this report can inform policy makers what the consequences are for (combinations of) different policies on a specific geographical scale, for certain groups and within different domains.

1.2 Focus area

The use of a focus area comes from WP4.1 of the PSBW, which aims to consolidate all findings from the different tasks in the PSBW 2024, in relation to the focus area. It will provide a report on the challenges, benefits and gaps when bringing BW theory/models/tools in to practice.

Within this report, the focus area in WP4.1 is used to test the three indicators and determine what is needed to make them functional using traffic model data. This testing can reveal what data is already present, what population groups and distribution effects are available, and also what is not available (at the moment) to make the indicator function adequately.

The WP4.1 focus case is the *Brainport Area* surrounding Eindhoven. It is the same area as the *COROP gebied* Zuid-Noord-Brabant. We used the BBMA database, since this is the best available database for the given area, and processed the data with a digital twin to allocate (among others) origin-destination (OD) data, road types, traffic zones and traffic accident risk data. In theory, this step is not mandatory for testing the indicators, since only one scenario is used, the situation as it is in the database. Though, when simulating different scenarios, a digital twin can be used for this purpose, to implement specific policies, trends, interventions, accidents, road constructions, etc. Therefore, we have used this step in our testing of the indicators. For this *WP2.1 Development of 3 BW indicators*, we have chosen to use only the municipality of Eindhoven. This is because using less traffic zones makes the application more manageable. As a consequence this yields less information, but we consider that the (traffic zones in the) municipality of Eindhoven have enough information for us to trial the indicators.

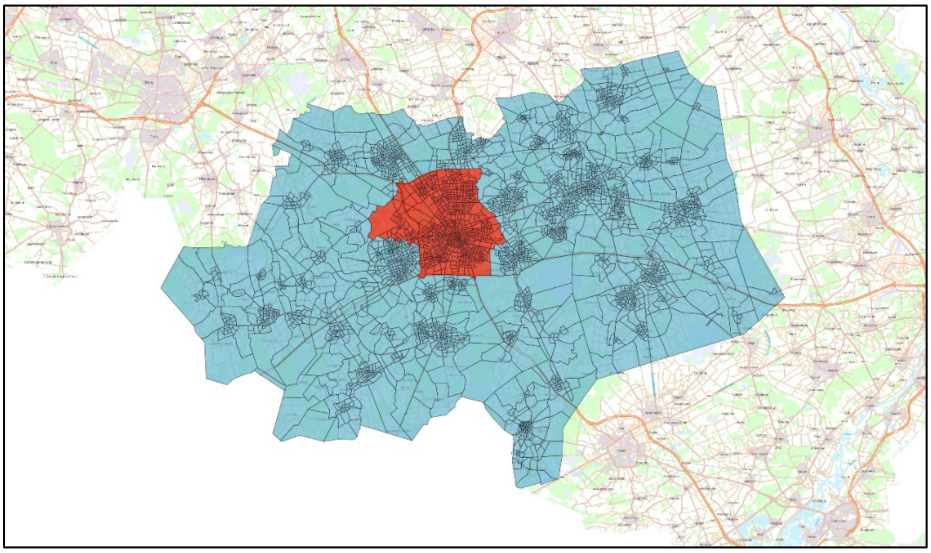


Figure 1: Selection of traffic zones from BBMA database Brabant Zuid-Oost. Brainport region in blue, municipality of Eindhoven in red

The BBMA database includes information on trips from origin to destination (OD), distances (km) and travel times (hours) between zones. It has this for transport modes car, freight, public transport (train and bus), cycling, and access & egress *('voor- en natransport')* for public transport (walking, cycling). Furthermore, the database has socio-demographic data, among others, about the number of people, households, age groups, locations of hospitals, education, jobs, etc. per zone. Walking as a mode of transportation is absent in the database, which proved to be a barrier for the indicator share of active mobility. We used the data as it is included in the database without any alterations and scenarios, since this will provide us with enough information with testing the indicators.

1.3 Indicators

The three indicators are:

- Accessibility of (vital) locations and amenities
- Traffic safety
- Share of active mobility

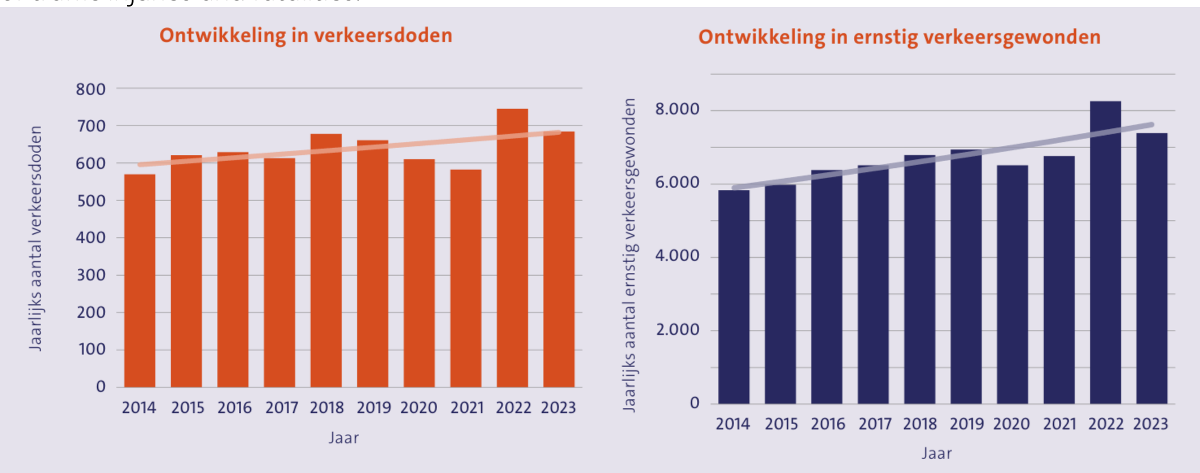
The selection of the three indicators resulted from conversations between TNO and IenW. they are part of the base list provided by the IenW BW indicator working group team. IenW aims to strongly encourage policy evaluators to use at least these base indicators in their assessment. There are (at the moment of writing) between 9 to 12 such base indicators which have high priority to IenW and TNO. The key advantage of these three indicators is that, while certain elements or versions of them are already used in traffic models, they are not yet sufficiently specific to effectively capture distribution effects between different groups. This is something we will investigate in this report.

2 Safety - accidents

This chapter concerns the development of a traffic safety indicator. Initially the approach was to apply findings from literature review to develop the indicator, however, along the way it became clear that a model-focussed approach was more fitting for the use-case. This approach bases itself on an existing indicator module of TNO's digital twin and does not make use of the former literature review. This split in methodological approach is visible in the below text, but is kept as the literature review might be useful for future work.

2.1 Introduction

The traffic safety indicator is of particular interest due to a concerning trend in the number of traffic injuries and fatalities:



Afbeelding 1: Aantal verkeersdoden en de trend daarin, in de periode 2014-2023. Bron: CBS.

Afbeelding 2: Aantal ernstig verkeersgewonden en de trend daarin, in de periode 2014-2023. Bronnen: DHD, IenW en SWOV.

Figure 2: Development of traffic-related injuries and fatalities [2]

By developing an indicator on accidents that can be linked to "conventional" mobility performance, such as accessibility and vehicle loss hours, it can provide policy makers insights on what the impact might be of a mobility intervention.

For simplicity, the number of accidents is chosen (instead of splitting into injuries or deaths) in the hope to strike a balance between possibility to relate this mobility performance indicators and complexity. The expectation is that estimating the (risk of) injuries or deaths requires detailed information on the accident characteristics, which is not readily available. If the indicator would show that the amount of accidents is changing (due to some mobility change) it is deemed sufficient for policy makers to direct their attention.

[2] J. Oude Mulders, 'De Staat van de Verkeersveiligheid 2024; Daling in Aantal Slachtoffers, Maar Trend Is Stijgend' (Den Haag: SWOV, 13 December 2024), 5–6, https://swov.nl/nl/publicatie/de-staat-van-de-verkeersveiligheid-2024.

2.2 Definition

Traffic accidents are defined as in[3]:

> *An accident which occurred or originated on **a way or street open to public traffic**; resulted in one or more persons being **killed or injured**, and at least **one moving vehicle** was involved.*

This therefore includes:

- Collisions between vehicles
- Collisions between vehicles and pedestrians
- collisions between vehicles and animals or fixed obstacles
- single sided accidents in which one vehicle alone (and no other road user) as involved

This **excludes** accidents where only material damage has occurred, but in contrast to the OECD indicator definition [4] this indicator will also include non-motor vehicles such as bicycles.

2.2.1 Perspectives

The indicator can be seen from two perspectives, which allows for answering different questions:

- From the viewpoint of the traffic participants that were involved:
    - What mode of transports are susceptible to accidents?
    - What type of travellers (grouped by e.g. personal/household characteristics) are at risk for traffic accidents?
    - What kind of journeys (characterized by e.g. duration, motive) are at risk for traffic accidents?
- From the viewpoint of the local inhabitants, given that they share the space where accidents tend to happen.
    - What areas are more accident prone?
    - What people (personal/household characteristics) live in accident prone areas?

The former viewpoint fits a more common mobility analysis, where the traveller and the effect a trip has on e.g. their travel time and their economic activity is focussed on. The latter viewpoint can perhaps be useful for spatial analyses that investigate the liveability of regions and the effect mobility can have on that.

Most reviewed literature (see section 2.3) has focussed on the first perspective: they look at the traffic safety impact on the traveller, the current indicator will follow suit. Note however it is not the only possible perspective and depending on the desired analysis a different perspective might be more appropriate.

[3] OECD, 'OECD Health Statistics 2023 Definitions, Sources and Methods - Injuries in Road Traffic Accidents', OECD Health Statistics 2023 (OECD, July 2023), https://www.oecd.org/els/health-systems/health-data.htm.
[4] OECD, 'Road Accidents' (OECD, 5 July 2024), https://doi.org/10.1787/2fe1b899-en.

2.3 Literature

On EU level work has been done to define a common set of indicators to allow EU Member States to monitor their road safety performance over time[5]: Part of this work involved identifying existing indicators used across the EU, these are depicted in Figure 3.

N.	Indicator	Computation	DPSEE model position	Data Sources
1	Mortality rate due to traffic accident	**$(M_t/P)*100,000$** **M_t** is the totalnumber of deaths due to traffic accidents **P** is the total population	**EFFECT**	**Data on deaths** are based on police records and death certificates
2	Pedestrian aged 10–14 dead/Population	**$(M_{p\ 10\text{–}14}/P)*100,000$** **$M_p$**: is the total number of pedestrians dead because of traffic accidents **P** is the total population	**EFFECT**	**Data on deaths** are based on police records and death certificates
3	Death/motor vehicles	**(Mt/V per year)*10,000** **M_t** is the number of deaths due to traffic during a fixed period of time usually one year. **V** motor vehicle fleet in the country during the period of interest	**EFFECT**	**Data on deaths** are based on police records and death certificates **Data on vehicles** are provided by public motor vehicle registries
4	Death/km travelled	**(Mt/KM_t)** **M_t** is the number of deaths due to traffic **Km_t** total amount of km travelled for different categories of road users	**EFFECT**	**Data on deaths** are based on police records and death certificates **Data on km travelled** are based on surveys using questionnaires or odometer monitoring, or sales of fuel
5	Deaths/accident	**$(M_t/A)*1,000$** **M_t** is the totalnumber of deaths due to traffic **A** is the total number of road traffic accidents	**EFFECT**	**Data on deaths** are based on police records and death certificates **Data on accidents** are based on police records
6	Death/km of road	**$(M_t/l_r)*1,000$** **M_t** is the totalnumber of deaths due to traffic **l_r** is the length of the roads in Km	**EFFECT**	**Data on deaths** are based on police records and death certificates **Data on road length** are provided by ministries of transport and road directorates
7	Injury rate by traffic accident	**$(I_t/P)*10000$** **I_t** is the total number of injured due to traffic accidents **P** is the total population	**EFFECT**	**Data on injuries** are based on police statistics, registration of medical care
8	Fatality rate	**(M_t/M_t+I_t)** **M_t** is the totalnumber of deaths due to traffic accidents **I_t** is the total number of injured due to traffic accidents	**EFFECT**	**Data on deaths** are based on police records and death Certificates **Data on injuries** are based on police statistics, registration of medical care
9	Accident/vehicle	**(A/V)*10000** **A** is the total number of road traffic accidents **V** is the total amount of vehicle	**EXPOSURE**	**Data on accidents** are based on police records **Data on vehicles** are provided by public motor vehicle registries
10	Vehicle fleet or (Motoritation index)	**(V/P)*1000** **V** is the total number of vehicles **P** is the total population	**PRESSURE/STATE**	**Data on vehicles** are provided by public motor vehicle registries

Figure 3: Existing road accident indicators identified in the literature review performed in the work of Farchi et al. [6]

Besides common traffic safety indicators that quantify traffic safety in one way or another, the literature scan of the current chapter also focussed on research that connected accidents with other (spatial) variables.

The following literature was deemed relevant in that context:

- Research that investigates the relative road safety performance of Polish regions using regression models that relate the accident, injury and fatality rates to regional characteristics such as the road length, GDP, and motorisation rate. It shows how to create a regression model for different zones using their accident timeseries, allowing to derive what zone characteristics have an effect on accident rate[7].
- Other work shows, using UK geo-spatial accident data in combination with the OpenStreetMap network, how to estimate a model that can create a risk map for a

[5] Sara Farchi et al., 'Defining a Common Set of Indicators to Monitor Road Accidents in the European Union', *BMC Public Health* 6, no. 1 (11 July 2006): 183, https://doi.org/10.1186/1471-2458-6-183.
[6] [NO_PRINTED_FORM]
[7] Katarzyna Brzozowska-Rup and Marzena Nowakowska, 'Modelling Road Traffic Safety Indices by Means of Regression with Panel Data', *Engineering Management in Production and Services* 12, no. 4 (1 December 2020): 40–51, https://doi.org/10.2478/emj-2020-0026.

whole road network. It uses two years of road accident data to estimate a model that can predict the accident rate for a given road segment[8].
- SWOV estimated risk factors for the occurrence of accidents per million km's, for specific road types and road intensities using data on incidents, road intensities and road characteristics[9].
- Similar risk factors have been estimated for the IMA 2021, which takes into account characteristics of the main road network such as the number of lanes, presence of emergency lanes and road congestion[10].
- SWOV developed a method to extrapolate the past accidents rate (accidents/km) for each population group (age, gender) and modality found in hospital records to a number in the future. By multiplying that found number with the expected km's driven in the future an expected number of accidents is derived[11].

2.4 Data

Rijkswaterstaat provides an overview of available data sources for accident numbers [12]. These are not independent of each other, but re-use parts of each other's data sources to augment their own. Not all data is fully public, but it can be obtained from the relevant institute if needed for specific research.

- Bestand geRegistreerde Ongevallen in Nederland (BRON): this source originates from police reports and contains data about location and time of accidents.
- CBS accident statistics: aggregated estimates of the number of traffic fatalities, based on BRON, court- and police reports.
- SWOV: aggregated estimates of the number of traffic injuries based on BRON augmented with information from Landelijke Basisregistratie Ziekenhuiszorg (LBZ)
- Smart Traffic Accident Reporting (STAR): collaboration between police and insurers, helps augment the BRON data.
- Additionally crowdsourced data is available at https://nl.roaddanger.org/ [13] which bases itself on incidents reported in online news articles. This data contains the involved parties, their modes and location (not always available).

2.4.1 Relation to model output

The most straightforward approach is to use kilometres travelled per mode or the intensity obtained from the model as input for a risk calculation.

- DOKdata had an API that could calculate risk based on intensity on a road.
    - A new project would need to be started with DOKdata to make use of this again, unlikely to happen at the moment.

[8] Somnath Chaudhuri, Pablo Juan, and Jorge Mateu, 'Spatio-Temporal Modeling of Traffic Accidents Incidence on Urban Road Networks Based on an Explicit Network Triangulation', *Journal of Applied Statistics* 50, no. 16 (10 December 2023): 3229–50, https://doi.org/10.1080/02664763.2022.2104822.
[9] F Poppe, 'Risico's Onderscheiden Naar Wegtype; Eindrapportage van Het Kencijfer-Project Uit Het Onderzoekjaarplan 1995' (Leidschendam: SWOV, 1 January 1996), https://swov.nl/nl/publicatie/risicos-onderscheiden-naar-wegtype.
[10] ARCADIS and SWECO, 'Methodiek Verkeersveiligheid in de Integrale Mobiliteitsanalyse', Integrale Mobiliteits-analyse 2021, 12 March 2021, https://www.rijksoverheid.nl/documenten/kamerstukken/2021/06/29/integrale-mobiliteitsanalyse-2021.
[11] W.A.M. Weijermars et al., 'Verkeersveiligheidsprognoses 2030; Geschat Aantal Verkeersdoden En Ernstig Verkeersgewonden Zónder Strategisch Plan Verkeersveiligheid 2030' (Den Haag: SWOV, 31 December 2018).
[12] RWS, 'Bronnen voor ongevallencijfers', Verkeersveiligheid en ongevallencijfers, 6 May 2024, http://www.rijkswaterstaat.nl/wegen/wegbeheer/onderzoek/verkeersveiligheid-en-ongevallencijfers/bronnen-voor-ongevallencijfers.
[13] Thalia Verkade and Jan Derk Stegeman, 'Over deze site', roaddanger, 6 May 2024, https://nl.roaddanger.org/aboutthissite/.

- TNO's digital twin model with amongst others a fast traffic assigner [14], has a readymade indicator module, based on SWOV risk factors [15], that relates intensity and road characteristics to expected number of accidents.
    - The SWOV model is promising as it does not require new implementation, just a configured US setup that recalculates this indicator when intensities change.

2.4.2 Indicator definition

As stated in the introductory text of this chapter, the original idea was to implement the findings from the literature and data search in the current indicator. However, along the way it became a priority that this indicator should be able to show the impact of a measure applied in a model scenario. To attain this, the focus moved away from the found literature and data and the process relied more on typical model output such as the kilometres travelled (e.g. the digital twin indicator above). When a scenario alters that output because of some measure, the traffic safety indicator can use the new values to show how the scenario impacts traffic accidents.
The current traffic safety indicator is therefore defined by a combination of:

- the traffic model after the traffic assignment
- accident risk factors (from literature)
- travellers characteristics per origin-destination pair.

To be able to say something about the distribution effects the impact should be visible per user group, i.e. age, income, car ownership, urbanisation and gender. This requires that either the model output is differentiated by these factors or the applied accident risk factors. The choice is made to focus on the model output differentiation due to limited availability of the risk factors per user group.

The expected steps to be taken to determine the indicator are listed below, the relation between them is shown in Figure 4.

- Determine number of trips between zones
- Determine distance between zones
- Find how the route between every zone is distributed over the different road types
- Find how the trips between zones are distributed per user group
- Determine risk factors that are based on road type and intensity
- Split the number of trips between each OD into:
    - Number of trips per road type
    - Number of trips per road type and user group
- For each OD-pair multiply the distance travelled per road type and user group with the risk factors, taking into account road type and the intensity on each road segment.

[14] Walter Lohman et al., 'Building Digital Twins of Cities Using the Inter Model Broker Framework', *Future Generation Computer Systems* 148 (November 2023): 501–13, https://doi.org/10.1016/j.future.2023.06.024.
[15] Poppe, 'Risico's Onderscheiden Naar Wegtype; Eindrapportage van Het Kencijfer-Project Uit Het Onderzoekjaarplan 1995'.

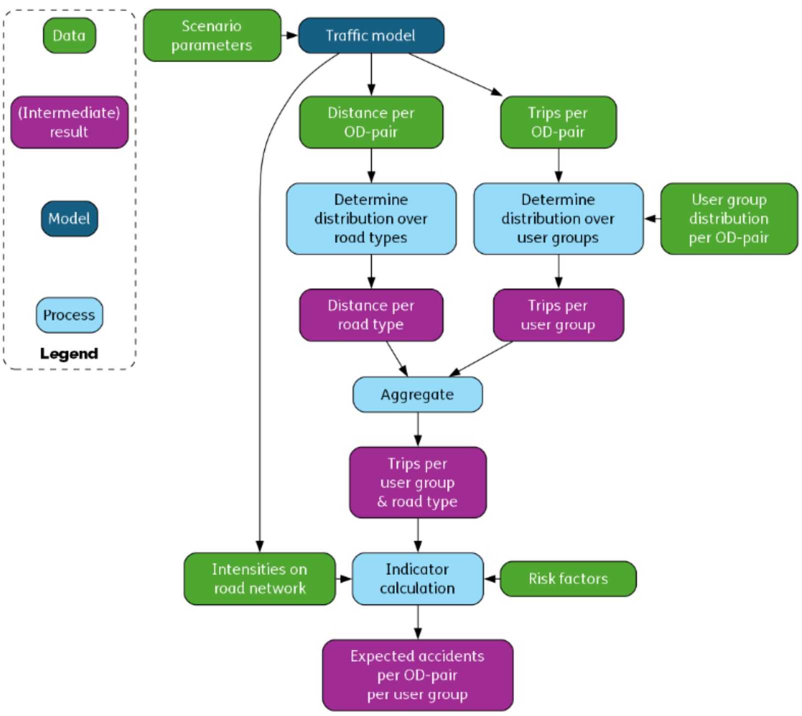


Figure 4: Process to derive expected accidents from traffic model

The calculated indicator is a number of expected accidents per OD-pair and user group, for the specified model scenario, which can be aggregated for all OD-pairs, or per user group. This number will change if the model scenario output changes the total travelled distance between zones, or if the user group composition per zone is adjusted.

2.5 Illustration of steps using dummy data

To describe how this indicator should be calculated, this subsection describes all steps using fictional, arbitrarily chosen dummy data. Section 2.6 then addresses the availability of real data to replace the dummies.

2.5.1 OD- and distance-matrix

An origin-destination-matrix (OD-matrix), for a specific mode and daypart, is the starting point of this method, this is delivered by any traffic model and could look as shown in Table 1. It shows the number of trips (for a specific scenario) between all the different zones in the model.

Even though accidents occur between travel modes, it's a conscious decision to segment this by mode to match the mode-segmented data traffic models provide. Additionally, the accident rate used for this indicator (see section 2.6.4) is only defined for cars at the moment.

Table 1: OD-matrix for the car in the morning peak motive work (dummy data)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	-	64	20	40	59	62	34	87	24	65
2	21	-	67	41	75	7	7	14	67	48
3	40	86	-	70	69	72	15	45	77	78
4	100	57	33	-	14	68	56	34	27	8
5	98	31	65	59	-	31	45	17	82	97
6	81	22	94	47	83	-	17	30	42	27
7	8	80	49	73	26	52	-	6	75	27
8	62	68	82	58	90	99	10	-	40	38
9	62	7	59	41	36	39	74	14	-	95
10	77	60	76	46	75	93	51	7	92	-

The model can also supply Level of Service data in the form of a distance matrix that shows the distance between all zones for a specific mode (Table 2). It is assumed that intrazonal travel is not modelled, hence these cells (e.g. trips from zone 1 to zone 1) are empty.

