Q-Park Student Award 2024

Dr. Giuliano Mingardo

QPARK

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ERASMUS CENTRE FOR
URBAN, PORT AND TRANSPORT ECONOMICS

Q-Park Student Award

- It’s an important step to bridge the knowledge gap in parking and mobility;
- It’s a joint project of Q-Park and Erasmus University Rotterdam
- For the best student projects on parking and mobility
- It’s open to all European Universities in Europe
- Started in 2014

10th Anniversary!!!

- 80+ theses submitted


UNIVERSITEIT ROTTERDAM


Ward Vleugels Q-Park Scriptieprijs 2016
2E PRIJS € 1.000,-
Winnaar: DENNIS VAN DER MEER
Ward Vleugels Q-Park Scriptieprijs 2016
1E PRIJS € 2.500,-
Winnaar: BARBARA JEPMA
Ward Vleugels Q-Park Scriptieprijs 2016
3E PRIJS € 500,
Winnaar: INES ELINE FERRIER

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Themes

The students’ projects have covered a vast variety of topics, such as:

- Parking demand and behaviour
- Parking and electric vehicles
- Car ownership
- Bicycle parking
- MaaS / Hubs /...
- Logistics
- Transport injustice/poverty/social exclusion
- ...

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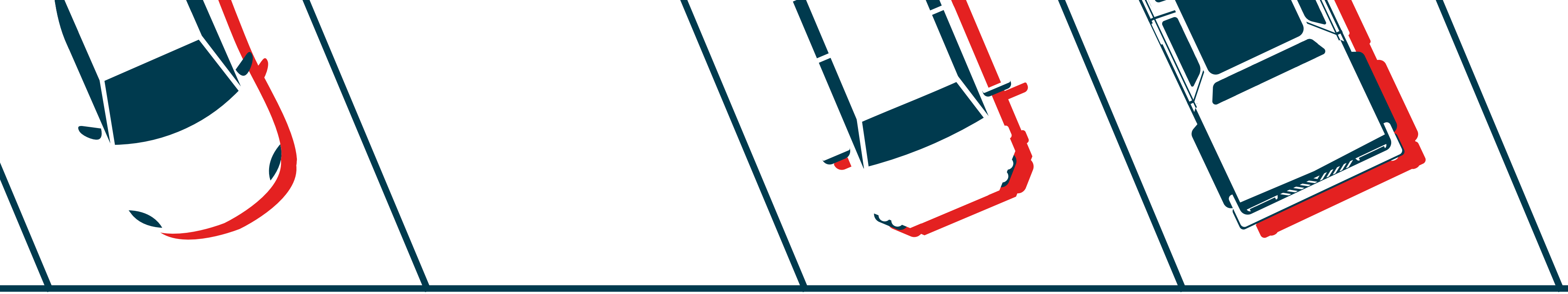
Q-Park Student Award 2024

The winners:

- Laura Drechsel – *Stories of Aging and Access*
- Agata Oskroba – *Parking Demand Prediction: Time Series Forecast for subscription and reservation customers*
- Evi Rombouts – *Suitable locations for drop zones for free-floating forms of micromobility*



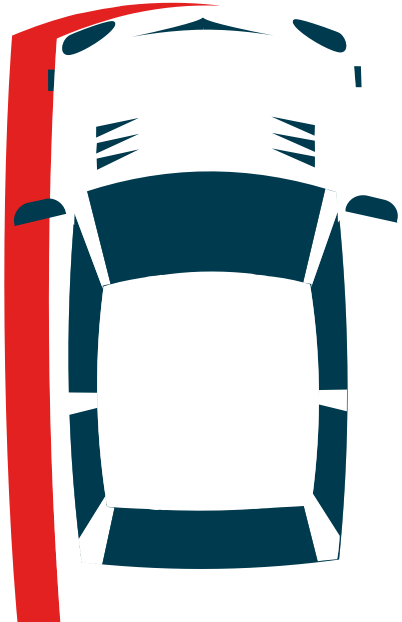
Parking Demand Prediction: Time Series Forecast for Subscription and Reservation Customers with Event-Correction Framework

Agata Oskroba | Q-Park Student Awards

BUSINESS CASE

- Growth in mobility sector leads to higher demand for parking spaces.
- Parking providers offer a range of products to meet customer needs
  - Subscriptions, occasional reservations for guarantees spots.
- Shift in approach: Moving away from traditional first-come, first-serve systems.
  - Emphasis on convenience and certainty for users.
  - Enhanced customer satisfaction through flexible and guaranteed parking options.