Table 2: Distance matrix (dummy data)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	-	16	13	19	14	14	15	5	13	20
2	10	-	13	18	18	18	14	5	8	10
3	6	11	-	15	8	5	16	10	18	19
4	12	20	10	-	17	20	17	6	5	5
5	20	16	7	13	-	19	17	6	5	13
6	12	6	12	9	18	-	7	5	12	12
7	15	8	11	15	19	20	-	10	15	6
8	17	8	9	9	13	14	12	-	8	11
9	12	6	11	12	16	10	14	6	-	7
10	11	19	11	10	15	8	13	5	20	-

2.5.2 Road type

Once the trips between two zones are assigned to the network, every trip traverses one or more road types. This results in a distribution of the total distance (Table 2) over the road types. Table 3 shows an example of a distribution that defines per OD-pair what travel distance share will be taken up by each road type, in this fictional example we arbitrarily assume three road types in total. Note how each row sums to 1, as the total distance driven over each road type should sum to the total distance between the zones.

For example: the route from zone 1 to 3 passes for 38.2% of the distance over road type 1, for 52% over road type 2 and for 9.8% over road type 3.

Table 3: Road type distribution (truncated dummy data)

o	d	type1	type2	type3
1	1	-	-	-
1	2	0.78143	0.163593	0.054976
1	3	0.382263	0.519919	0.097818
1	4	0.044456	0.780342	0.175202
1	5	0.656083	0.282122	0.061795
…	…	…	…	…
10	6	0.468529	0.506152	0.025319
10	7	0.089724	0.35785	0.552426
10	8	0.40461	0.582239	0.01315
10	9	0.000949	0.746343	0.252708

2.5.3 User group: age

For this illustration only the age will be considered, but this step should be repeated for other user groups. Assuming age is defined using 5 groups, the data should provide the age of travellers for each OD-pair as shown in Table 4. This table e.g. shows that 8% of the travellers from zone 1 to 2 is in age group 1, 53% in group 2, 17.5% in group 3, etc. This factor can be multiplied with the trips from the OD (Table 1) and the distance matrix (Table 2) to determine the number of trips and distance travelled per age group.

Table 4: Age group distribution (dummy data)

o	d	group1	group2	group3	group4	group5
1	1	-	-	-	-	-
1	2	0.080757	0.53019	0.17514	0.051505	0.162407
1	3	0.008406	0.236142	0.138626	0.522204	0.094623
1	4	0.277295	0.310148	0.11438	0.216737	0.08144
1	5	0.054584	0.186846	0.266339	0.216446	0.275786
…	…	…	…	…	…	…
10	6	0.118486	0.03761	0.203935	0.426463	0.213507
10	7	0.121829	0.24534	0.357115	0.155001	0.120716
10	8	0.084157	0.128044	0.092094	0.297773	0.397933
10	9	0.489619	0.0241	0.163268	0.021533	0.301479

2.5.4 Accident rate

Finally the risk factors are required. Ideally these would be defined based on multiple factors (road intensity bins, age of driver, mode, etc…) but for now it is assumed that these factors are defined per road type and road intensity category (Table 5). This assumption neglects important road design characteristics like the width and curvature, this is unfortunately required due to the lack of data on how these elements affect the accident rate on a macroscopic scale.

Table 5 shows that e.g. for road type 2, when the intensity is between 200-500 vehicles/hour/lane, the accident rate is 0.004815. For road type 3 with intensities above 1000 the rate is 0.70106. The rate indicates the expected number of accidents per million km's (as this is dummy data this exact quantity might not make sense).

Table 5: Accident rate for road type and intensity

road	intensity_min	intensity_max	accident_rate
type1	0	200	0.01753
type1	200	500	0.022308
type1	500	1000	0.003344
type1	1000	9999	0.819966
type2	0	200	0.00536
type2	200	500	0.004815
type2	500	1000	0.00542
type2	1000	9999	0.572353
type3	0	200	0.010971
type3	200	500	0.031849
type3	500	1000	0.036636
type3	1000	9999	0.70106

Now that all required data is in place, the calculation can take place. For each OD-pair the intensity (Table 1) and distance driven (Table 2) data is multiplied by the road type distribution of Table 3 and the age group distribution of Table 4. This results in Table 6, that e.g. shows that from zone 1 to 2, 140.1 km is travelled by age group3 on road type 1.

Table 6: OD-matrix split by road and age (dummy data)

o	d	road	age	intensity	km
1	2	type1	group1	4.0	64.6
1	2	type1	group2	26.5	424.2
1	2	type1	group3	8.8	140.1
1	2	type1	group4	2.6	41.2
1	2	type1	group5	8.1	130.0
...	...	...	...	...	...
10	9	type3	group1	11.4	227.7
10	9	type3	group2	0.6	11.2
10	9	type3	group3	3.8	75.9
10	9	type3	group4	0.5	10.0
10	9	type3	group5	7.0	140.2

To find the correct accident rate from Table 5 the road type alone is not sufficient. It is necessary to know the hourly intensity on the road as well.

The intensity per road segment is typically known after a traffic model has completed its assignment, and it needs to be stored per OD-pair. Once that is complete, the accident rate for every OD-pair can be looked up and multiplied by the distance travelled by the specific user group, on a specific road type (Table 7). Note that the distance should be scaled appropriately before multiplying with the accident rate, such that the resolution matches (accident rate is in #/million km's, so distance should be in million km's).

Table 7: Calculated accident number (dummy data)

o	d	road	age	intensity	km	accident_rate	accidents
1	2	type1	group1	4.0	64.6	0.001454	9.40E-08
1	2	type1	group2	26.5	424.2	0.001454	6.17E-07
1	2	type1	group3	8.8	140.1	0.001454	2.04E-07
1	2	type1	group4	2.6	41.2	0.001454	5.99E-08
1	2	type1	group5	8.1	130.0	0.001454	1.89E-07
...	...	...	...	...	...	...	...
10	9	type3	group1	11.4	227.7	0.0016	3.64E-07
10	9	type3	group2	0.6	11.2	0.0016	1.79E-08
10	9	type3	group3	3.8	75.9	0.0016	1.21E-07
10	9	type3	group4	0.5	10.0	0.0016	1.60E-08
10	9	type3	group5	7.0	140.2	0.0016	2.24E-07

Once this table is available, the indicator can be aggregated by e.g. grouping by the age group or road type (or other user group parameters not included in this example).

A change in a scenario, e.g. the addition of a school, can trigger a change in the resulting OD-matrix (Table 1), but also in the distance matrix or the road type distribution. This change will propagate through the indicator and will result in a different indicator value, allowing one to compare the effect of various model measures on the accident development.

2.6 Application in focus area

The steps from section 2.5 are carried out in this section with the data from the BBMA model in the Eindhoven region, which consists of 810 traffic analysis zones.

2.6.1 OD- and distance-matrix

The model supplies the OD- and distance matrix per mode and daypart. In this case only the car matrix for the morning commute is considered, for dummy purposes the trips and distance matrix is plotted below, it maps the values of the matrix to a colour for each OD-pair.

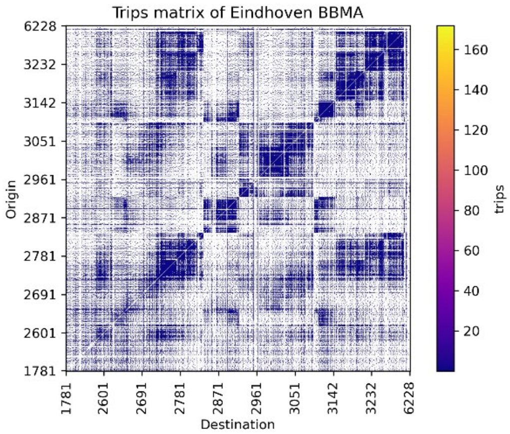


Figure 5: Car trips matrix of the BBMA Eindhoven area

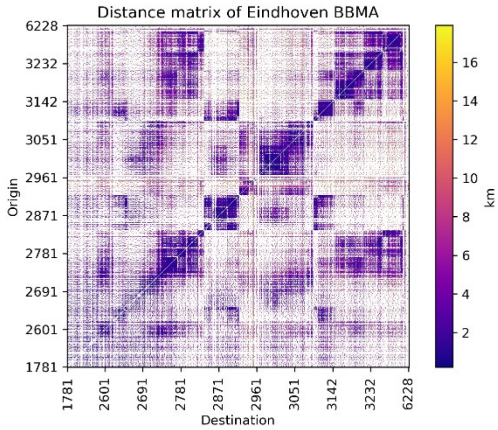


Figure 6: Car distance matrix of the BBMA Eindhoven area

A more detailed example is shown in Figure 7, where the distance and trips, obtained from the OD-matrix, between the centroid of zone 2513 and a few other zones is depicted.

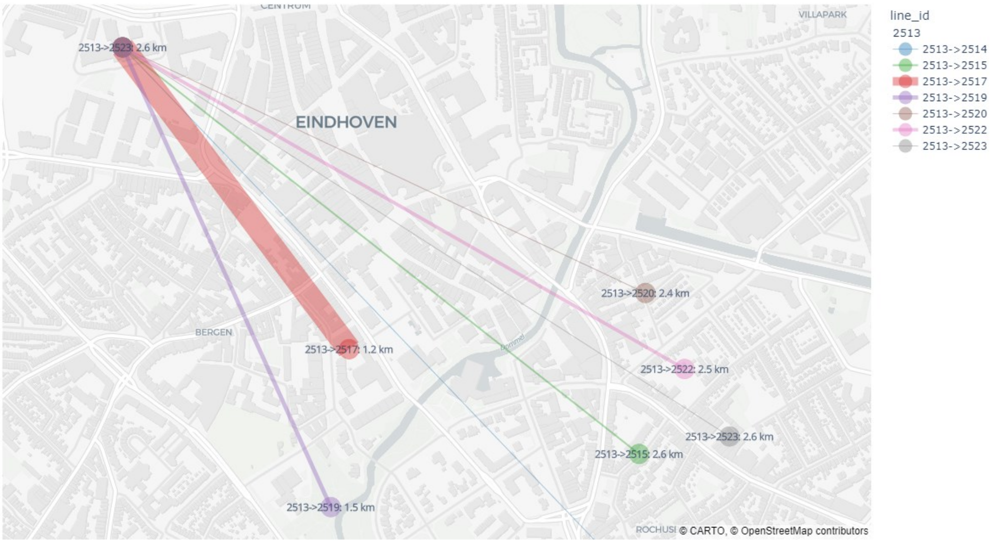


Figure 7: Several OD-pairs originating from traffic zone (code) 2513. Dots indicate the centroid of the traffic analysis zone; the thickness of the line refers to the number of trips on the OD-pair and the label at the destination zone shows the distance between the pair as stored in the BBMA model.

2.6.2 Road type

While the Urban Strategy traffic assignment model calculates the distance that is traversed between each OD-pair of the BBMA over each road type, this information is currently not stored for re-use. A minor developmental effort is needed to adjust this, but this has not been undertaken in the scope of this project. Because of this, it is currently not possible to obtain the distribution over the different road types per OD-pair, as was proposed with the dummy data in Table 8.

In total there are 18 road types in the network, this includes “virtual” roads such as feeder links that connect zone centroids to the main network. These 18 road types are mapped to 3 main types by the author: through-roads, distributor roads and access roads. The resulting network is shown in Figure 8.

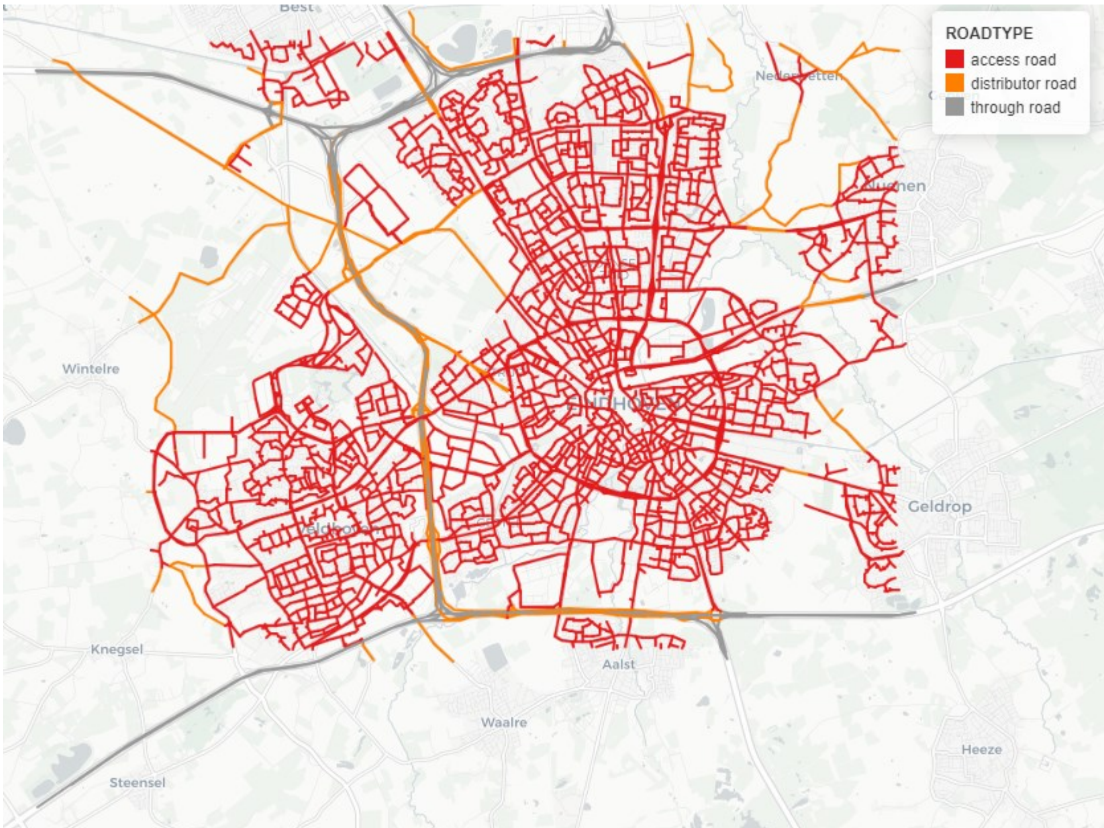


Figure 8: Aggregated road types in the Eindhoven BBMA network.

To work around the lack of actual distribution over road types per OD-pair, an estimation of the distribution is required. Firstly, it is assumed that the distribution over road types is the same for each OD-pair. A very important note is that this assumption is very generic and does not capture the difference between long and short trips well, but is used as an estimation.

Secondly, the road type distribution is estimated from the vehicle kilometres, derived from lengths and intensities, of all the roads. By dividing the vehicle kilometres driven on e.g. all access roads by the vehicle kilometres from all roads, a proportion is found that estimates the distance driven on the access road type.

In the current model case the following proportion is found:

Table 1: Approximated road type distribution

Access road	Distributor road	Through road
0.35	0.22	0.43

In other words: it is estimated that every trip (regardless of OD-pair) travels over access roads for 35% of the distance, over distributor roads for 22% and for 43% over through roads. Again, this is a very generic assumption, coming from the lack of distribution over road types. This looks as follows in the table format from the dummy data (Table 1).

Table 2: Approximated road type distribution per OD-pair

o	d	Access road (type1)	Distributor road (type2)	Through road (type3)
1781	1781	-	-	-
1781	2513	0.35	0.22	0.43
1781	2514	0.35	0.22	0.43
1781	2515	0.35	0.22	0.43
1781	2516	0.35	0.22	0.43
...	...	...	...	...
6228	6224	0.35	0.22	0.43
6228	6225	0.35	0.22	0.43
6228	6226	0.35	0.22	0.43
6228	6227	0.35	0.22	0.43

2.6.3 User group: age

In the current macroscopic traffic model there is no distinction between travellers and their characteristics. The model reports the number of vehicles moving from one zone to the other, it is unknown what the age of the traveller is. While other sources, such as the ODiN travel survey[16], do provide a link between traveller and trip characteristics, the number of respondents becomes very low when the data is grouped by origin, destination and age group. To work around that issue a less granular approach can be taken: by assuming that the urbanisation degree of the origin zone is driving the age distribution of the traveller and by assuming that the traveller departs from home in the morning commute it is possible to determine an age group distribution per urbanisation degree and use that for departing zones with matching urbanisation degrees.

For example: travellers going from traffic zone 2513 by car in the morning commute depart from a highly urbanised zone. To approximate their age distribution one can retrieve the age distribution of travellers in Eindhoven that live in a highly urbanised area and have a car in general. Similarly this can be repeated for zones with another urbanization degree.

This approximation is attempted with respondents data from ODiN 2018 until 2023. Only respondents that lived in Eindhoven and indicated to have at least one car are included in the analysis. This resulted in 1794 matching respondents. For these respondents their age and home postal code is retrieved, after which the latter is augmented with the urbanisation degree found in the PC4 data [17]. The age is grouped into three classes (0-17, 18-44, 45+) and the age distribution of respondents is determined per urbanisation degree. The outcome of this approximation is shown in Table 3 and visualized in Figure 9. Note that the age group 0-

[16] CBS and RWS, ‘Onderzoek Onderweg in Nederland - ODiN 2023’ (DANS Data Station Social Sciences and Humanities, 4 July 2024), https://doi.org/10.17026/SS/FNXJEU.

[17] CBS, ‘Statistische gegevens per vierkant en postcode 2021-2022-2023’, GPKG, webpagina, 18 July 2024, https://www.cbs.nl/nl-nl/longread/diversen/2024/statistische-gegevens-per-vierkant-en-postcode-2021-2022-2023?onepage=true.

17 never occurs due to the data selection criteria: these respondents don't have a car in the used data.

Table 3: Age group distribution for car owners per urbanization degree. Note that the selected data did not have information for urbanization degree 5, a 50/50 split per age group is therefore assumed.

Urbanization degree	Age group	Proportion
1	18-44	0.427545
1	45+	0.572455
2	18-44	0.339744
2	45+	0.660256
3	18-44	0.372263
3	45+	0.627737
4	18-44	0.214286
4	45+	0.785714
5	18-44	0.5
5	45+	0.5

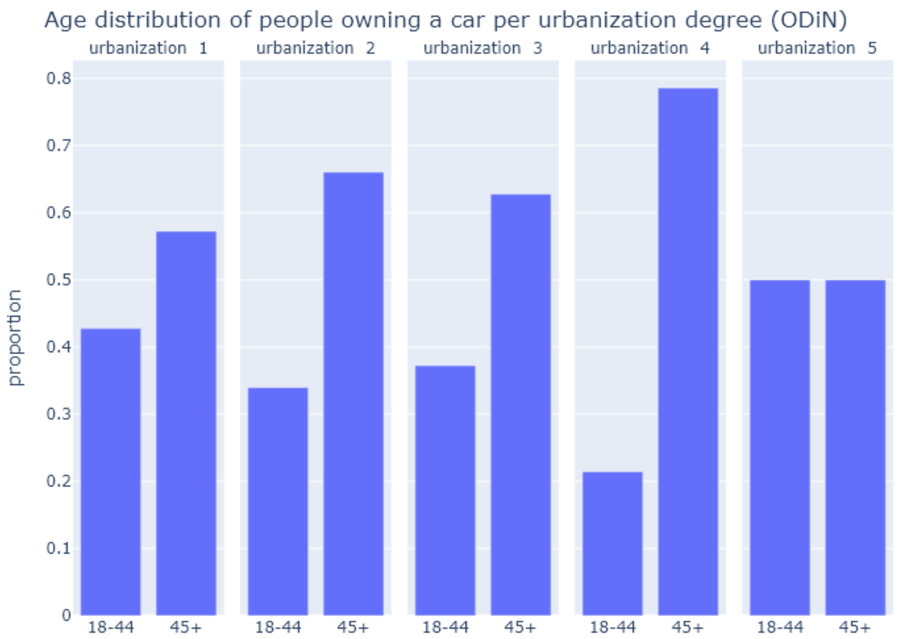


Figure 9: Age group distribution for car owners per urbanization degree. An urbanization degree of 1 is highly urbanized.

These proportions can now be used to estimate the age group distribution for each OD-pair, based on the urbanization degree of the origin zone. An excerpt of the resulting table is shown in Table 4.

Table 4: Age group distribution based on the urbanization degree of the origin zone

o	d	Urbanization degree origin	0-17 (group1)	18-44 (group2)	45+ (group3)
1781	1781	2. strong	-	-	-
1781	2513	2. strong	0	0.339744	0.660256
1781	2514	2. strong	0	0.339744	0.660256
1781	2515	2. strong	0	0.339744	0.660256
1781	2516	2. strong	0	0.339744	0.660256
…	…		…	…	…
6228	6224	4. little	0	0.214286	0.785714
6228	6225	4. little	0	0.214286	0.785714
6228	6226	4. little	0	0.214286	0.785714

2.6.4 Accident rate

While the current model has a data field available for the risk of death or injury for each road segment, this information was not filled in. Therefore another approximation is made based on literature [18], which notes expected accidents per million car kilometres for 8 different road types, further split by their average daily intensity[19]. The 3 aggregated road types from section 2.6.2 are related to these 8 types in Poppe[20] as follows:

Through-road:
- 3-4 strooks rijbaan ASW
- 2-strook rijbaan ASW

Distributor road:
- Bubeko, enkel, 1 parvz, gesl. voor fiets en bromfiets
- Bubeko, enkel, geen parvz, gemengd verkeer
- Bibeko dubbelbaans verkeersader met gesloten verklaring
- Bibeko enkelbaans verkeersader met gesloten verklaring

Access road:
- Bibeko dubbelbaans verkeersader voor alle verkeer
- Bibeko enkelbaans verkeersader voor alle verkeer

To arrive at expected accidents for these 3 road types, the values from the underlying road types are averaged, i.e. the expected accident rate for “Access road” is assumed to be the average of “Bibeko dubbelbaans” and “Bibeko enkelbaans”. The dependency on the intensity is dropped as it appeared impossible to determine which roads are traversed per OD-pair (see section 2.6.2), so neither is it possible to indicate if travelling between the OD-pair occurs at a high or low intensity road. It is acknowledged that this is a large gap in the current methodology as the intensity plays an important role in the magnitude of the expected accident rates in Poppe[21]. Before this method can be applied to calculate an indicator for policy decision support this gap needs to be addressed as otherwise the resulting values are too far removed from reality.

[18] Poppe, ‘Risico’s Onderscheiden Naar Wegtype; Eindrapportage van Het Kencijfer-Project Uit Het Onderzoekjaarplan 1995’, 15.
[19] This is rather old literature, but the Urban Strategy indicator that the current work is based on uses this literature as well. A newer reference with fitting similar data has not been found.
[20] ‘Risico’s Onderscheiden Naar Wegtype; Eindrapportage van Het Kencijfer-Project Uit Het Onderzoekjaarplan 1995’.
[21] [NO_PRINTED_FORM]

However, to be able to “close the loop” and test the methodology out, this blunt simplification is made, nonetheless. The removal of the intensity dependency results in the following, simplified accident rate table:

Table 5: Accident rates aggregated to three road types

road type	accident_rate per mln. veh. km’s
Through road (type1)	0.06075
Distributor road (type2)	0.2660
Access road (type3)	0.5000

2.6.5 Result

Now all elements needed for the calculation are available and the number of expected accidents can be estimated for every OD-pair. These steps are followed per OD-pair:

1. Take the number of trips and the distance between the origin and destination from the OD-matrix
2. Set the distribution over road types in accordance with Table 1
3. Lookup the urbanization degree of the origin zone from the zonal data
4. Based on the found urbanization degree, link the relevant age group distribution
5. Calculate the distribution of trips per road type by multiplying the number of trips by the different proportions for each road type for this OD.
6. Calculate the km’s driven per road type by multiplying the OD distance with the trips per road type.
7. Calculate the trips per road type and age group by multiplying the trips per road type with the different proportions for each age group for this OD.
8. Calculate the km’s driven per road type and age group by multiplying the trips from the previous point with the distance between the origin and destination.
9. The latter km’s driven is a value representing a single morning commute. The accident rates are defined per million km’s, per year. Therefore the km’s driven from step 8 are multiplied by 365 (to convert to a year) and then divided by 1 million to scale it to the level the accident rate expects.
10. Finally this scaled distance driven is multiplied by the accident rate per road type from Table 5 to get a number of expected accidents per year for the morning commute.

Aggregating the results on an OD-pair level to a single number, shows that this method expects **13.5** accidents in the morning commute on a yearly basis, mostly occurring on access roads (67%). This is of course an unrealistic low number, and is likely the result of the various approximations and simplifications made in the above steps. Regardless, Figure 10 until Figure 12 show how this indicator can be used on a map. In Figure 10 it shows the number of expected accidents for trips departing from a certain zone; the most accidents are expected in trips starting from the zone around Eindhoven airport. A similar map is made in Figure 11, but for trips arriving at a zone. As a distinction is made between age groups, it is also possible to plot the expected difference in accidents between the 45+ and the 18-44 age group (Figure 12). It shows that in large parts in the west of the city and some areas in the city centre the difference is small, but there are also areas where the expected accidents for age group 45+ is higher.

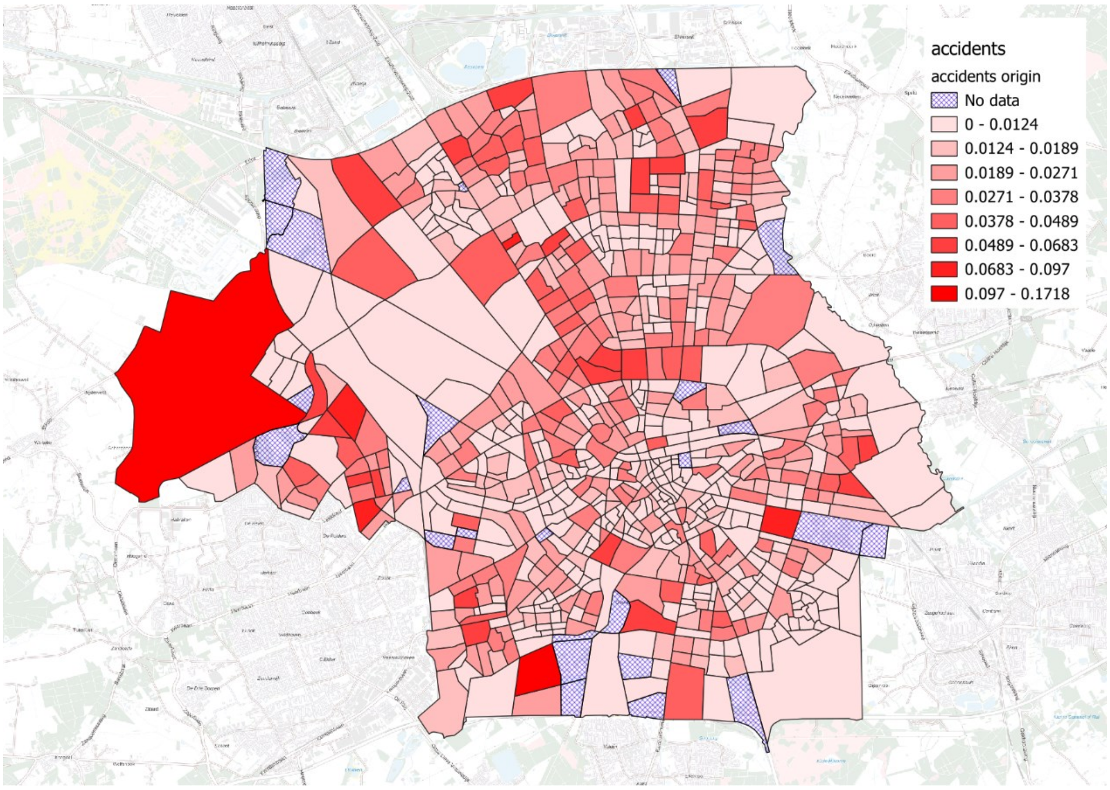


Figure 10: Zones coloured by the expected amount of accidents for trips departing from these zones. This depicts expected accidents, in the morning commute for the whole year, based on the trips that depart from each zone, regardless of trip destination or age group of the traveller.

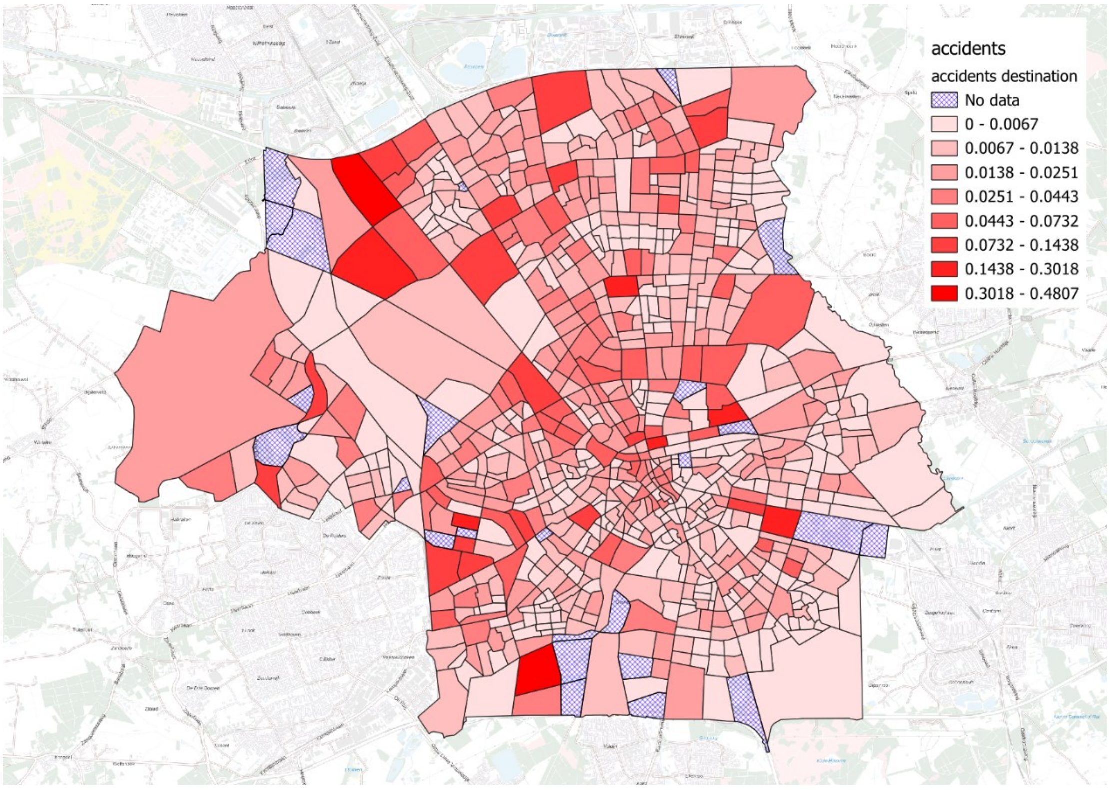


Figure 11: Zones coloured by expected amount of accidents for trips arriving at the zones.

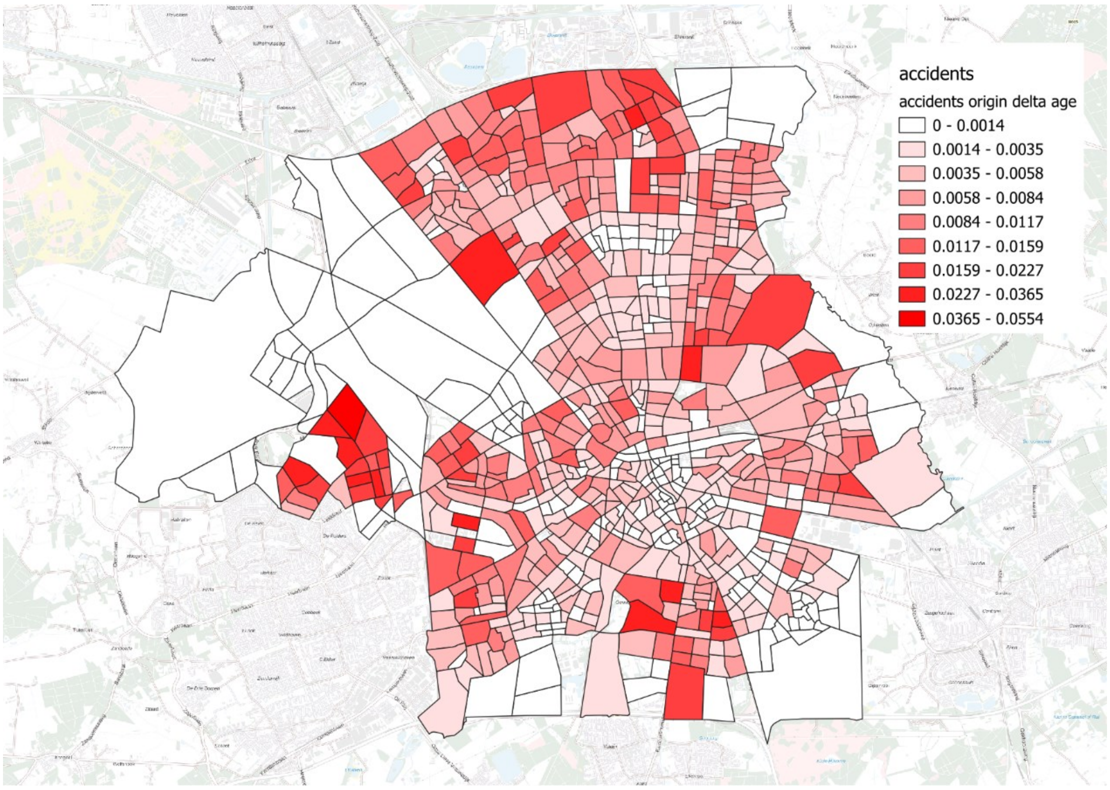


Figure 12: Difference in expected accidents between age group 45+ and 18-44 for trips departing from the zones. The delta is determined by subtracting the number of expected accidents for age group 18-44 from the expected accidents for age group 45+.

2.7 Discussion

While a final result is obtained, it unfortunately yields a result orders of magnitude lower than expected. However, following the process did bring to light several issues that pose a challenge for the calculation of such an indicator from model output, providing useful pointers for further research.

The application of the proposed method in the focus area shows that a macroscopic model on itself does not contain sufficient information to determine a safety and accidents indicator. The model needs to be augmented with auxiliary data and approximations of accident rates, user group behaviours and accident risk to complete the calculation. While this auxiliary data is available, it is at a lower level of detail than the traffic model operates on. Compare for example the granularity of trip information – which is known per daypart, OD-pair and mode – with the level of detail of age group distribution. The latter is estimated on a higher level, i.e. urbanisation degree, and cannot be retrieved for each OD-pair.

Additionally the absence of a relation between the assigned route for an OD-pair and the traversed road types (see section 2.6.2), poses a large gap in the validity of the outcome. It makes it impossible to find what the intensity was that the trips for that OD-pair encountered along the way, and subsequently not possible to lookup the accident rate adjusted for the intensity.

These points weaken the effect that this indicator can show at the moment as a result of a model intervention, as there are many “dampening” approximations that do not react directly on the detail level of the model and “average” out some effects.

These shortcomings can partially be resolved by minor model changes, such as in the case of the distribution over road types (section 2.6.2), but some improvements will require another modelling approach. To show how, in this case, safety effects are distributed over user groups the traffic model needs to take the different user groups into account on the same level of detail as modes and motives (as is for example done in an Activity-Based Model).

3 Accessibility of jobs

3.1 Introduction

This chapter explores the topic of accessibility to jobs. It begins with definitions and a brief literature review of accessibility from a mobility perspective (sections 3.2 and 3.3). Next, sections 3.4 and 3.5 discuss the data needed to compute and visualise a dummy example of accessibility to jobs in a specific area. Finally, section 3.6 expands on the application of the accessibility to jobs measure, applying it to two different income groups (Bottom 40%; Top 10% - based on ODiN income properties) and three transportation modes (car, bicycle, public transport) in the Eindhoven area.

3.2 Definition

There are multiple definitions of accessibility. In a simple form, accessibility *"refers to people's overall ability to reach desired services and activities, together called opportunities"*[22]. Conversely, accessibility can also be seen as a characteristic of places and opportunities in terms of how easily people can reach such places[23]. Accessibility therefore can be seen as referring to the ease with which any activity can be accomplished from any location by means of using a specific transport system[24].

In the context of the Netherlands, the IMA report of 2021 defines the accessibility of activities as the number of activities (e.g. work, education, health care and nature) that can be reached by a given mode of transport from a given area within a reasonable travel time.

Based on the above definitions, some important components of accessibility become apparent:

- Opportunities or activities (the actual places people want to be able to reach). These constitute the collection of activities that people want to reach in order to fully engage in, contribute to, and benefit from the social, cultural, economic, political, and spiritual aspects of society[25].
- Locations, corresponding to the origin (where people live or start the journey) and destination (the location of the desired activity or opportunity).
- Transportation mode, corresponding to the way in which people reach the desired opportunities or activities (e.g., walking, driving, using public transportation, cycling, or other means).

[22] Todd, L. (2024). Evaluating accessibility for transportation planning: Measuring people's ability to reach desired services and activities. Victoria Transport Policy Institute. https://www.vtpi.org/access.pdf
[23] PEREIRA, Rafael H. M.; HERSZENHUT, Daniel. Introduction to urban accessibility:
a practical guide with R. Rio de Janeiro: Ipea, 2023. 152 p. ISBN: 978-65-5635-065-3.
DOI: http://dx.doi.org/9786556350653
[24] Dalvi, M. Q., & Martin, K. M. (1976). The measurement of accessibility: Some preliminary results. Transportation, 5(1), 17–42. https://doi.org/10.1007/bf00165245
[25] Nykiforuk, C. I., Glenn, N. M., Hosler, I., Craig, H., Reynard, D., Molner, B., Candlish, J., & Lowe, S. (2021). Understanding urban accessibility: A community-engaged pilot study of entrance features. Social Science & Medicine, 273, 113775. https://doi.org/10.1016/j.socscimed.2021.113775

It becomes clear that not only the type (or purpose) of opportunities (e.g., work, education, leisure etc), but also the transportation mode (e.g., car, bike, public transportation) are important factors to take into account when discussing accessibility.

3.3 Literature

There is plenty of literature discussing accessibility in urban contexts. Pereira and Herszenhut (2024)[23] present a discussion of different accessibility measures, including Place-based measures and Person-based measures. Place-based metrics assess accessibility as a feature of a specific area. These metrics presume that all persons in the same location have equal access to the activities spread throughout the city (which is something that we aim to investigate better). These are the most common measurements used by transportation organisations and researchers. The most common measures of place-based accessibility include:

- **Minimum travel cost (or time)**. This measure indicates the **lowest cost required to reach the nearest opportunity from a given origin**. It enables the calculation of, for instance, how long it would take to get from each city block to the nearest health facility[23].
- **Cumulative opportunity measures**. This metric determines how many opportunities can be reached within a specified travel cost (time) limit. This indicator, for instance, can be used to calculate how many jobs can be reached by public transportation in up to 60 minutes or how many schools can be reached by foot in up to 30 minutes[23]. In a cumulative measure, once a threshold is passed (e.g., 35 min if the threshold is 30min), that activity is no longer considered as accessible.
- **Gravity measures**. Similar to the cumulative opportunity measure, gravity accessibility measures also consider the sum of opportunities that can be reach. But as travel cost (time) rises, the quantity of opportunities at each location is progressively discounted. That means that **opportunities that are more easily accessed are valued more highly, and that the weight of each opportunity diminishes with increasing difficulty in reaching them from the trip origin place**. Gravity measures use what is called travel decay functions to discount the weight of opportunities as the travel time increases. Gravity-based accessibility measures can be computed using a variety of decay function types, and Kapatsila et al. (2023)[26] provide a comparison of the performance of commonly used decay functions.

For the purposes of this discussion on the accessibility indicator, the gravity-based accessibility will be considered and further explained in the next sections. The selection of the gravity-based measure is justified by the fact that it has been referred to in academic literature as more theoretically sound than the cumulative measure, as it does not restrict accessibility to a single time or cost threshold[27].

[26] Kapatsila, B., Palacios, M. S., Grisé, E., & El-Geneidy, A. (2023). Resolving the accessibility dilemma: Comparing cumulative and gravity-based measures of accessibility in eight Canadian cities. Journal of Transport Geography, 107, 103530. https://doi.org/10.1016/j.jtrangeo.2023.103530

[27] Palacios, M. S., & El-Geneidy, A. (2022). Cumulative versus Gravity-based Accessibility Measures: Which One to Use? Findings. https://doi.org/10.32866/001c.32444

3.4 Data

3.4.1 Traffic zones

Traffic zones, also known as Traffic Analysis Zones (TAZs), are geographic areas that serve as the fundamental unit of analysis in macroscopic models. Data on employment, population, land use, and other socioeconomic factors that affect travel behaviour are aggregated using traffic zones. Therefore, a traffic zone is a specific area defined by state and/or local transportation authorities for the purpose of tabulating traffic-related data.

3.4.2 Types and number of activities per traffic zone

Urban traffic models are usually used to determine the boundaries of each traffic zone. For example, the Amsterdam Traffic Model (*Verkeersmodel Amsterdam – VMA*) is an urban traffic model for the city of Amsterdam, which is intended for strategic road and public transport studies, and can be used to make future forecasts of the number of traffic movements, for different scenarios.

In the context of calculating accessibility, the total number of opportunities (e.g., jobs, education, shops etc) per traffic zone is retrieved from the corresponding traffic model. A table with all this information can then be developed, as illustrated in Table 6.

Table 6. Example of total number of activities/opportunities per zone (dummy data)

Zone	Jobs	Working population	Shops	Education
Zone 1	3000	4860	18	20
Zone 2	2973	4471	8	19
Zone 3	2660	4106	2	5
Zone 4	2120	4046	14	19
Zone 5	2619	3894	17	10

3.4.3 Travel decay curves

As mentioned in section 3.3, the gravity measure computes the accumulated number of opportunities that can be reached from a given origin zone considering all other destination zones, discounting the value of opportunities as the travel time (or travel cost) increases. This is performed via travel decay curves.

Travel decay curves use the concept of impedance to discount the value of opportunities as the travel time (or travel cost) increases. The concept of impedance explains how challenging it is to move from one location to another. Travel time, travel distance, travel expenses, or a mix of these (generalised costs) are frequently used to compute the impedance[28]. Figure 13 provides some examples of different travel decay curves identified in the literature. For each curve, the x-axis represents travel time, while the y-axis represents impedance weight, which is a function of travel time. For example, the CUMR40 displays a cumulative rectangular decay curve, where a weight of one is assigned to an opportunity within zero to 40 minutes, and zero is assigned to opportunities 40 minutes or further away (i.e., 40 minutes is the threshold beyond which opportunities are no longer considered accessible). Conversely, the EXP0.15 shows a decay curve that gradually reduces the value of

[28] Travel Forecasting Resource. (n.d.). https://tfresource.org/topics/Impedance.html

an opportunity as travel time increases, rather than a hard threshold like the CUMR40. For instance, an opportunity 10 minutes away would have an impedance weight of 1 with CUMR40, and approximately 0.22 with EXP0.15.

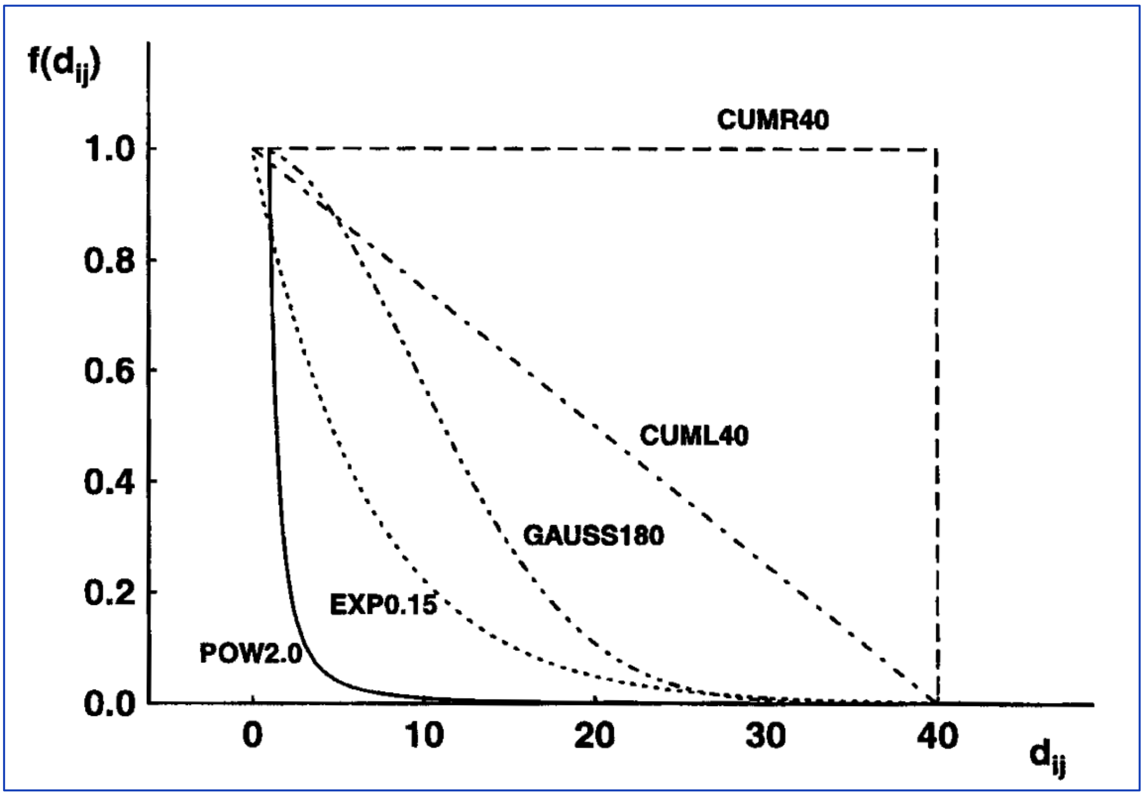


Figure 13. Examples of Impedance Functions (source: Kwan, M. (1998)[29])

In the context of this report, the travel decay curves were derived from ODiN dataset from CBS[30]. The ODiN dataset provides information on the daily mobility of the Dutch population and describes the travel behaviour of the Dutch population according to place of origin and destination, time of transport, means of transport used and reasons for travelling.

ODiN data is collected throughout each year by the CBS across the country. About 37.000 respondents per year fill in a travel diary for a single day, recording all their trips, down to a trip-leg-level, on that day. Additionally, the respondents provide information regarding their vehicle ownership, household composition, and personal characteristics. CBS augments this information using data from the census and provides a datafile per year with personal, household, trip, and trip-leg-data.