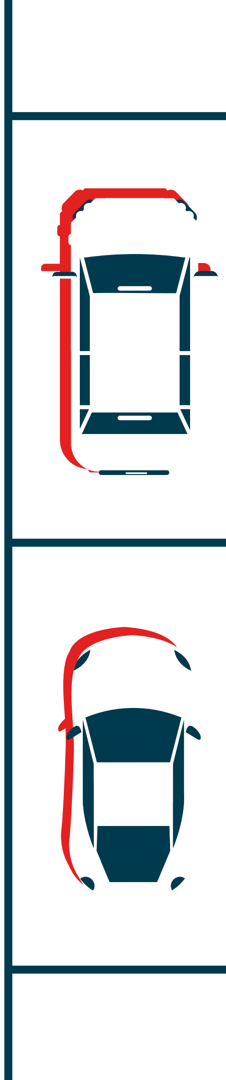
Where is the problem?



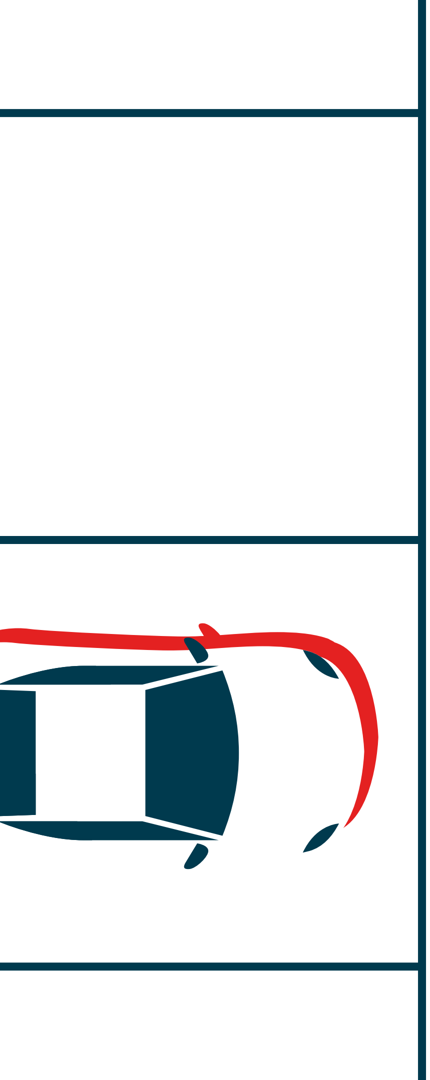
BUSINESS PROBLEM

- Balancing customer needs of diverse customer types;
  - Short Term Parking (STP) - unregistered and unplanned parking visitors.
  - Long Term Parking (LTP) – subscriptions for parking on specified days/hours.
  - Pre-booking (PB) – online parking reservations.
- LTP and PB customers do not always adhere to their scheduled times leaving spots unused.
- Efficient allocation;
  - Ensuring maximum occupancy while guaranteeing spots for LTP and PB.
  - Adjusting spot availability for STP customers dynamically.

How can we predict actual parking demand?



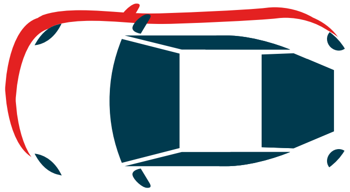
PROPOSED SOLUTION



- Parking demand forecast allowing to make informed decisions
- Customer specific approaches:
  - LTP – predict **occupancy** directly based on historical occupancy data
  - PB – event-correction framework predicting **relative differences** between actual arrival/departure times and the pre-booking start/end times to forecast demand based on expected arrival/departure times
- Proof of concept on one selected parking facility of high demand

AVAILABLE DATA - LTP

- Parking facility occupancy (number of parked cars) between May 2022 and December 2023.
- Based on entries and exits data for every 15 minutes timestamp.
- Data exhibits strong daily and weekly seasonality;
  - Low occupancy at night, high during the day.
  - Higher occupancy on weekdays and during daytime and low occupancy during nighttime and weekends.
- Feature engineering;
  - Timestamp-based features: day of year, month, day of week, hour.
  - Lagged features for past one to three weeks.
  - Sinusoidal transformations to capture cyclical patterns.