Based on the data available in the ODiN dataset, curve fitting methods can be used to derive the most suitable decay curves for different transportation modes (e.g., car, bike, public transportation), motives (e.g., work, education, shopping), as well as other relevant properties available (e.g., age, income, car ownership etc). Figure 14 provides an illustrative example of travel decay curves for car, bike, and public transportation. Actual examples of

[29] Kwan, M. (1998). Space-Time and Integral Measures of Individual Accessibility: A comparative analysis using a point-based framework. Geographical Analysis, 30(3), 191–216. https://doi.org/10.1111/j.1538-4632.1998.tb00396.x

[30] More information available at [Research on Movements in the Netherlands (ODiN) | CBS]

travel decay curves for purpose work (*banen*) based on ODiN income property are provided later on in this chapter (see Figure 18).

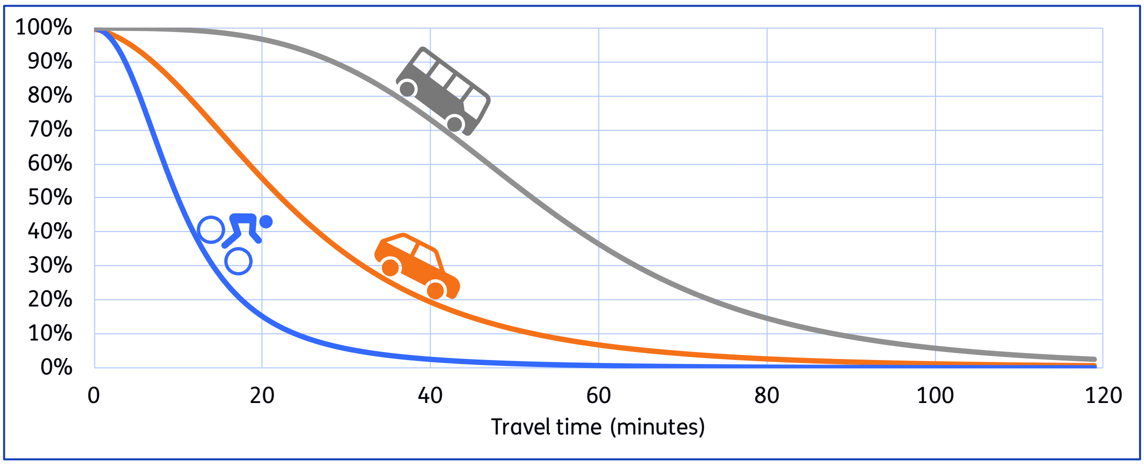


Figure 14. Dummy example of travel decay curves for different transportation modes (bicycle, car, bus). Opportunities that are more easily accessible are valued more highly, i.e., the weight of each opportunity diminishes with increasing difficulty (travel time, cost, or other relevant measures) in reaching them from the trip origin place.

3.5 Illustration of steps using dummy data

3.5.1 Calculation of accessibility

The computation of the accessibility is based on the following formula:

$$A^M_{O,i} = \sum_{\substack{j=1 \\ i \neq j}}^{N} N_{O,j} \times D^M_O\left(T_{ij}\right) \qquad \text{Equation 1}$$

In which:

- $\boldsymbol{A^M_{O,i}}$:Accessibility to opportunities of type $\boldsymbol{O}$ in zone $\boldsymbol{i}$ using transport mode M
- $\boldsymbol{i}$: Origin zone
- $\boldsymbol{j}$: Destination zone
- $\boldsymbol{O}$: Opportunities O = {jobs, shops, education,...}
- $\boldsymbol{M}$: Transportation modes M = {car, bike, public transport,...}
- $\boldsymbol{N}$: total number of destinations in the study area
- $\boldsymbol{N_{O,j}}$: Number of opportunities of type O in zone j.
- $\boldsymbol{D^M_O(T_{ij})}$: Travel decay factor based on travel time from zone i to zone j for opportunity O using transport mode M. The travel decay factors are a function of the travel time, the transportation mode, and the opportunity.

For the explanation regarding the calculation of the accessibility indicator, an illustrative part of Amsterdam[31] is used, as depicted in Figure 15. There are ten zones represented in Figure

[31] In this indicator, the example for the dummy data is used from Amsterdam. The reason is that this dummy example was chosen earlier than the WP4.1 focus case. We have chosen to leave the Amsterdam example in.

15 (depicted by dashed borders). The orange circles represent the centroid of each traffic zone – where all trips from and to that zone take place.

Figure 15. Dummy representation of some traffic zones in an area

3.5.2 Step 1 – Identification of types and number of activities per traffic zone

Table 7 provides the list of activities and the total number for each activity per zone presented in Figure 15. The numbers provided are for illustrative purposes only and do not represent actual number for each zone.

Table 7. Example of total number of activities/opportunities per zone in the focus area (dummy data)

Zone	Jobs	Working population	Shops	Education
Zone 1	3000	4860	180	20
Zone 2	2973	4471	83	19
Zone 3	2660	4106	222	5
Zone 4	2120	4046	140	19
Zone 5	2619	3894	73	10
Zone 6	3422	4222	55	12
Zone 7	1789	3897	236	11
Zone 8	2456	2369	354	22
Zone 9	3298	3456	122	23
Zone 10	1000	3894	170	15

3.5.3 Step 2 – Identification of travel time (or travel cost) from each origin zone to each destination zone

Based on the focus area depicted in Figure 15 and using traffic models, it is possible to derive the travel time from each origin zone Z_O to each destination zone Z_D. Table 8 provides a dummy representation of the travel time for three transportation modes (car, bike, public transportation) for the origin zone Zone 1 to all other zones. The same logic would apply for the other zones, but this is not presented for visualisation purposes in order to minimise clutter.

Table 8. Example of travel times (in min) from origin zone Zone 1 to all other zones (dummy data)

From Zone 1 to Zone… → By transportation mode… ↓	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
Car	-	11	14	18	45	7	23	33	10	29
Bike	-	19	50	31	36	18	46	69	22	44
Public Transportation	-	28	11	21	23	17	16	39	25	73

3.5.4 Step 3 – Application of discount factors per transportation mode via travel decay curves

In order to compute the accumulated number of opportunities that can be reached from a given origin zone considering all other destination zones while taking into account the effect of travel time, discounting factors derived from travel decay curves are applied. Table 9 presents a dummy case with discounting factors associated to the accessibility to jobs by car. The same type of table can be derived for other transportation modes (i.e., bike, public transportation).

Therefore, if the travel time to an activity by car is e.g. 43 minutes, one could look at the corresponding travel decay discounting factor (i.e., for a travel time 42 min – 43 min) and use it to discount the number of activities. As a result, if the travel time from Zone 1 to Zone 2 is of 43 minutes by car, and the discounting factor for the travel time to jobs between 42 min – 43 min is of 0.172, and Zone 2 has 2973 jobs, then the total number of jobs in Zone 2 accessible by someone Zone 1 is equal to 511.356 (= 2973 x 0.172).

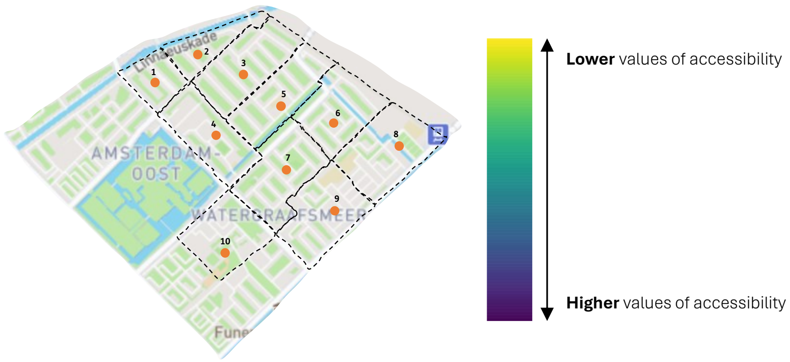
Table 9. Example (limited to 99 min for visualisation purposes) of discounting factors for different travel times by car for opportunity type jobs (dummy data)

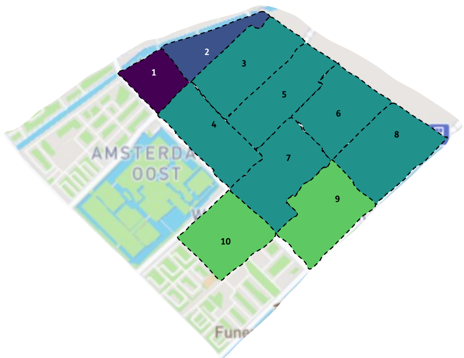
Travel time interval (min)	Discount factor	Travel time interval (min)	Discount factor	Travel time interval (min)	Discount factor
0 - 1	0.999	33 - 34	0.283	66 - 67	0.048
1 - 2	0.993	34 - 35	0.268	67 - 68	0.046
2 - 3	0.984	35 - 36	0.253	68 - 69	0.044
3 - 4	0.972	36 - 37	0.24	69 - 70	0.042
4 - 5	0.957	37 - 38	0.227	70 - 71	0.04
5 - 6	0.94	38 - 39	0.215	71 - 72	0.038
6 - 7	0.921	39 - 40	0.203	72 - 73	0.036
7 - 8	0.901	40 - 41	0.192	73 - 74	0.034
8 - 9	0.878	41 - 42	0.182	74 - 75	0.033
9 - 10	0.854	42 - 43	0.172	75 - 76	0.031
10 - 11	0.829	43 - 44	0.163	76 - 77	0.03
11 - 12	0.803	44 - 45	0.154	77 - 78	0.028
12 - 13	0.777	45 - 46	0.146	78 - 79	0.027
13 - 14	0.749	46 - 47	0.138	79 - 80	0.026
14 - 15	0.722	47 - 48	0.131	80 - 81	0.024
15 - 16	0.694	48 - 49	0.124	81 - 82	0.023
16 - 17	0.666	49 - 50	0.118	82 - 83	0.022
17 - 18	0.638	50 - 51	0.111	83 - 84	0.021
18 - 19	0.61	51 - 52	0.106	84 - 85	0.02
19 - 20	0.583	52 - 53	0.1	85 - 86	0.019
20 - 21	0.557	53 - 54	0.095	86 - 87	0.018
21 - 22	0.531	54 - 55	0.09	87 - 88	0.018
22 - 23	0.505	55 - 56	0.085	88 - 89	0.017
23 - 24	0.481	56 - 57	0.081	89 - 90	0.016
24 - 25	0.457	57 - 58	0.077	90 - 91	0.015
25 - 26	0.434	58 - 59	0.073	91 - 92	0.015
26 - 27	0.412	59 - 60	0.069	92 - 93	0.014
27 - 28	0.391	60 - 61	0.066	93 - 94	0.013
28 - 29	0.371	61 - 62	0.062	94 - 95	0.013
29 - 30	0.351	62 - 63	0.059	95 - 96	0.012
30 - 31	0.333	63 - 64	0.056	96 - 97	0.012
31 - 32	0.315	64 - 65	0.054	97 - 98	0.011
32 - 33	0.299	65 - 66	0.051	98 - 99	0.011

3.5.5 Illustrative visualisation of accessibility

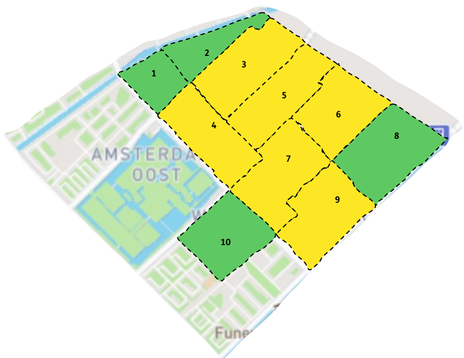
By following steps 1-3 presented in the previous section for all the zones inside the dummy area in Amsterdam (illustrated in Figure 15), one can obtain choropleths that depict the accessibility to different activities (e.g., jobs, education, shops, among others) by each transportation mode (car, bike, public transportation).

This section presents an dummy calculation of such accessibility choropleths using data on number of jobs per zone provided in Table 7, the corresponding versions of Table 8 (considering zones 2-10 as origin zones Z_O and zones 1-10 as destinations zones Z_D) and the discounting factors presented in Table 9.

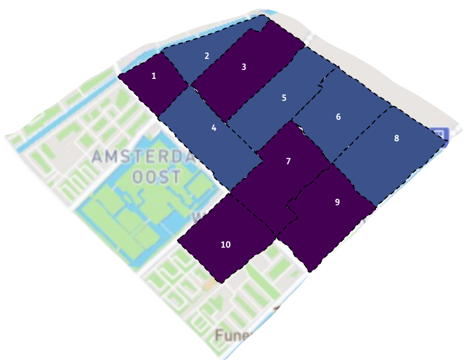




	Car (# jobs)	Interval
Zone 1	13,708	13,140 - 20,094
Zone 2	7,618	7,397 - 13,140
Zone 3	4,826	4,508 - 7,397
Zone 4	5,828	4,508 - 7,397
Zone 5	5,791	4,508 - 7,397
Zone 6	5,225	4,508 - 7,397
Zone 7	5,365	4,508 - 7,397
Zone 8	7,250	4,508 - 7,397
Zone 9	2,661	1,835 - 4,508
Zone 10	4,031	1,835 - 4,508



	Bike (#jobs)	Interval
Zone 1	1,846	1,835 - 4,508
Zone 2	2,043	1,835 - 4,508
Zone 3	1,787	401 - 1,835
Zone 4	1,513	401 - 1,835
Zone 5	1,685	401 - 1,835
Zone 6	1,794	401 - 1,835
Zone 7	1,299	401 - 1,835
Zone 8	1,942	1,835 - 4,508
Zone 9	401	401 - 1,835
Zone 10	2,543	1,835 - 4,508



	Public transport (#jobs)	Interval
Zone 1	20,094	13,140 - 20,094
Zone 2	13,076	7,397 - 13,140
Zone 3	13,393	13,140 - 20,094
Zone 4	11,770	7,397 - 13,140
Zone 5	12,334	7,397 - 13,140
Zone 6	10,685	7,397 - 13,140
Zone 7	13,740	13,140 - 20,094
Zone 8	12,227	7,397 - 13,140
Zone 9	14,504	13,140 - 20,094
Zone 10	18,803	13,140 - 20,094

Figure 16. Dummy example of choropleths depicting accessibility to jobs (cumulative number of jobs) per zone in the focus area and per transportation mode

3.6 Application in focus area

The process explained in section 3.5 was applied to the focus area of Eindhoven. The analysis was performed for opportunity type jobs (banen) and transportation modes car, bicycle, and public transportation (OV). Travel decay curves were also derived for two distinct population groups based on ODiN income property HHGestInkG (standardised disposable household income, (10% groups)) and used for the calculations. The groups considered were Bottom 40% and Top 10% regarding standardised disposable household income groups.

3.6.1 Step 1 – Identification number of jobs per traffic zone in focus area

Data on jobs per traffic zone was obtained from the traffic model BBMA[32]. The following steps were performed:

1. Selecting data for the focus area. This was performed by filtering the BBMA dataset on *"Gemeentenaam"* attribute ("Eindhoven" was selected).
2. Retrieving data on jobs for the traffic zones (ZOB_ZONE) related to Eindhoven.

The above steps result in an area with 810 zones and a total of 166.097 jobs, as depicted in Figure 17.

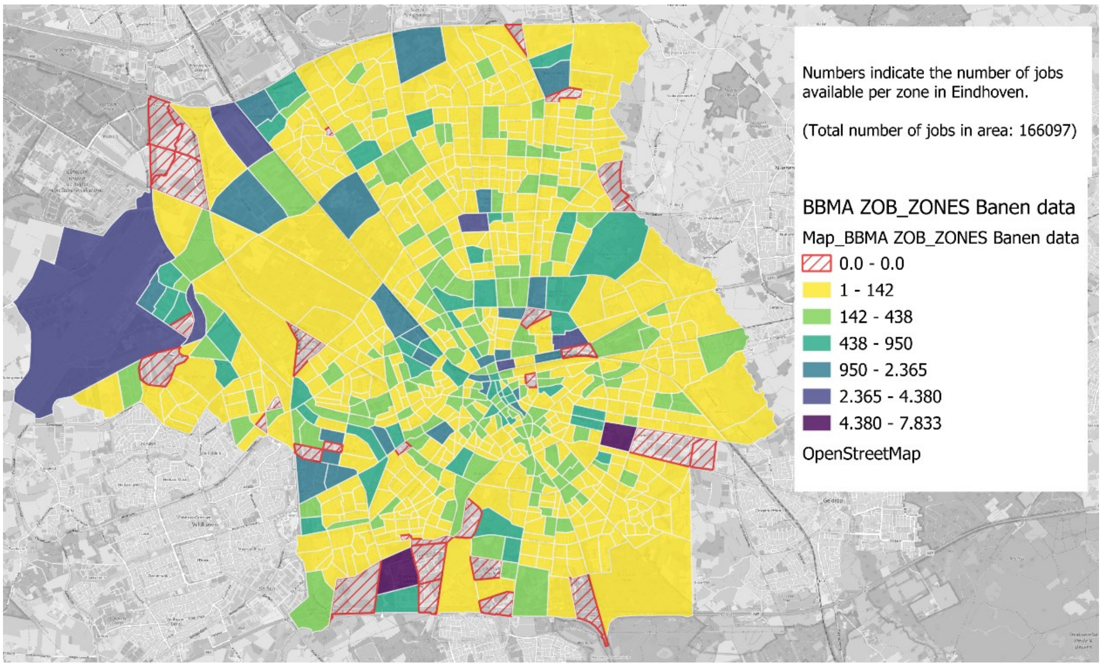


Figure 17. Choropleth depicting number of jobs per zone in Eindhoven

[32] More information available at [Home - Traffic model BBMA]

3.6.2 Step 2 – Identification of travel time from each origin zone to each destination zone in focus area

Data on travel time from each origin zone Z_O and each destination zone Z_D were obtained from TNO's Digital Twin traffic assignment model for different transportation modes (auto, bicycle, and public transportation).

The data is composed of three origin-destination (OD) matrices (one per transportation mode) with 810 Z_O x 810 Z_D.

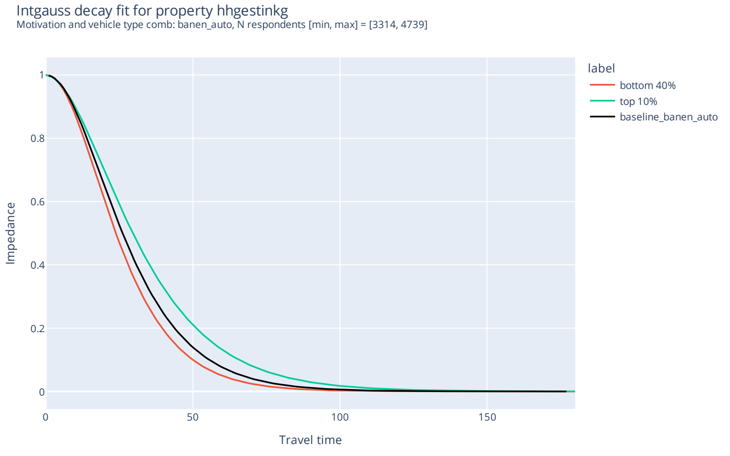
3.6.3 Step 3 – Application of discount factors per transportation mode and user group via travel decay curves

Travel decay curves for two groups based on the BBMA property regarding standardised disposable household income were obtained. The selected groups were "Bottom 40%" and "Top 10%". The choice of these groups was inspired by the Palma Ratio. This measures was proposed after the Chilean economist José Gabriel Palma, which argued that income inequality is due to shifts in the income shares of the wealthiest (Top 10%) and the poorest (Bottom 10% - Bottom 40%), while the income share of the 'middle' group, which includes the 5th to the 9th decile (50% – 90%), remains unchanged[33].

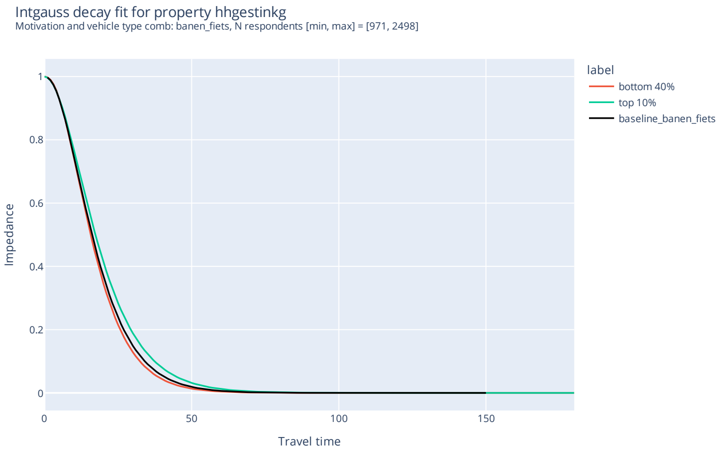
Even though the Palma Ratio was originally developed for wealth and income inequality purposes, there has been applications of it in other areas, such as accessibility inequality[23 34 35]. In such studies, accessibility inequality is usually investigated by classifying the different areas (e.g., zones) into deciles (D1[10%] – D10[100%], according to some relevant income measure (e.g., average household income)) and then the average accessibility levels are computed for the two Palma Ratio groups (Bottom 40%; Top 10%). The Palma Ratio for accessibility is then obtained by dividing the average accessibility for the Top 10% group by the average accessibility for the Bottom 40%. One of the primary benefits of the Palma Ratio is its ease of communication and interpretation (values above 1 indicate a situation where the wealthiest 10% have greater average accessibility levels than the poorest 40%)[23]

For this study, the differences between the Top 10% and Bottom 40% groups were analysed via distinct travel decay curves obtained for each group, as can be seen in Figure 18. As travel time increases, the weight of each job opportunity diminishes with increasing difficulty in reaching them from the trip origin place. However, as Figure 18(a), Figure 18(b), and Figure 18(c) show, the decaying curves are different for the different groups (Top 10%; Bottom 40%), which impacts the cumulative number of job opportunities accessible (via functioning of Equation 1). For an explanation on how these decay curves are established, please refer to appendix A.2.

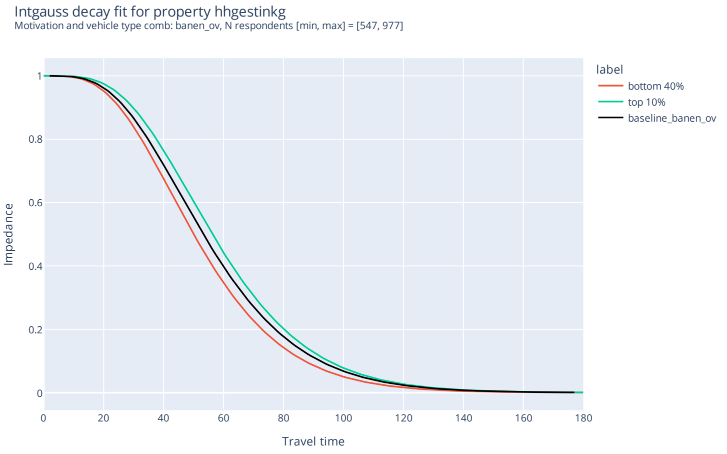
[33] Cobham, A., Schlogl, L., & Sumner, A. (2015). Inequality and the Tails: The Palma Proposition and Ratio revisited (DESA Working Paper No. 143). United Nations Department of Economic and Social Affairs. https://www.un.org/ht/desa/inequality-and-tails-palma-proposition-and-ratio-revisited
[34] Pritchard, J. P., Tomasiello, D., Giannotti, M., & Geurs, K. (2019). An International Comparison of Equity in Accessibility to Jobs: London, São Paulo, and the Randstad. Transport Findings. https://doi.org/10.32866/7412
[35] Guzman, L. A., & Oviedo, D. (2018). Accessibility, affordability and equity: Assessing 'pro-poor' public transport subsidies in Bogotá. Transport Policy, 68, 37–51. https://doi.org/10.1016/j.tranpol.2018.04.012



(a) Banen auto (travel time in minutes)



(b) Banen fiets (travel time in minutes)



(c) Banen OV (travel time in minutes)

Figure 18. Travel decay curves per transportation mode for property hhgestinkg (standardised disposable income of the household). Decay curve for Bottom 40% is depicted in red, and decay curve for Top 10% group is depicted in green.