AVERAGE WEEKLY OCCUPANCY- LTP

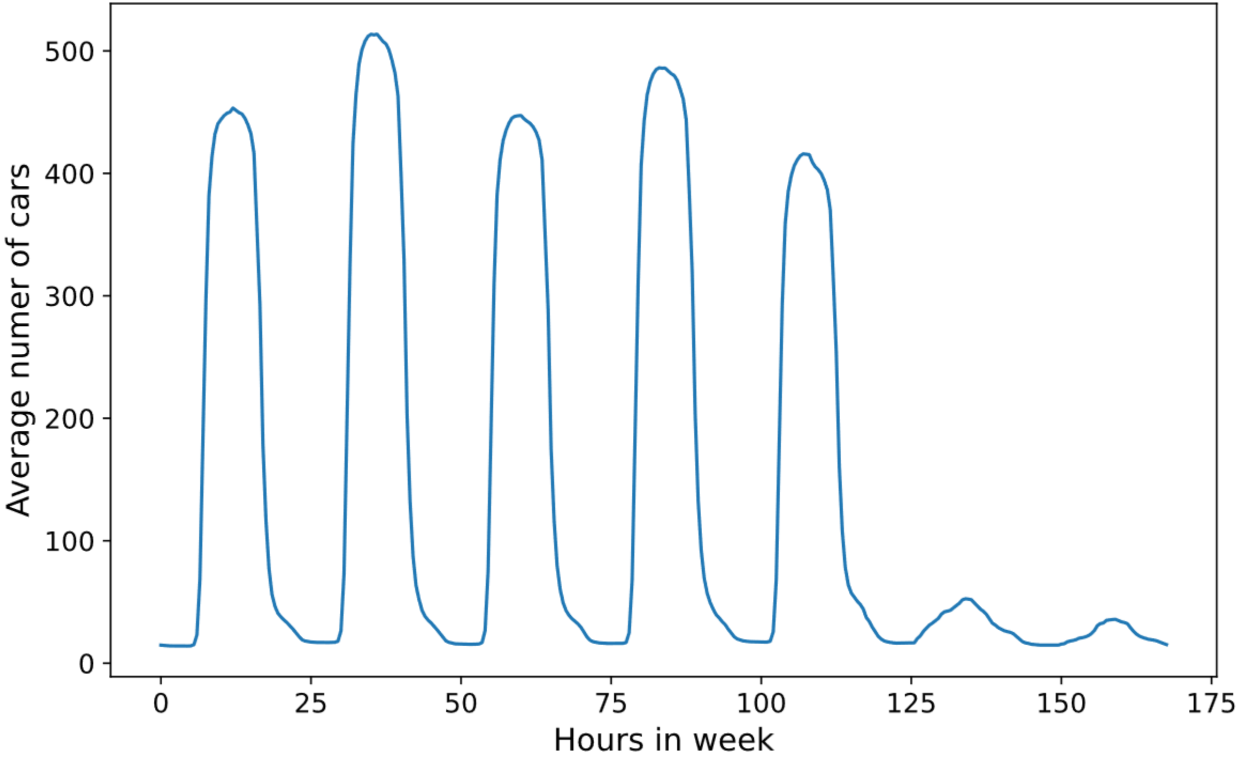


Fig. 1. Average week of LTP occupancy at the parking facility.