3.6.4 Visualisation of accessibility for focus area

By following steps mentioned earlier for all the 810 zones in Eindhoven, the accessibility to jobs by different transportation modes (car, bicycle, public transportation) and for different groups (Bottom 40% and Top 10% regarding standardised disposable household income) can be computed by using Equation 1.

The results are presented in following figures. Figure 19, Figure 22, and Figure 25 show the accessibility for the group Top 10% for each zone. Figure 20, Figure 23, and Figure 26 show the accessibility for the group Bottom 40%. Figure 21, Figure 24, and Figure 27 show the difference between the two groups ($A_{jobs\ (Top\ 10\%)} - A_{jobs\ (Top\ 40\%)}$).

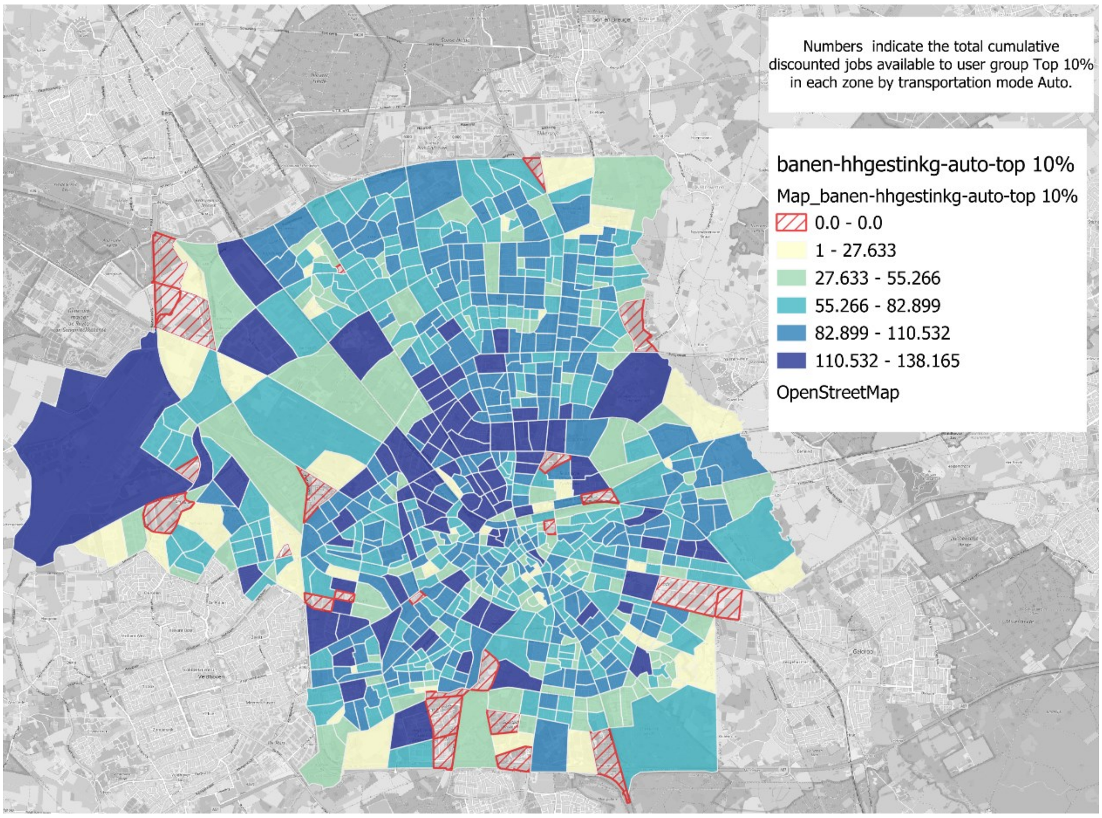


Figure 19. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by car** (group Top 10%)

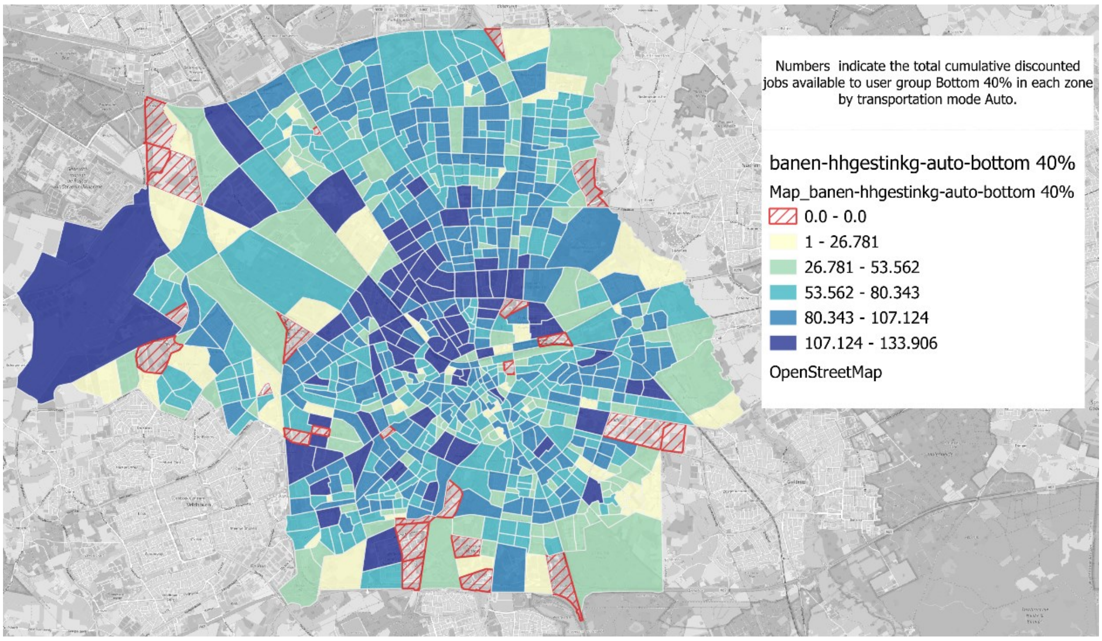


Figure 20. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by car** (group Bottom 40%)

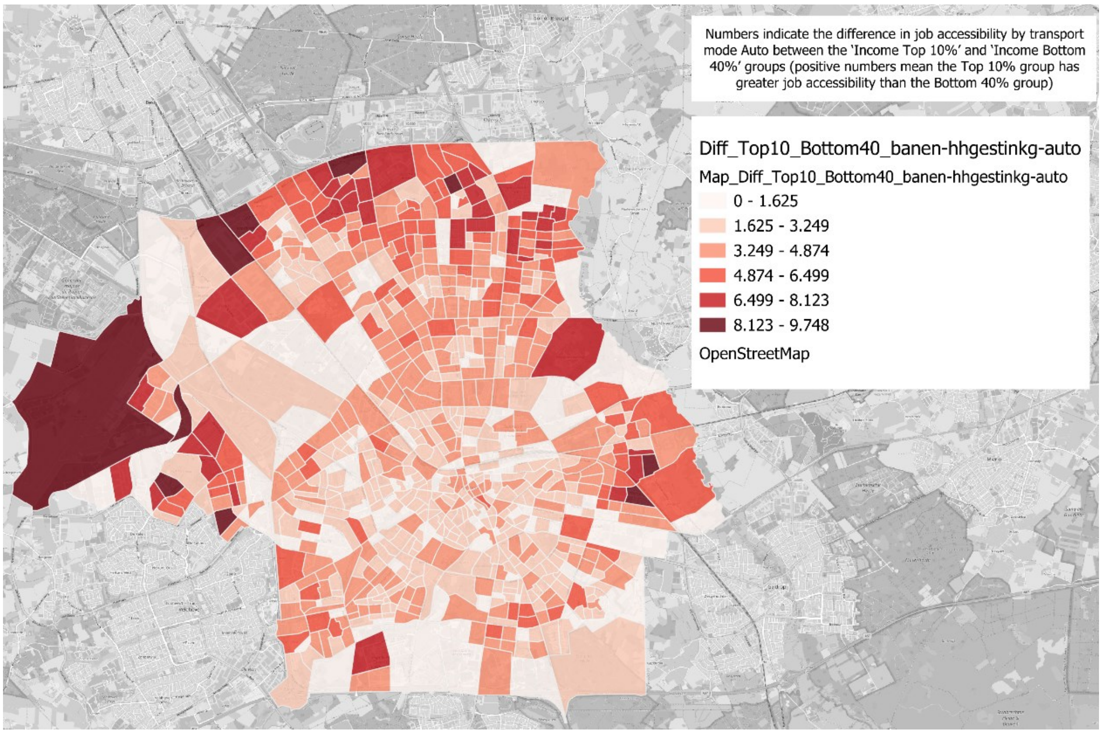


Figure 21. Difference in accessibility to jobs (cumulative number of jobs) per zone in the focus area **by car** between the groups (Accessibility $_{\textbf{Top 10\%}}$ - Accessibility $_{\textbf{Bottom 40\%}}$)

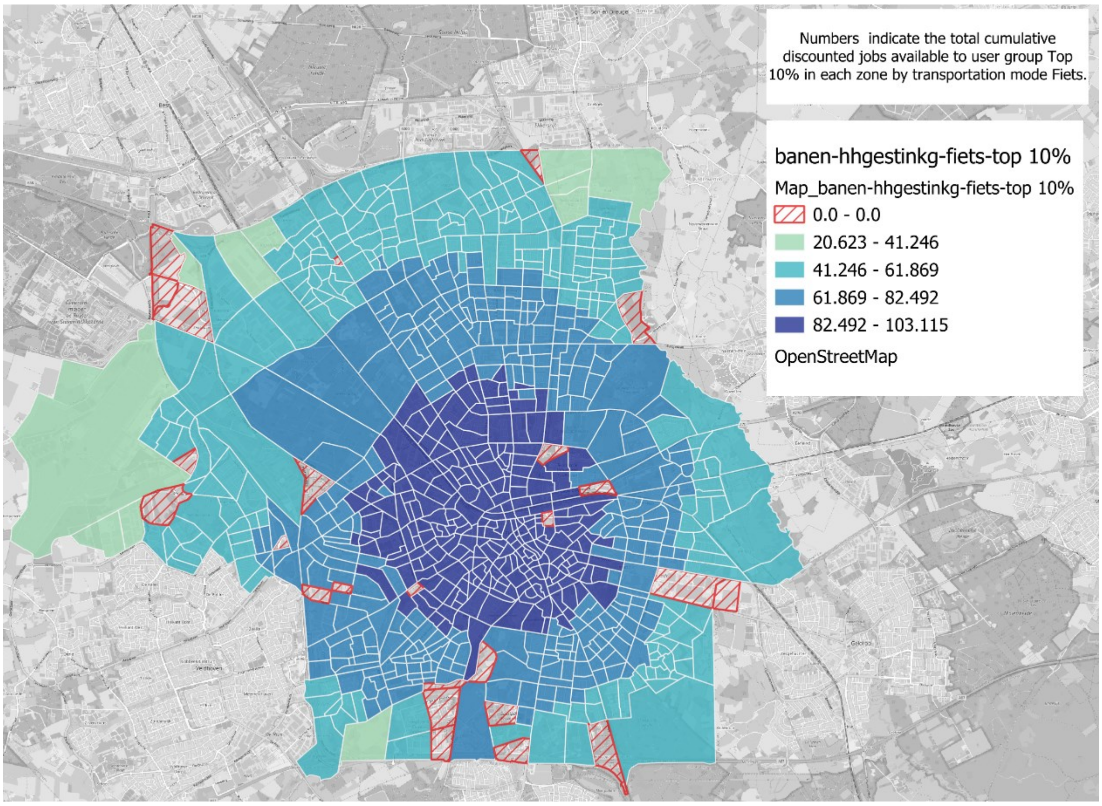


Figure 22. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by bicycle** (group Top 10%)

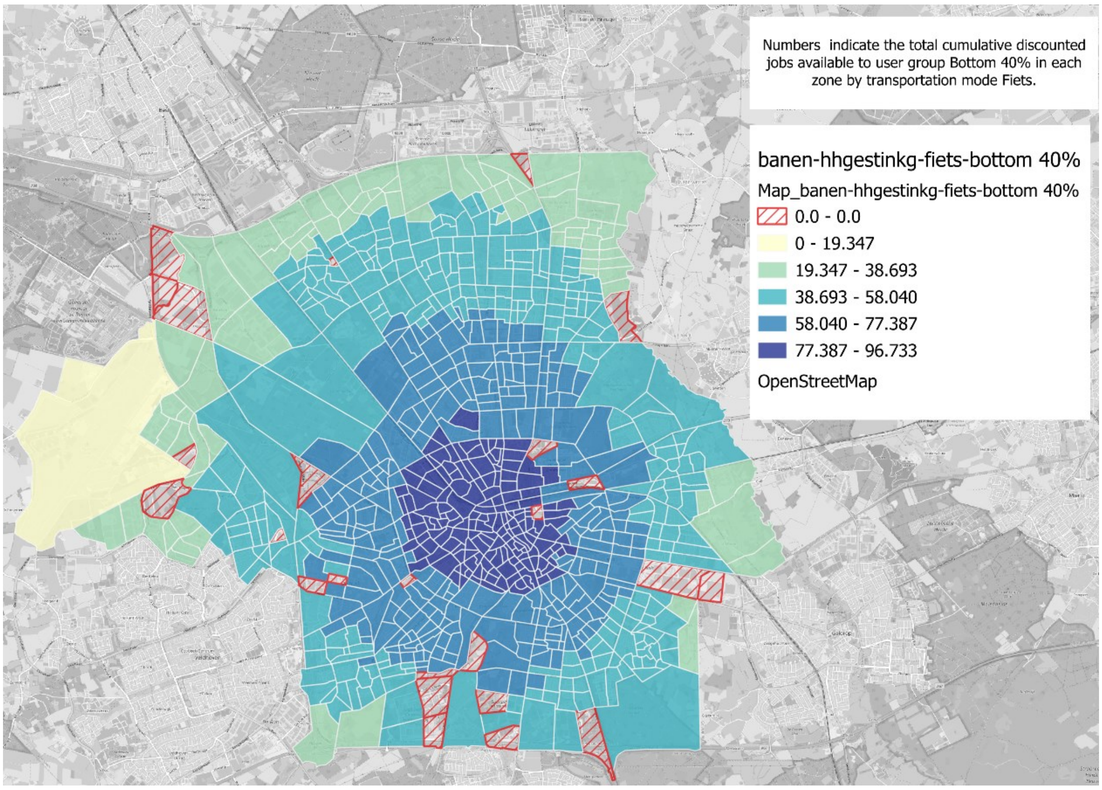


Figure 23. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by bicycle** (group Bottom 40%)

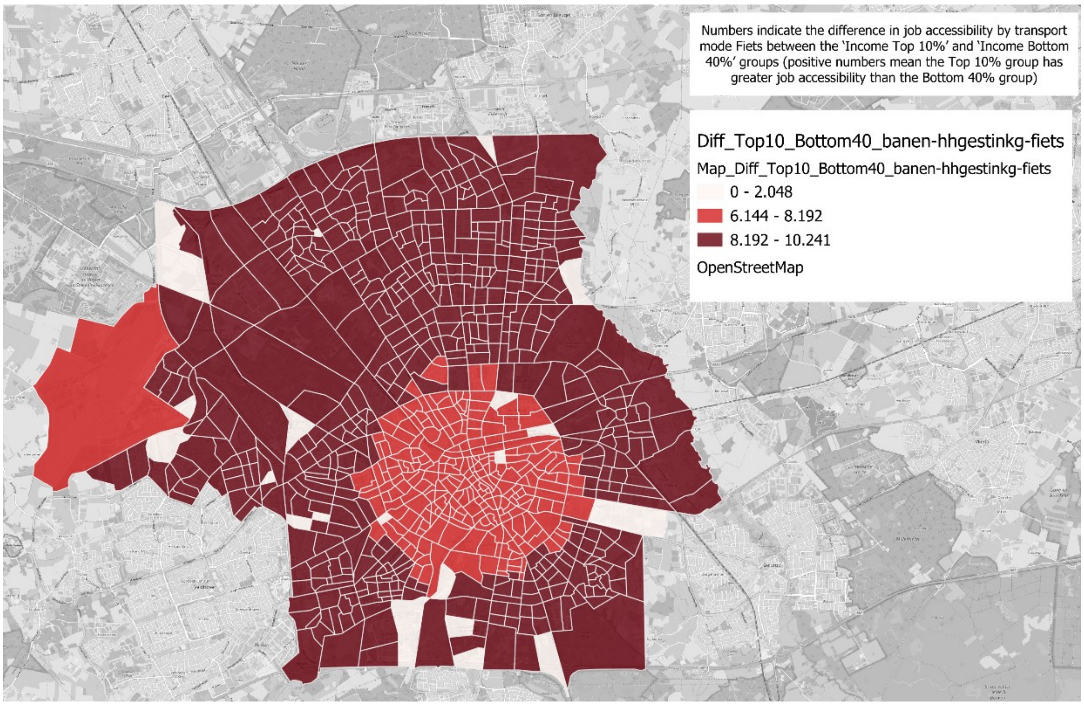


Figure 24. Difference in accessibility to jobs (cumulative number of jobs) per zone in the focus area **by bicycle** between the groups (Accessibility $_{\text{Top 10\%}}$ - Accessibility $_{\text{Bottom 40\%}}$)

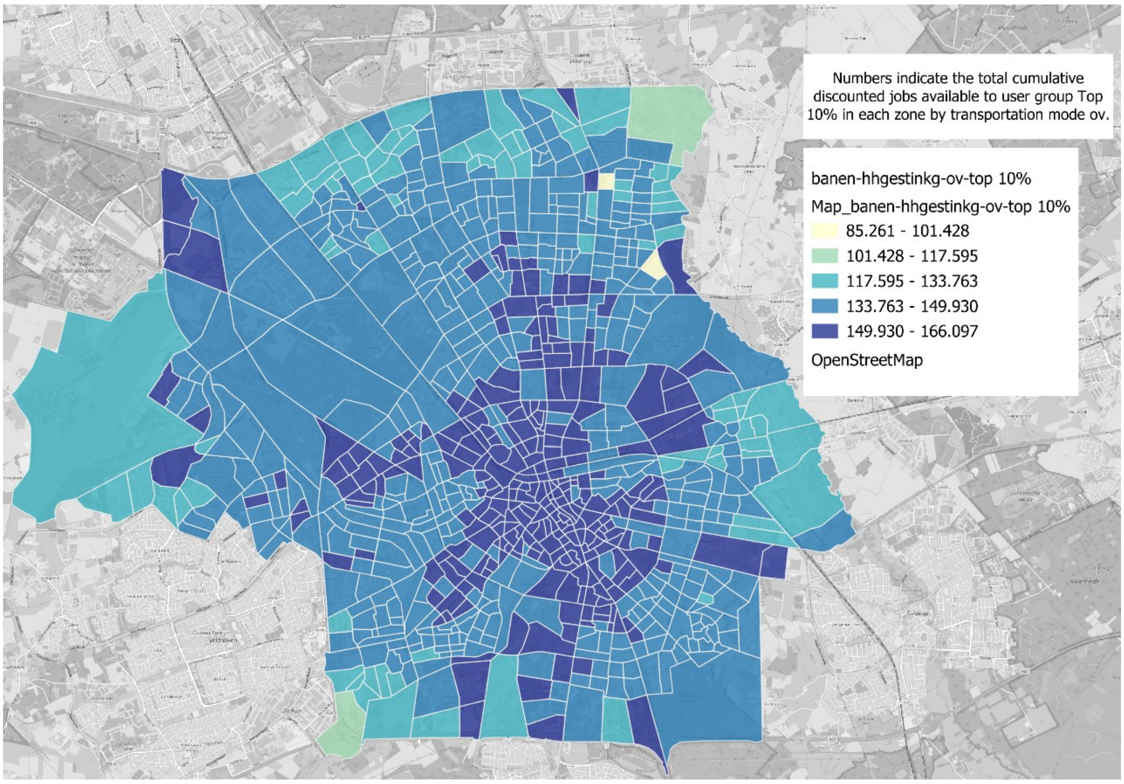


Figure 25. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by public transportation** (group Top 10%)

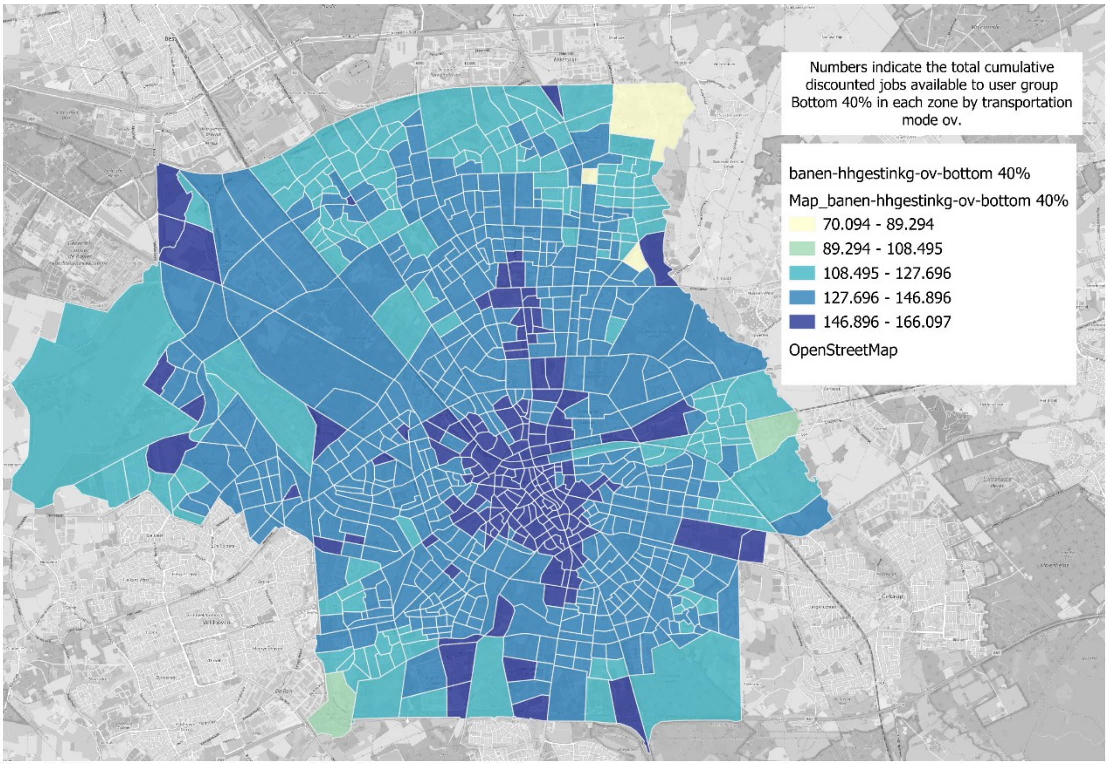


Figure 26. Accessibility to jobs (cumulative number of jobs) per zone in the focus area **by public transportation** (group Bottom 40%)

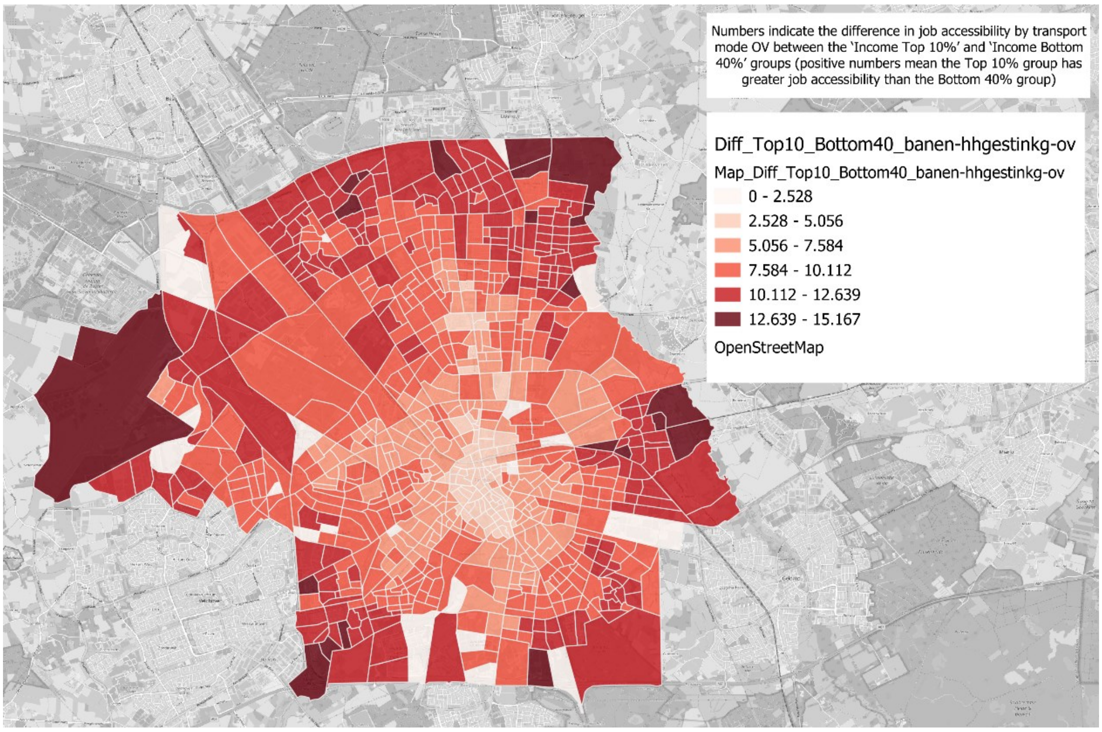


Figure 27. Difference in accessibility to jobs (cumulative number of jobs) per zone in the focus area **by public transportation** between the groups (Accessibility $_{\textbf{Top 10\%}}$ - Accessibility $_{\textbf{Bottom 40\%}}$)

3.7 Discussion

3.7.1.1 Zones with no jobs

As can be seen in Figure 17, there are 27 zones in Eindhoven in which there is no number of jobs available from the BBMA dataset used. These zones are shown with a red hatching as background. Figure 28 highlights the zones with no jobs.

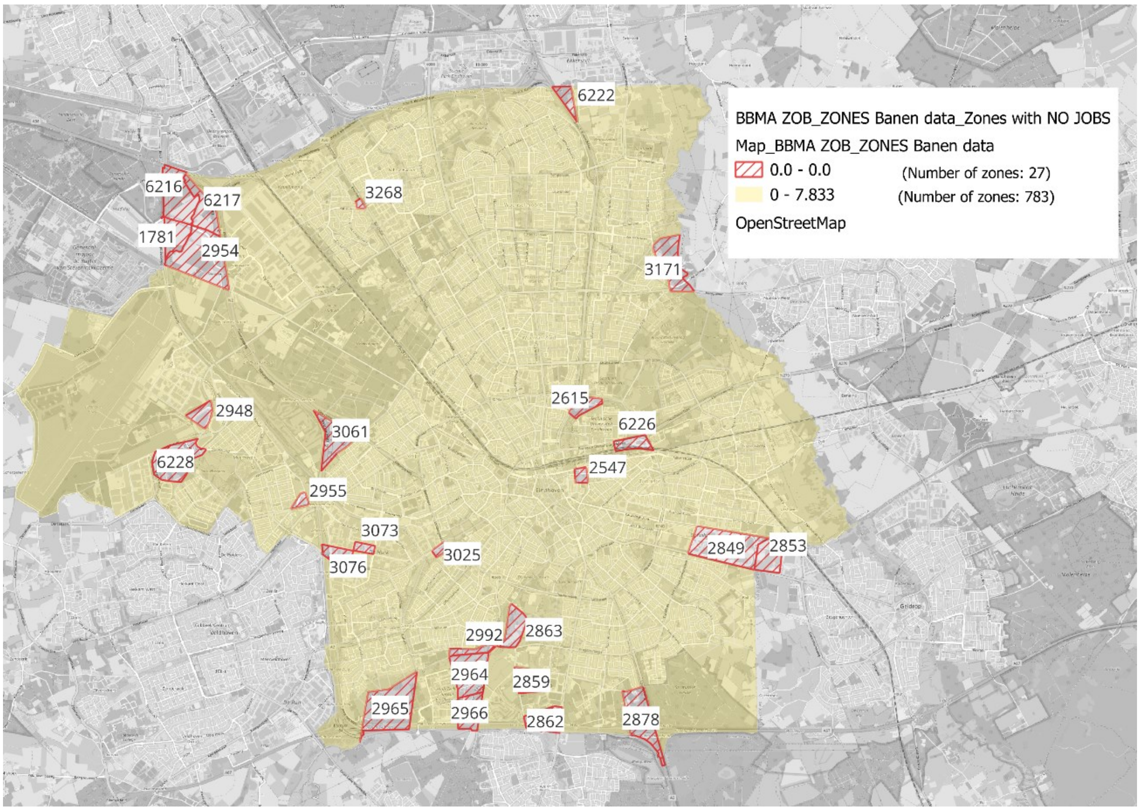


Figure 28. Zones with zero jobs (shown with a red hatching – based on BBMA dataset). Labels depict zone ID.

This does not necessarily mean that someone leaving from one of these 27 zones will have no jobs accessible to them (since there are 783 other zones out of the total 810 with one or more jobs – see yellow zones in Figure 28). However, it means that when calculating the number of jobs accessible from a given origin zone Z_O, these 27 zones will not add to the cumulative number of jobs accessible from that origin zone Z_O (as they have zero jobs). A detailed discussion on why these zones have no jobs available is beyond the scope of this analysis. However, possible reasons could be that they are residential-only areas, parks or other natural areas, or the data might simply be missing or outdated.

3.7.1.2 Zones with no accessibility to jobs

Different from section 3.7.1.1, which discusses zones with no available data for jobs from the BBMA dataset, this section discusses the cases per transportation mode (auto, bicycle, public transportation) in which a given origin zone Z_O does not have jobs accessible in other destinations zones Z_D. These cases are depicted with a red hatching as background in Figure 19 (Top 10%) and Figure 20 (Bottom 40%) for transportation mode auto, Figure 22 (Top

10%) and Figure 23 (Bottom 40%) for transportation mode bicycle, and Figure 25 (Top 10%) and Figure 26 (Bottom 40%) for transportation mode public transportation.

Beginning the discussion on the transportation mode auto, there are 25 zones with no accessible jobs, as shown in Figure 29. This means that, theoretically, these zones do not have accessibility to jobs in the focus area of Eindhoven. This happened due to a lack of travel time information by car between these zones and other zones in the traffic model used as input, which results in Equation 1 yielding absence of jobs accessible for these zones. Almost all of the 27 zones without linked jobs (Figure 28) also lack travel time by car (i.e., there is no information on travel time from trips originating in these zones as origin zones Z_O to other destination zones Z_D), with only zones ‘2965’ and ‘6217’ being exceptions (i.e., not having jobs linked to them but having more than zero jobs accessible to someone starting their journey from these zones by car). A detailed discussion on why these 25 zones lack travel times to any other zones in the focus area would require further investigation, but potential causes could include the traffic model not modelling trips starting from these zones for a given trip purpose, missing data, among others.

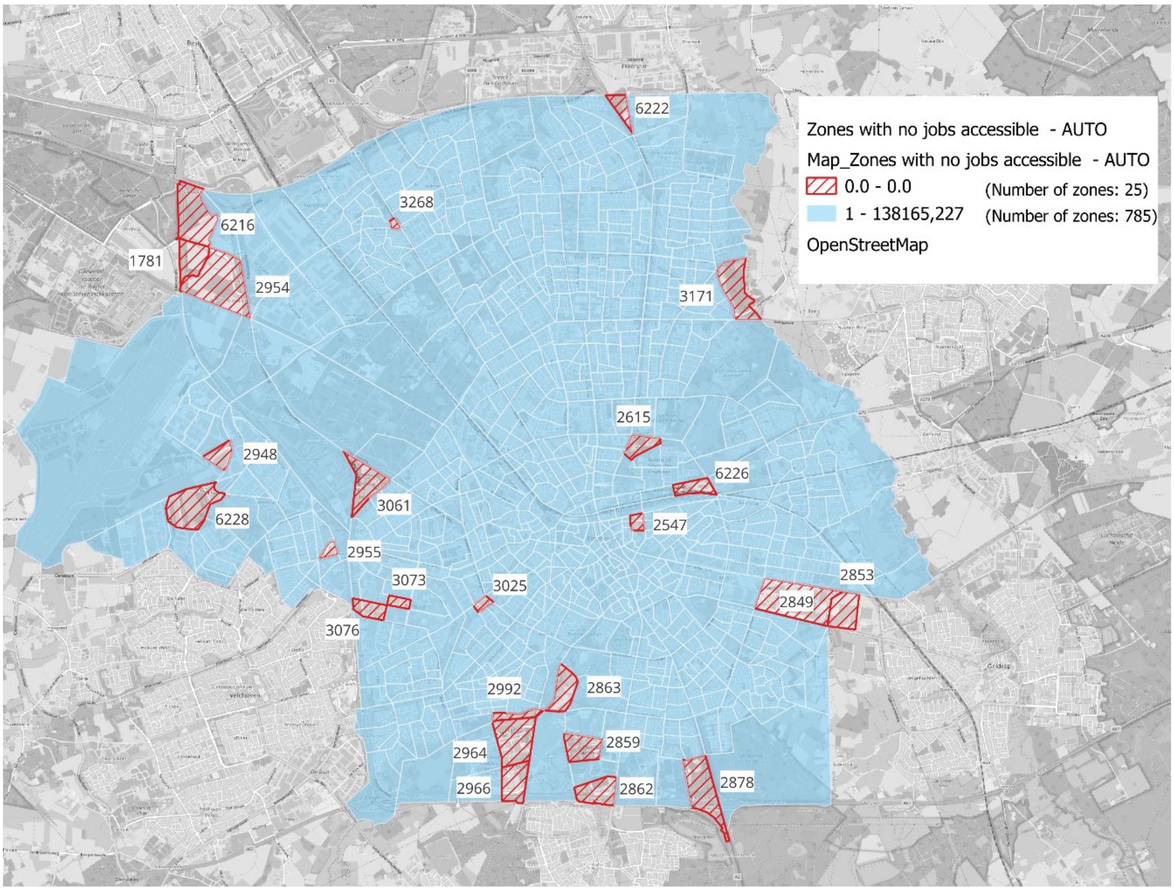


Figure 29. Zones with no accessible jobs by car (shown with a red hatching). Labels depict zone ID.

The analysis performed for transportation mode bicycle shows that the same zones don’t have accessibility to jobs by bicycle due to lack of travel time data for that mode in the input data. Figure 30 shows the results.

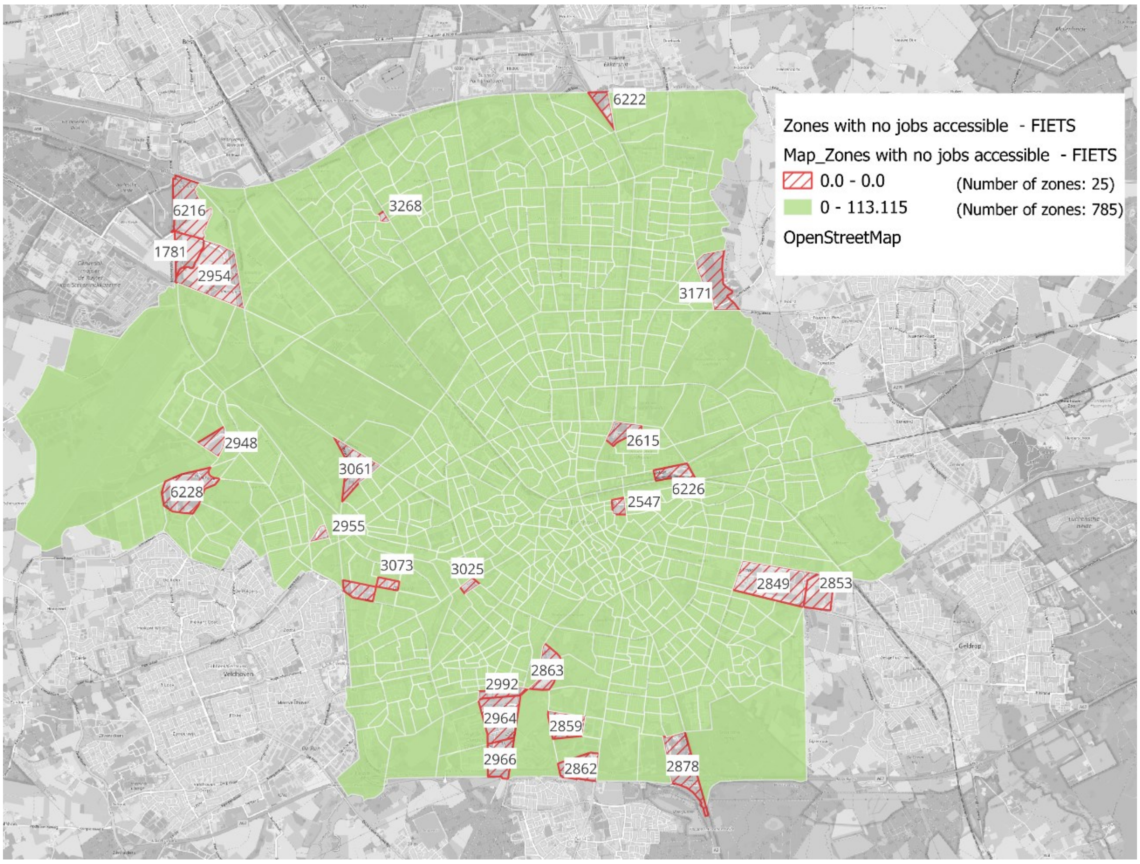


Figure 30. Zones with no accessible jobs by bicycle (shown with a red hatching). Labels depict zone ID.

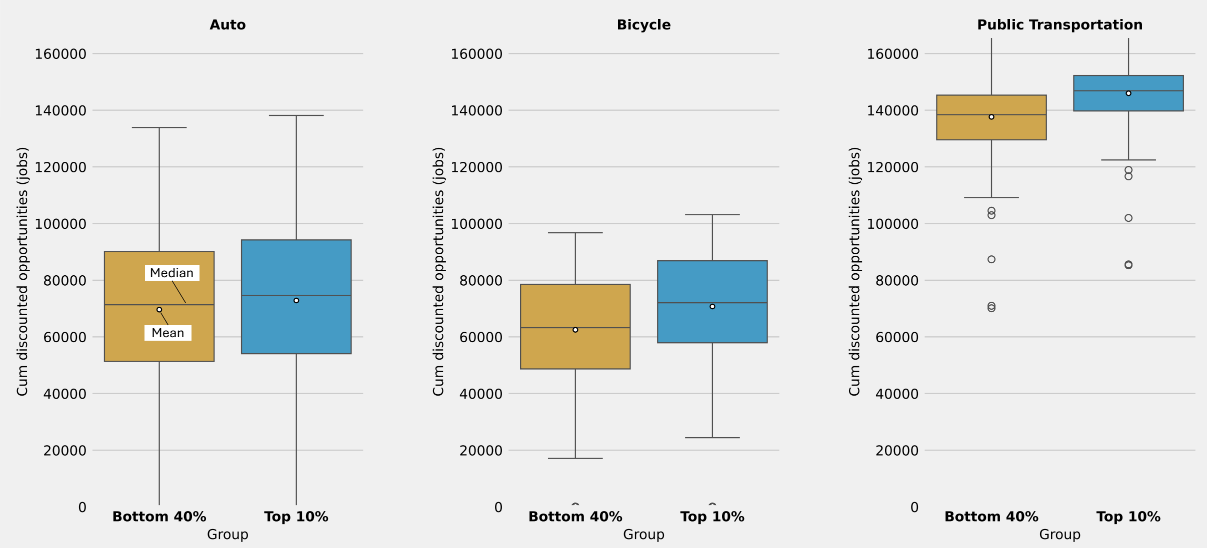
As for public transportation mode, instead of having zones with no accessible jobs (as for auto and bicycle), the results shows some zones with a maximum job accessibility (i.e., the total number or jobs available in Eindhoven area, as depicted in Figure 17). This happened because instead of not having travel time data between origin-destination pairs, such zones had a travel time of zero, which is different than a NaN travel time (as observed for auto and bicycle for the same zones). With a zero-travel time the travel decay curves yield a discount factor of one, which essentially does not apply any discounting to such jobs – as in theory there is no travel time to them. Figure 31 shows the results for public transportation.

Figure 31. Zones with maximum accessible jobs by public transportation (shown with a purple colour). Labels depict zone ID.

These 25 zones that depict unusual travel times for the different transportation modes – either not present, or equivalent to zero – should be further investigated in order to correctly identify their travel times and consequently derive a more realistic number of jobs accessible for each zone.

3.7.1.3 Accessibility differences between groups (Top 10% and Bottom 40%)

When comparing job accessibility between the Top 10% and Bottom 40% groups, the difference maps for each mode of transportation – Figure 21 (auto), Figure 24 (bicycle), and Figure 27 (public transportation) – consistently show that the Top 10% group has greater job accessibility than the Bottom 40% group. This is due to the distinct travel decay curves for each group (see Figure 18 charts (a), (b), and (c)). For any given mode of transport (car, bicycle, public transport) and travel time, the decay curves for the Top 10% group (in green) always result in a higher value compared to the decay curves for the Bottom 40% group (in red). Thus, based on the ODiN dataset, when deriving travel decay curves using standardised disposable household income, the Top 10% group has higher job accessibility than the Bottom 40%. Figure 32 shows the distribution of accessibility to jobs by transportation mode for each group.



Auto	Mean	Median
Bottom 40%	69,613	71,328
Top 10%	72,847	74,643

Bicycle	Mean	Median
Bottom 40%	62,493	63,234
Top 10%	70,720	72,028

Public Transportation	Mean	Median
Bottom 40%	137,647	138,427
Top 10%	145,977	146,863

Figure 32. Boxplots depicting the distribution of accessibility between groups Top 10% and Bottom 40% for each transportation mode

Figure 32 indicates that public transport provides the highest accessibility. The travel decay curves for PT (see Figure 18c) yield higher values in general than for auto (Figure 18a) and fiets (Figure 18b). For a 30min travel time, for example, the decay factor (top 10% group) for car is 0.492059, for fiets is 0.18885, and for OV is 0.897618. For Bottom 40% the values are 0.357115 (car), 0.128811 (fiets), and 0.839063 (OV). Therefore, it is clearly visible that after a few minutes (around 10 or so), jobs by PT start to count much more than by the other transport modes.

We had 25 cases of zones with zero (0) travel time to all the other zones (see Figure 31). With a zero-travel time, there is no decay factor applied (i.e., it is equal to 1), therefore, these 25 zones in theory had access to all possible jobs in Eindhoven area (166,097 - see Figure 17). Therefore, these zones also affected the average for PT by pushing it higher.

To further investigate these accessibility differences, one can calculate the Palma Ratio for each mode of transportation, as previously discussed in section 3.6.3. The Palma Ratio for each transportation mode can be determined using the formula provided below.

$$PalmaRatio^{M} = \frac{\overline{A^{M}_{O,Top10\%}}}{\overline{A^{M}_{O,Bottom40\%}}} \qquad \text{Equation 2}$$

In which:

- $\boldsymbol{PalmaRatio^{M}}$: Palma Ratio for transportation mode M
- $\overline{\boldsymbol{A^{M}_{O,group\ i}}}$: Average accessibility to jobs of type $\boldsymbol{O}$ (e.g., jobs) by transport mode **M** for each group (Top10%, Bottom40%)
- $\boldsymbol{M}$: Transportation modes M = {car, bike, public transport}

The application of Equation 2 yields a Palma Ratio of 1.046 for cars, 1.132 for bicycles, and 1.061 for public transport. This indicates that for every job accessible by car to the Bottom 40% group, there are 1.046 (4.6% more) jobs accessible to the Top 10% group by car. Similarly, for every job accessible by bicycle to the Bottom 40% group, there are 1.132 (13.2% more) jobs accessible to the Top 10% group by bicycle. Likewise, for every job accessible by public transport to the Bottom 40% group, there are 1.061 (6.1% more) jobs accessible to the Top 10% group by public transport.

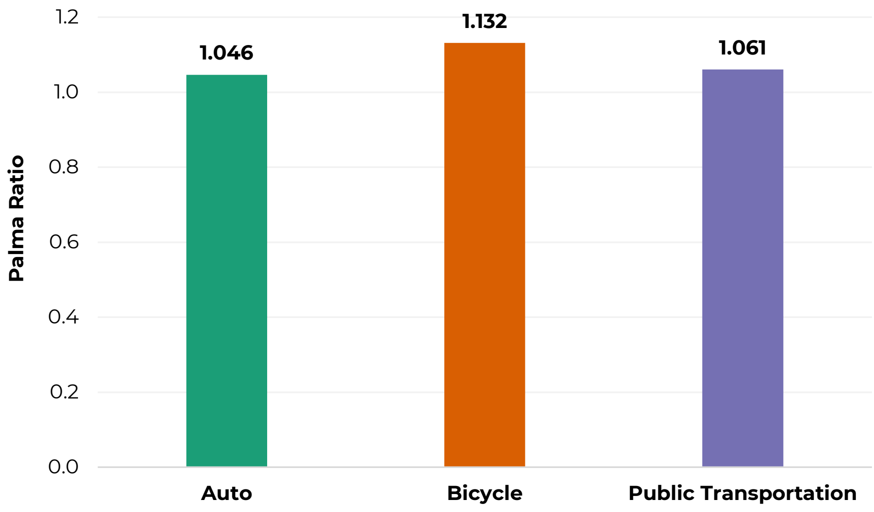


Figure 33. Job accessibility Palma Ratio by transportation mode

4 Share of active mobility

4.1 Introduction

Active mobility provides several advantages in the BW domains of health and the living environment. According to the WHO, active mobility contributes to numerous benefits in our health, environment and society. Walking and cycling enhance mental health and well-being and reduce the risk of many noncommunicable diseases, including cancer, heart and artery diseases and obesity[36]. In case of modal shift, it can reduce chances of congestion and energy usage, and in case of non-ZE mobility, lower emissions of GHG emissions and air pollutants. The effects on safety are more complex, since risk factors for cycling are higher than for cars, although a relatively large portion of severe cycling accidents come from collisions with motorized vehicles[37].

4.2 Definition

We define active mobility as the mobility of people and goods through means of human physical activity. Modes that are often included are, in very basic terms, non-motorized walking and cycling. More specifically, this encompasses modes of human-powered transportation such as walking, cycling, skateboarding, rollerblading, running, etc[38].

We are aware that the term active mobility has become more ambiguous, since more and more vehicles have been introduced that include some form of hybrid driveline, consisting out of a fossil fuel engine or electric motor and physical propulsion. Decades ago, the Spartemet and Solex were one of the first vehicles that included a hybrid driveline of physical activity coupled with a fossil fuel engine. Currently E bikes (in many different forms) fulfil this function. There are also modes of transport that use infrastructure dedicated to active mobility, but do not require physical activity for propulsion, such as mobility scooters. The exact benefits on emissions rely on the substitution of the respective modes of transport. Either going from walking or cycling to hybrid active mobility (increasing of GHG emissions), or this hybrid mobility replacing for instance car trips (reduction of GHG emissions).

For our initial release of this indicator, we take the mode**, cycling (no E-bike) and access and egress (walking/cycling) to public transport**. The reason is that these modes are present in the BBMA dataset. An initial limitation is the lack of walking as main traffic mode in the database. If further data becomes available in the future, the scope of modes could be expanded in later versions of the indicator.

[36] Promoting healthy active mobility
[37] Fietsers
[38] (23) Mastering mobility: understanding the health benefits of active mobility | LinkedIn

4.3 Literature

4.3.1 Active mobility guidelines

Share of active mobility can be expressed in three different ways. Either in the share of trips, distance travelled or travel time. Depending on the policy question, either one of these results may prove most appropriate. As an example, the number of trips can answer questions on the intensity of the road or sidewalk infrastructure. Distance covered and travel time can both tell something about how much physical activity has come from travelling. Distance and intensity also provide answers for traffic safety estimations of a network. And travel time and distance can answer accessibility questions using travel decay curves.

The subject of active mobility is often positioned in the quadrant of health in the BW. Therefore we will take the policy perspective of health contribution of active mobility. Also, as presented in 4.1, this indicator can also be used to answer questions on modal shift related policy questions. We will take this perspective as well.

Active mobility and health

At this moment, 44% of Dutch society satisfies the exercise guidelines[39]. The Dutch government has the ambition that 75% of Dutch society satisfies this guideline in 2040[40]. When this guideline is met, chances on physical and mental health problems are reduced (see also Figure 34).

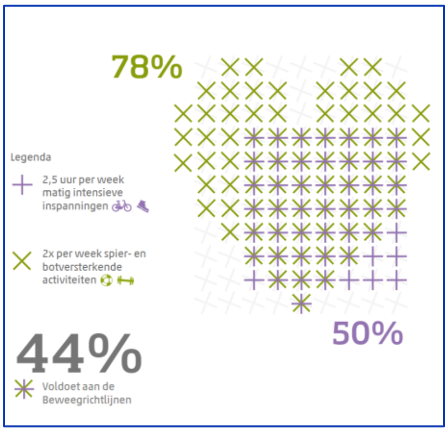


Figure 34 infographic about Dutch population that satisfies the mobility guidelines (source CBS, 2023)

The Dutch exercise guidelines are segmented by age groups: 0–4 years, 4–18 years, and 18 years and older. For the 4–18 age group, the guidelines state that: [41, 42, 43, 44];

- At least one hour per day moderate to intense exercise
- At least three times per week muscle and bone strengthening activities
- Avoid prolonged sitting

For the segment above 18 years old the guideline states;

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[39] Ruim 4 op de 10 volwassenen bewegen voldoende | CBS
[40] In 2023 zijn meer Nederlanders wekelijks gaan sporten | RIVM
[41] Beweegrichtlijnen 2017 | Advies | Gezondheidsraad
[42] Beweegrichtlijnen - Kenniscentrum Sport en Bewegen
[43] Cijfers en feiten sport en bewegen | Loketgezondleven.nl
[44] Bewegen | Verantwoording | Definities | Volksgezondheid en Zorg (vzinfo.nl)

- At least 150 minutes per week moderate or intense exercise, spread over multiple days
- At least twice a week muscle and bone strengthening activities
- Avoid prolonged sitting

These guidelines are applicable to everyone, including people with a physical or mental disability and pregnant women. However, adjustments are possible to accommodate individual cases[45].

The '*Volksgezondheid en zorg*' website[46] by the Dutch government states that moderate intensity activities include (among others) walking and cycling. The energy varies between 3,0 and 5,9 MET (metabolic equivalent)[47]. E-bike cycling is classified as 2,8 MET[48]. That would mean that cycling an E-bike is not classified as active mobility based on MET values. Though, as we started this indicator chapter, further scoping needs to be determined what we consider as active mobility, also considering potential modal shifts less 'active' modes to E-mobility on longer trips[49].

Active mobility and modal shift

Active mobility emits no (walking, cycling) or relatively very low GHG and air pollutants (e-bike)[50] from travelling. A shift from car and public transport trips to active mobility therefore has a positive effect on emissions and the environment. Also the direct living environment benefits from lower air contaminants (NO_x and PM_{10}) from active mobility.

Another effect on the living environment is the impact on space used by modes of transport. Our cities are densifying and space is becoming sparser. Passenger cars, either driving or parked, take more space than public transport, cycling and walking (see Figure 35). A modal shift from passenger car to active mobility can positively impact available space in urban areas. Important to note is that if people, in the long term, get rid of their car because they do not need it anymore, this also has a positive effect on space used. But, if people use active mobility more while leaving their car home, this will not have a positive effect on parked cars.

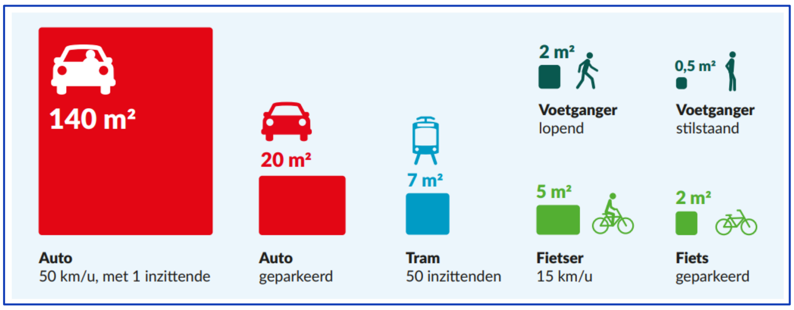

Figure 35: Use of space by modes of transport and per passenger. Space taken for mODiNg tram is absent in this figure.[51]

[45] Beweegrichtlijnen - Kenniscentrum Sport en Bewegen
[46] Bewegen | Verantwoording | Definities | Volksgezondheid en Zorg (vzinfo.nl)
[47] De metabole equivalent (MET) | Jeugdmonitor
[48] Hoeveel calorieën verbrand je met Fietsen op een E-bike? - Online Calculator! (calorieenverbranden.nl)
[49] Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: Insights based on health and transport data from an online survey in seven European cities - ScienceDirect
[50] CE_Delft_210383_Effect_of_shared_electric_mopeds_on_CO2_emissions_FINAL.pdf
[51] Milieudefensie (2017) – Van wie is de stad?

The number of deaths in traffic is highest for the mode cycling. This is also the case if we take into account the number of kilometres driven and the number of trips in the Netherlands[52], meaning that cycling has the highest accident risk per km. It seems that a modal shift from car to cycling has the (theoretical) effect of increased traffic deaths. This is because the accident risk for cycling is higher than for other modes of transport, so more km by bike than by car means higher risk of accidents. Important to note is that this involves no further changes to the traffic system. The highest number of deaths in cycling come from accidents that involve a passenger car[53]. If we assume a noticeable modal shift occurs, where car kms are substituted by cycling km, and therefore interaction between cars and bikes become less, total accident risk could change differently. The exact effect on traffic safety of this modal shift therefore is not straightforward to assume.

4.3.2 Population groups

The split in activity guidelines for different population groups shows that population group factors are an important aspect to consider. Apart from the age factor, other benefits per age category have been researched. Being active provides numerous health benefits, including reducing depressive symptoms, improving muscle strength, enhancing insulin sensitivity in children, lowering the risk of diabetes in adults, supporting weight management in both children and adults, strengthening bones in children and the elderly, boosting cognitive abilities in the elderly, and increasing walking speed in older adults[54].

The national government describes population groups that often do not meet these guidelines[55]. These groups include people with lower education, non-Western migrants, elderly, people with chronic diseases, people with physical or cognitive impairments. The indicator share of active mobility could be interesting in this regard, mapping out which regions (with a certain population group composition) or groups specifically meet these guidelines, since there is a lot to gain with these groups in this area. Data availability is this area is often difficult. The context in which the indicator will be used will dictate which groups turn out to be relevant. The process of determining such groups is presented in T2.3 of the PSBW 2024.

4.4 Data

4.4.1 Share of active mobility - trips

This report focuses on the four population group factors which were defined at the start of this report. These factors are age, income, car ownership and urbanization. Using CBS Statline[56] ODiN data, we can gain insight into the data about trips and passenger kilometres for the factors age, income, education, car ownership and level of urbanization[57], see also appendix A.1). The ODiN data is gathered via an annual questionnaire, to collect a sample of the Dutch population on how these people travel. This particular datasheet has travel modes car, passenger in car, train, bus/tram/metro, cycling, walking and 'other'. We take % share of

[52] Hoeveel reisden inwoners van Nederland en hoe? | CBS
[53] Verkeersdoden in Nederland
[54] Beweegrichtlijnen 2017 | Advies | Gezondheidsraad
[55] Cijfers en feiten sport en bewegen | Loketgezondleven.nl
[56] StatLine - Mobiliteit; per persoon, persoonskenmerken, vervoerwijzen en regio's
[57] 'Zeer sterk stedelijk'; 'matig stedelijk'; 'niet stedelijk'

active mobility as walking/cycling versus the total, minus ‘other’. As an example, from the ODiN sample, 49% of all (sample) trips in the Netherlands are done by active mobility.

Table 16 and Table 17 present age categories and the share of active mobility. What we see is that in general children and young adults have a higher share of active mobility than adults. Also (relatively) elderly adults have higher active mobility than adults. This seems to be in contrast of what we mentioned earlier, elderly people being one of the groups that often do not meet the activity guidelines. A potential explanation is that this group do use active mobility, but potentially other activities in their daily lives are lacking to meet the guidelines.

This is also the case in factors age, income, education and car ownership. This can be related that travel distances are higher in less urban areas, as can be seen in the passenger kilometres, where share of passenger kilometres become (relatively) less compared to trips.

Table 10 presents the relation between three urbanization levels and the share of active mobility trips for the ODiN sample. What we can also see (in general) is the lower the level of urbanization, the lower the share of active mobility. Note that we have stated share of trips in percentages, and passenger kms and travel duration in km and minutes. This is done on the one hand to have this data in the correct format (trips are used for modal shift, distance and time for health guidelines), and on the other hand because not all people do not necessarily cycle and walk in the same ratio, these could be different people.

Table 10: Share of active mobility (cycling, walking) compared to other modes of transport for all of the Netherlands, including urbanization level. We taking urbanization categories of CBS, namely ‘Zeer sterk stedelijk’ (high), ‘matig stedelijk’ (mid) and ‘niet stedelijk’ (low).

Cycling/walking	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
Cycling (total NL)	31%	26%	21%	3,0	3,0	2,8	17,5	16,0	14,2
Walking (total NL)	25%	18%	17%	1,3	1,1	1,0	17,4	14,3	12,7
Total active mobility	56%	44%	39%						

Table 18 in appendix A.1 presents the share of active mobility for 5 income categories. In almost all urbanization levels, the lowest income category has the highest share of active mobility. This is in contrast to the highest income categories, which show lower share of active mobility.

Although not part of the initial factors of groups, we have included Table 20 which presents the factor education. Lower education, or practical education, has often a higher share of active mobility than middle or high (scientific) education categories. But in high urban areas this contrast is not as strong.

Car ownership in Table 22, according to the CBS data, reveals that households with a car have a lower share of active mobility than the ones without.

4.5 Illustration of steps using dummy data

Figure 36 presents an illustration of how the indicator could function. It uses a traffic model to generate data for a baseline and interventions scenarios. The traffic model provides Origin-Destination (OD) data per modality in the form of trips, travelled distance and travelled time. Active mobility is separated from the other modalities.

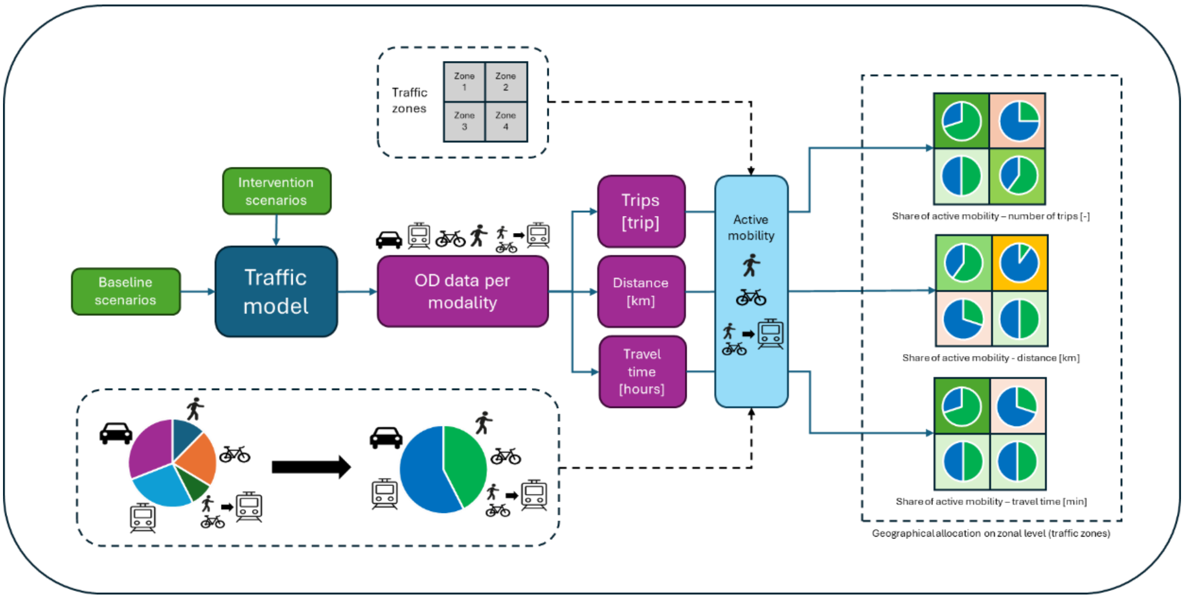

Figure 36: Representation of indicator share of active mobility

To further explain how the indicator should work (theoretically) we will use dummy data. The OD-data used in this dummy example is generated randomly. In this case it is an urban area during morning peak hours. The trips in Table 11 include walking, cycling, public transport and car. All 10 zones act as an origin from which people leave to destinations where people go for work, to school, recreation, social visits, etc. Note that we include inter zonal traffic, e.g. 14 trips occur within zone 1, not leaving the zone. In theory knowing inter-zonal traffic is important, especially active mobility, since travel distances are shorter compared to other mods such as PT and car trips.

Table 11: Number of trips during morning peak for 10 traffic zones

Trips	Destination										
	x	1	2	3	4	5	6	7	8	9	10
	1	14	15	45	38	48	27	30	41	31	3
	2	2	12	4	38	40	43	25	26	26	9
	3	48	27	6	31	26	12	15	29	49	36
	4	2	31	15	40	9	35	27	25	3	45
Origin	5	16	34	8	16	46	31	8	43	13	36
	6	12	46	25	24	46	25	16	29	11	3
	7	22	42	40	16	50	6	5	17	36	23
	8	28	47	24	33	39	5	48	13	23	16
	9	4	10	15	23	15	22	24	32	35	49
	10	48	45	40	4	1	6	43	4	48	50

When only walking and cycling are selected, the OD-matrix for trips looks like Table 12.

Table 12: Number of active trips during morning peak the 10 traffic zones

Trips	Destination										
Origin	x	1	2	3	4	5	6	7	8	9	10
	1	6	1	40	4	41	11	28	6	17	1
	2	2	5	3	4	30	30	6	4	24	7
	3	14	22	0	6	19	3	1	4	18	23
	4	0	4	6	33	1	2	25	8	2	19
	5	14	23	2	8	33	17	6	2	12	33
	6	1	38	19	17	40	6	1	7	5	1
	7	18	36	7	10	24	4	3	3	28	3
	8	3	2	5	10	7	1	6	2	3	4
	9	1	8	5	6	3	15	6	9	22	46
	10	29	40	34	2	0	4	8	1	40	7

The total number of trips is 2567 and the number of active trips is 1230. The share of active mobility for the entire fictional city is 48%. In Table 13, dividing the number of active trips by the number of total trips per field yields the percentage of active mobility per OD pair.

Table 13: Percentage of active mobility trips

Trips	Destination										
Origin	x	1	2	3	4	5	6	7	8	9	10
	1	44%	9%	88%	11%	86%	41%	92%	15%	54%	36%
	2	82%	41%	67%	11%	76%	70%	22%	15%	92%	77%
	3	30%	82%	5%	20%	72%	21%	6%	13%	37%	65%
	4	19%	14%	41%	82%	13%	5%	93%	32%	70%	43%
	5	86%	68%	30%	53%	72%	54%	72%	5%	91%	92%
	6	11%	82%	77%	69%	88%	23%	8%	24%	44%	30%
	7	81%	85%	18%	65%	48%	68%	61%	18%	77%	14%
	8	11%	4%	21%	30%	18%	20%	13%	15%	13%	25%
	9	33%	84%	33%	25%	22%	70%	23%	28%	62%	94%
	10	61%	88%	84%	60%	12%	73%	19%	25%	83%	13%

The weighted average of share of active mobility can be found in Table 14. The total number of trips and the share of active mobility are presented per traffic zone, either as origin or as destination. From zone 1, means all trips leaving zone 1 to the other zones. To Zone 1, means all trips ending in zone 1, coming from the other zones. In our case, zone 8 stands out as it has relatively low percentage of active mobility trips (this is purposely modelled). In our case this might be worthwhile to investigate why active mobility is relatively low here.

Table 14: Percentage of active trips, for the 10 traffic zones as origin and as destination

O/D	Zone	1	2	3	4	5	6	7	8	9	10
From zone	% Active	57%	57%	40%	48%	60%	59%	59%	16%	53%	58%
To zone	% Active	45%	58%	55%	38%	62%	44%	37%	18%	62%	54%

Travel time is calculated from the travel time between zones, multiplied by the number of trips. This will provide the average travel time per trip, originating from that particular zone. We do this for active trips. We then can compare these outcomes to the number of trips that are made per person, and what the added value is to the exercise guidelines.

In contrast to this dummy data, real or model data may reveal that longer distances between zones are more often covered by public transport or car than with active mobility. Although many other factors, such as accessibility of the infrastructure, safety, attractiveness (noise/air quality), also play a part in which mode of transport people choose, and therefore the share of active mobility.

Note that a larger share of total trips count does not necessarily mean more distance covered or travel time by active mobility. The number of trips needs to be multiplied by the distance between zones. Alternatively, as seen in Figure 36, the OD-matrix with travel time or total distance driven between zones can be used.

4.6 Application in focus area

We were able to test the indicator on share of active mobility for cycling. Because of the absence of walking in the dataset, we used the percentage of cycling trips in relation to the overall trips (cycling, public transport, car) in Eindhoven. As a reference we have used CBS data to have overall results for the Netherlands and for high, moderate and low urbanization levels, see Table 10 and also Appendix A.1 for urbanization level, age, income, education and car ownership. We would expect a share of active mobility, in this case for cycling due to walking being absent from the dataset, of between 31% and 26%. This is because the municipality of Eindhoven can be classified as a high urban area (city centre) and moderate urban area (suburbs).

As a reference, Eindhoven has a relative high number of car trips originating from Eindhoven, according to CBS ODiN data, compared to other modes of travel (see Figure 37). Walking and public transport seem relatively low, compared to other large cities in the Netherlands.

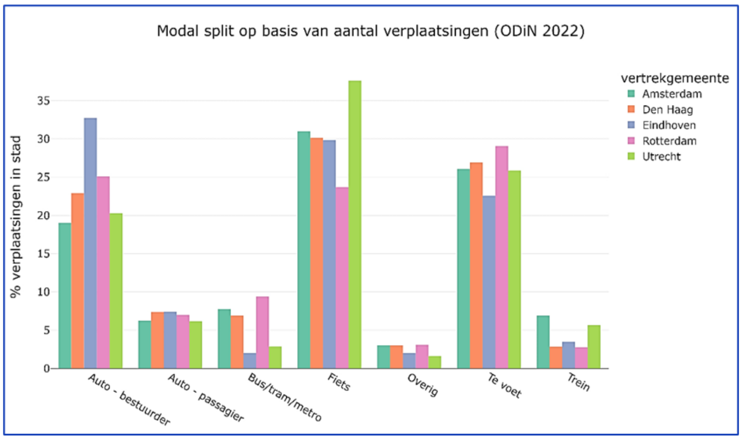

Figure 37: Modal split for number of trips for Amsterdam, Den Haag, Eindhoven, Rotterdam and Utrecht. Based on ODiN 2022

The result of the indicator active mobility can be seen in Figure 38. High share of active mobility can be found in and around the city centre, and in the North of Eindhoven. On average, from the OD-data, 66% of all trips within Eindhoven are made by cycling, compared to car and public transport. This seems high compared to what we said earlier (between 31% and 26%). Even if we compare this to Figure 37, cycling should be roughly the same as the number of car trips. We expect this comes from our selection of Eindhoven zones, which only include trips from one Eindhoven zone to another. This is an important observation, because it means that trips that have either only an origin or a destination in

Eindhoven are excluded. To give an example, a trip starting in Eindhoven but ending in Den Bosch does not show up in this data, neither does one vice-versa. We expect that more car and public transport trips are missing in this aspect than those of active mobility. The solution is to include all zones from the BBMA (which include a less detailed zonal distribution outside Zuid-Oost Brabant), though consequently takes more time to process. This is something we take forward in a future iteration of the indicator.

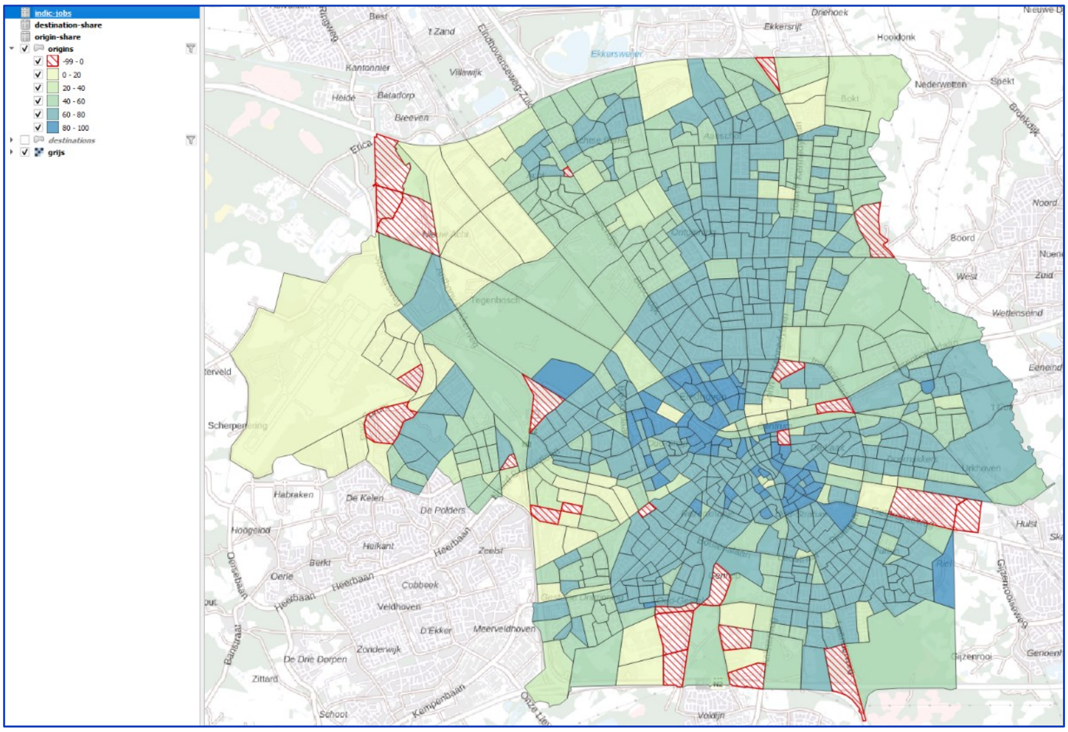

Figure 38: Share of active mobility (cycling), based on number of trips (cycling, car, public transport) that have an origin in Eindhoven, going to another zone in Eindhoven.

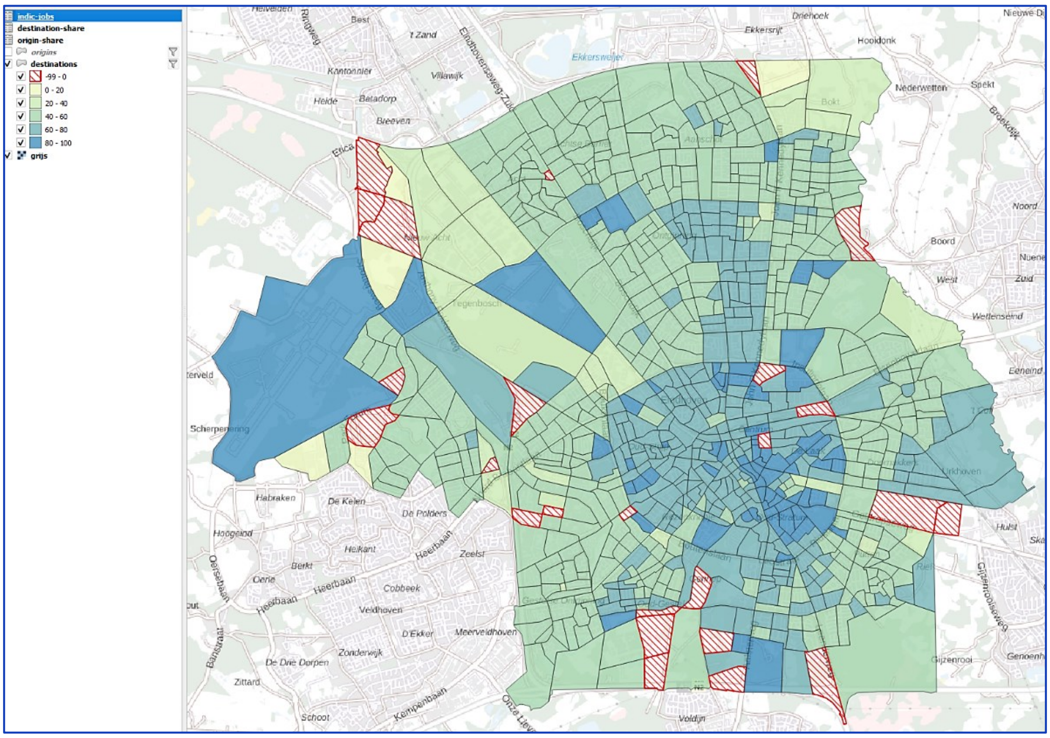

Figure 39: Share of active mobility, based on number of trips (cycling, car, public transport) that have a destination in Eindhoven, coming from another zone in Eindhoven

Travel times (hours) between zones are included in the model results. The highest travel times for cycling between zones (furthest apart) are just shy of an hour. If we take the sum of all OD connections coming from one origin, the average is 281 hours. This is the total travel time for the entire network for cycling, starting from one and the same origin, and travelling to all other zones. Unfortunately, the sum of travel time per zone is not usable in this case. This is because the data reveals that many OD pairs have trips that are (well) below 1, meaning that between 0 and 1 trips are made between zones. On average, this approach results in an average travel time for a trip by bicycle in Eindhoven of 183 minutes, which is far too long. It is therefore deceiving to take the sum of travel divided by the sum of trips.

The correct approach is to take an intermediate step to calculate the total travel time per origin zone. The example below illustrates calculating the total travel time for the OD-pair A to B. For A as origin this is subsequently done for A to C, A to D, A to E, etc.

$$Total\ time\ A \rightarrow B = (Travel\ time\ zone\ A\ \rightarrow zone\ B) \times (Number\ of\ trips\ zone\ A \rightarrow zone\ B)$$

The summation of all combinations starting from zone A (origin) gives us the total travelled time starting from A, considering the number of trips that have originated from A. The next step is that we can divide this by the number of trips departing from A. This gives the average travel time for trips departing from zone A. As an example the first 12 zones of 810 are presented in Table 15. Note that this includes the travel time considering the entire network (183,9 min per trip) and the average trip time using total time (32,6 min per trip).

$$\frac{Total\ travel\ time\ origin\ A}{Number\ of\ trips\ from\ origin\ A} = Average\ travel\ time\ from\ zone\ A$$

Table 15: First 12 traffic zones of 810 for Eindhoven, travel times active mobility

Traffic zone (origin)	Sum of travel time (minutes)	Sum reference trips	Travel time divided by trips (minutes)	Sum of total time (minutes)	Average travel time (minutes)
1781	(no trips)	0	0	0	0,0
2513	12.758	591	21,6	15.874	26,9
2514	13.924	169	82,2	5.160	30,5
2515	13.482	332	40,6	9.968	30,0
2516	13.758	35	391,8	1.037	29,5
2517	12.706	62	206,2	1.661	27,0
2518	13.529	67	203,0	1.923	28,9
2519	13.523	164	82,6	4.740	29,0
2520	13.239	291	45,5	8.437	29,0
2521	12.724	54	235,9	1.504	27,9
2522	13.241	138	96,0	4.007	29,0
2523	13.548	72	189,1	2.071	28,9
Etc.	[...]	[...]	[...]	[...]	[...]
Grand total	13.238.550	71.987	183,9	2.346.456	32,6

The average travel time for cycling in Table 15 is 32,6 minutes per trip. If we compare this with that average travel time in the Netherlands (Table 10) or more specific the level of urbanization (Appendix A.1), it seems that the average travel time is twice as high as we would expect. At the moment of writing we have not yet found the exact reason why travel times are relatively high for this dataset. We were able to come up with average travel times for cycling, although after inspection, this needs more work, since many average travel times were many hours in duration. Figure 10 presents the total overview of all average travel times for the 810 traffic zones that belong to the municipality of Eindhoven.

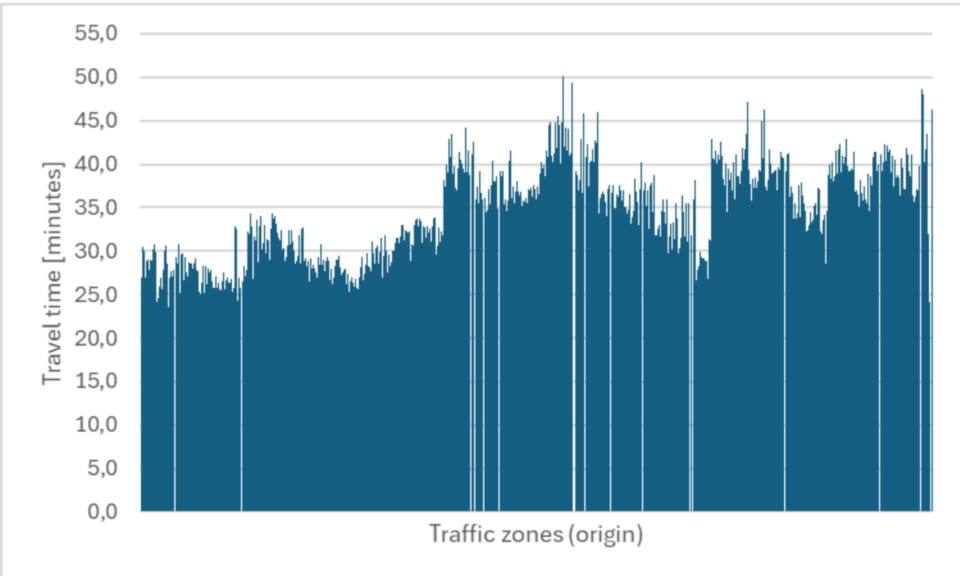

Figure 40: Average travel times for cycling for the 810 zones.

4.7 Discussion

After inspection of the BBMA dataset, we encountered a couple of limitations.

- Although trips within zones are given, meaning a trip is made which has the same origin (O) as destination (D), these did not include travel times or travel distances. This is especially limiting for modes of transport that are used for these kind of short trips, such as active mobility.
- The transport mode walking is not in the BBMA database, only walking for access and egress. This limits the total share of active mobility to only cycling, for now.
- Speed and distance are often correlated. Average speeds are used to calculate travel times. From the perspective of brede welvaart, average speed between population groups can differ. This still means that longer distances require more travel time and effort. This means that the same travel distance for two groups may give lower accessibility for the one having a lower travel speed.
- We do not have data on who is travelling at a given moment between a particular OD-pair (e.g. zone A to zone B). For instance, if due to an intervention, measure and/or policy the share of active mobility increases, we do not know if more individuals are cycling, or the people who are already cycling are cycling more frequent.
    - We can use socio-demographic averages coming from particular neighbourhoods, combined with what we know from ODiN data on for instance age, income, education categories and car ownership (see Appendix A.1). Knowing the regional composition of a neighbourhood provides an assumption who (on average) travels from the particular origin. It still, unfortunately, does not provide an accurate reflection what type of person (consisting out of population group factors) travels. The limitation on ODiN sample data is that it becomes sparse for a given region the more one zooms in. This loss of resolution limits the datapoints of travel information given the particular region. As an example, in appendix A.1, some data is missing because no answers were available for the particular data combination. Additional methods of determining who will actively travel more are needed, and this is a subject for future research in the topic of brede welvaart indicators.

5 Overall conclusions

In recent years, many brede welvaart indicators have been developed by Dutch research institutions, Ministries, Planning Bureaus and consultancy bureaus. These mostly rely on, for instance, CBS data of previous years, and present the recent (ex-post) situation of brede welvaart on that particular subject. Our goal was to use model data in order to simulate (ex-ante) scenarios, coming from policies, measures and interventions, such as simulated road closures, maximum allowed speed changes, the effects of densification, policy interventions, the introduction of new infrastructure and transport modes, etc. It allows us, instead of only looking behind, to make projections of what impact certain interventions may have on certain elements or dimensions of brede welvaart.

We were able to visualize all three indicators to a certain extent to the same focus case (Eindhoven). Given that we only used one baseline scenario for Eindhoven, we were able to present results on traffic zone level. Implementing another scenario, such as lowering speeds in the city centre, would have effects on all of the indicators, and we would see changes in the results and representations of these indicators. In that sense the indicators provide results, but more work is needed to make these indicators more precise, depict differences between groups and, importantly, validate the outcomes of the indicators. Models, i.e. their workings and their outcomes, should accurately replicate, as close as possible, actual real-life situations and cause and effect relations. The models, assumptions and outcomes from using indicators have to be validated, in order for decision makers to trust the outcomes of such models. This is an important next step in the process of these three indicators. Another aspect related to this is in which stage do these indicators, and the application of multiple scenarios of (combinations) of interventions or policies, come into play. This needs further work to make sure these indicators support decision making, while taking brede welvaart into account.

Distribution effects are a vital part of brede welvaart. We see that more work is needed in this area, to project more detailed distribution effects, since a lot of data revolves around averages or have a high granular level. An example are the risk factors only available for cars, walking OD-trips are not available, and no travel time and distance available for trips that occur in the same traffic zone. For accessibility of jobs, we were able to use travel decay functions, representing different income, age and car ownership groups, for the modes car, public transport and cycling. For traffic safety and share of active mobility we were not yet able to distinguish population groups. One other example are average speeds. Speed and distance are often correlated. Average speeds are used to calculate travel times, but actual travel speed can differ between population groups (younger and older groups). Such an example needs to be researched further in next iterations of brede welvaart indicators.

A macroscopic model on itself does not contain sufficient information to determine accurate distribution effects. The model needs to be augmented with auxiliary data and approximations and user group behaviours to complete the calculation. While this auxiliary data is available, it is at a lower level of detail than the traffic model operates on. Compare for example the granularity of trip information – which is known per daypart, OD-pair and mode – with the level of detail of age group distribution. The latter is estimated on a higher level, i.e. urbanisation degree, and cannot be retrieved for each OD-pair. Another example is the number of accessible (job) opportunities, where we use travel decay functions as an addition to the model data. For any given mode of transport (car, bicycle, public transport) and travel time, the decay curves for the Top 10% group always result in a higher value compared to the decay curves for the Bottom 40% group.

Some shortcomings can partially be resolved by minor model changes, but others need another modelling approach or the addition of detailed data on population group characteristics. Furthermore, additional methods are sometimes needed to represent meaningful outcomes, such as the Palma ratio, or further explanations of how results (e.g. on a map) should be interpreted. To show distribution effects over user groups, the traffic model needs to take the different user groups into account on the same level of detail as modes and motives (as is for example done in an Activity-Based Model). After all, from the data used in this report we do not have an indication yet who is travelling at a particular moment. An example in active mobility is that if more cycling trips are made, we do not know who are making these extra trips.

We foresee the further development of mapping distribution effects as one of the next steps, using synthetic populations and activity- and/or agent-based modelling.

Needed/considerations of data input in future iterations of the three indicators;

- We need to know more accurately who (their population group factors, in order to distinguish population groups on certain factors) is travelling from origin to destination. The average composition of population group factors provide a picture of an average person from a specific region, though this does not give us enough detail of which groups are actually travelling (or behaving) in a certain way.
- We do not accurately know what routes travellers take. We know where people have started their journey and ended their journey, but not which route they have chosen. This is problematic in determining risk factors for certain travellers, since we do not know what the distribution over road types is for a given OD-pair.
- Furthermore, some data is missing for traffic models, such as accurate traffic risk data for other modalities, or certain travel modes entirely.
- More population groups specifics should be used in traffic models, such as population group specific travel speeds.
- An important aspect of the use of brede welvaart indicators is;
    - What do the indicators represent, what do their results mean? This could be an important subject for future research, in which we dive deeper into how results can be relatively accessibly (‘toegankelijk’) interpreted by a wide range of people.
    - Validation of the indicator workings and outcomes. Do the indicators accurately replicate real world cause and effect relations? To what degree can these indicators answer questions about levels of brede welvaart, given scenarios of (combinations) of policies, interventions and/or measures.

Appendix

A.1 CBS data active mobility

Table 16: Share of active mobility (cycling) compared to other modes of transport. Age categories and urbanization level

Cycling	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
Total all persons	31%	26%	21%	3,0	3,0	2,8	17,5	16,0	14,2
Age 6-12	35%	41%	39%	2,1	2,6	2,3	18,9	21,4	18,2
Age 12-18	54%	60%	49%	4,7	6,2	7,3	28,5	32,4	29,8
Age 18-25	33%	24%	18%	2,9	2,5	1,8	16,8	10,4	7,9
Age 25-35	31%	16%	10%	3,4	2,0	1,1	19,2	9,3	No data
Age 35-50	29%	22%	16%	3,1	2,5	2,1	16,8	13,5	9,7
Age 50-65	27%	21%	17%	2,9	3,0	2,8	15,8	14,3	14,4
Age 65-75	25%	28%	23%	2,9	3,7	3,6	17,4	20,0	18,0
Age >75	19%	28%	27%	1,6	2,8	2,4	9,9	15,9	15,4

Table 17: Share of active mobility (walking) compared to other modes of transport. Age categories and urbanization level

Walking	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
Total all persons	25%	18%	17%	1,3	1,1	1,0	17,4	14,3	12,7
Age 6-12	29%	23%	19%	0,9	0,8	0,7	16,4	14,1	11,9
Age 12-18	17%	11%	No data	0,8	0,6	No data	11,6	6,3	No data
Age 18-25	24%	12%	No data	1,2	0,9	No data	14,6	7,7	No data
Age 25-35	25%	17%	14%	1,3	1,0	0,8	16,8	12,8	11,2
Age 35-50	24%	17%	17%	1,3	1,2	1,3	18,1	15,3	16,0
Age 50-65	25%	19%	18%	1,4	1,3	1,3	18,7	16,8	15,5
Age 65-75	32%	21%	19%	1,6	1,4	1,0	23,6	18,7	13,8
Age >75	35%	27%	22%	1,1	0,9	0,7	16,3	14,4	10,7

Table 18: Share of active mobility (cycling) compared to other modes of transport. Income categories and urbanization level

Cycling	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
1st 20% group	30%	28%	25%	2,6	2,8	3,0	16,5	17,6	18,9
2nd 20% group	28%	28%	25%	2,6	2,9	2,9	15,7	16,4	15,0
3rd 20% group	28%	28%	22%	2,9	3,3	2,8	17,1	17,1	14,0
4th 20% group	30%	27%	20%	3,3	3,0	2,7	17,9	15,7	12,6
5th 20% group	32%	23%	18%	3,5	2,9	2,7	18,3	13,9	13,4

Table 19: Share of active mobility (walking) compared to other modes of transport. Income categories and urbanization level

Walking	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
1st 20% group	32%	23%	19%	1,4	1,0	0,9	19,3	15,3	12,3
2nd 20% group	28%	21%	20%	1,2	1,1	0,8	17,0	15,1	10,9
3rd 20% group	24%	18%	18%	1,2	1,1	1,1	16,6	14,4	13,8
4th 20% group	23%	17%	15%	1,3	1,0	1,0	17,1	13,2	13,0
5th 20% group	22%	16%	15%	1,2	1,2	1,1	16,0	14,0	13,0

Table 20: Share of active mobility (cycling) compared to other modes of transport. Education categories and urbanization level

Cycling	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
Education low	24%	29%	25%	2,3	3,4	3,0	13,1	18,8	14,7
Education middle	26%	21%	16%	2,7	2,7	2,1	15,5	13,2	10,5
Education high	33%	23%	17%	3,6	2,8	2,8	19,3	13,6	14,2

Table 21: Share of active mobility (walking) compared to other modes of transport. Education categories and urbanization level

Cycling	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
Education low	28%	18%	17%	1,2	0,9	0,9	18,3	12,6	11,0
Education middle	24%	17%	15%	1,2	1,2	1,0	16,5	15,1	12,2
Education high	25%	19%	17%	1,4	1,3	1,2	18,0	15,7	15,5

Table 22: Share of active mobility (cycling) compared to other modes of transport. Car ownership and urbanization level

Cycling	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
DL, car on name	20%	18%	15%	2,5	2,5	2,3	12,9	13,1	11,7
DL, car in HH	27%	25%	19%	2,9	3,0	2,3	14,8	14,3	11,1
DL, no car in HH	39%	30%	No data	4,1	3,9	No data	21,9	19,0	No data
No DL, <17 yo	35%	35%	29%	2,9	3,0	3,3	19,2	16,1	17,8
No DL, >17 yo	44%	51%	45%	3,4	4,4	4,9	23,9	27,6	24,6

Table 23: Share of active mobility (walking) compared to other modes of transport. Car ownership and urbanization level

Walking	Trips			Passenger kilometres [km]			Travel duration [min]		
Urbanization→	High	Mid	Low	High	Mid	Low	High	Mid	Low
DL, car on name	21%	18%	16%	1,2	1,2	1,0	15,5	14,8	12,8
DL, car in HH	23%	17%	16%	1,3	1,2	1,1	16,8	15,7	13,3
DL, no car in HH	31%	19%	No data	1,6	1,2	No data	20,0	16,6	No data
No DL, <17 yo	23%	17%	17%	0,9	0,6	0,8	14,2	10,3	10,0
No DL, >17 yo	33%	24%	27%	1,4	1,0	1,1	19,9	13,4	14,2

A.2 Decay curves

The travel time decay curves are estimated from data of the national travel diary survey ODiN[58]. Each curve shows the decrease, or decay, of the number of trips that have a travel time equal to or longer than what is specified on the x-axis.
A curve is obtained as follows:

- Select all trips from the data that adhere to the criteria of the curve (e.g. car trips by travellers belonging to a top 10% household income group).
- Round the travel time of each trip to whole minutes.
- Group the trips by their travel time and count the number of trips for each group.
- Sort the result by ascending travel time and determine the reverse cumulative distribution of the trip count.
- The outcome shows that (fictional numbers).:
  - 100% of the trips has a travel time of 0 minutes or more
  - 90% of trips has a travel time of 10 minutes or more
  - 80% of trips has a travel time of 15 minutes or more
  - etc...
- Fit a curve through these points, resulting in the final decay curve.

This decay curve should be interpreted as a proxy for how many people are willing to travel for a certain duration, i.e.: 100% of the people are willing to travel 0 minutes or more, 90% of the people would travel for 10 minutes or more, etc...
It is understood that the revealed travel time choice is merely a proxy and not a direct estimation of what travellers would prefer in terms of travel time. Some travellers might not have an alternative to travelling 120 minutes by car. Using this method these travellers are assumed to belong to the group of travellers that "prefer" this travel time, which might not reflect reality.

By adjusting what trips are selected in the first step, different decay curves can be created for different traveller groups.

[58] CBS and RWS, 'Onderzoek Verplaatsingen in Nederland 2015', application/pdf,SPSS (.sav),XLS,XLSX,SPSS (.por),Stata (.dta),CSV (Data Archiving and Networked Services (DANS), 2017), https://doi.org/10.17026/DANS-Z2V-C39P.

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