METHODOLOGY- LTP

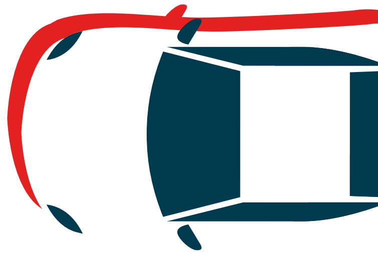
- Time series prediction model based on historical data to forecast LTP customer occupancy.
- Aim: Predict parking demand accurately one week ahead.
- Models are retrained regularly with a rolling window method to keep up with changing trends.
- Iteratively shifting window, incorporating latest data and removing oldest data.
- Using 6 different models to find the most suitable: linear regression, Lasso linear regression, Decision Tree regression, Random Forest regression, XGBoost regression, Support Vector regression.

	Name
Input	Hour
	Day of week
	Month
	Quarter
	Week of year
	Day of year
	Weekend
	Cosine hour
	Sine hour
	Cosine day of week
	Sine day of week
	Cosine week of year
	Sine week of year
	Lag 7 days
	Lag 14 days
	lag 21 days
Output	# Parked

Tab. I Variables overview - LTP

RESULTS - LTP

- XGBoost model offered on average the best accuracy and consistent performance over weeks.
- **Goodness of fit of 0.95** suggests model explains data trends well.
- Due to stable patterns of LTP visits no extra tuning needed.
- Issues:
    - All models performed worse in last week of December – holiday impact.



FEATURE IMPORTANCE XGBOOST - LTP

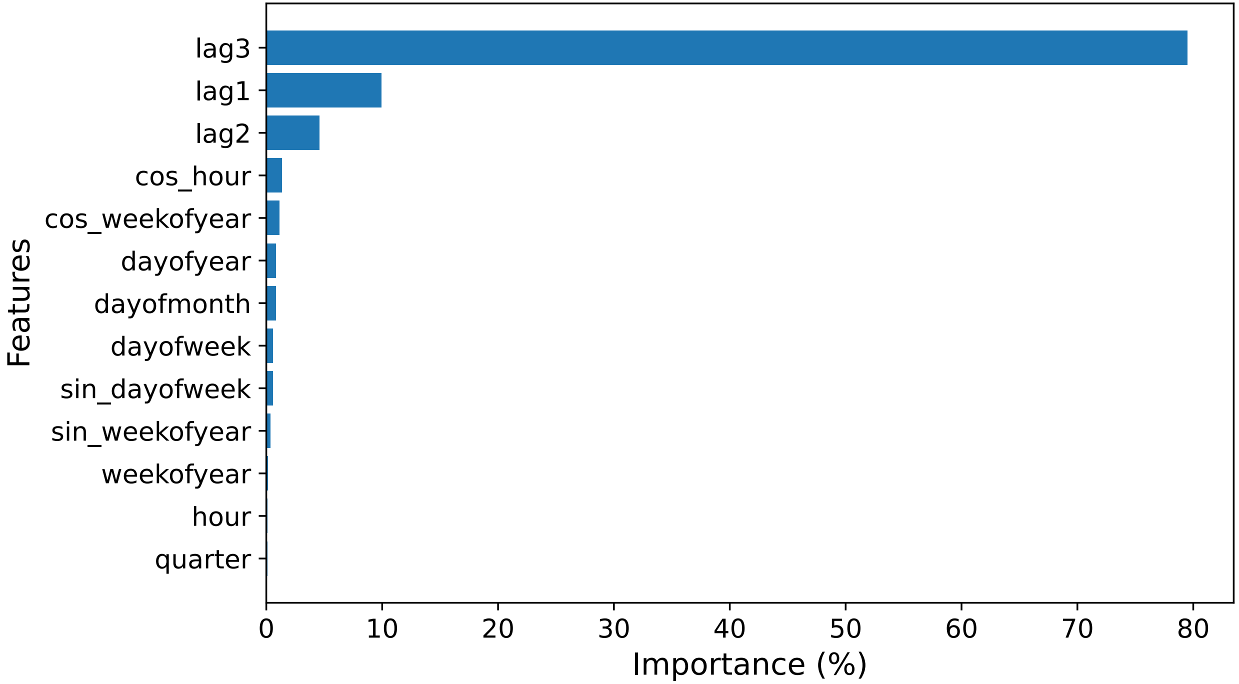
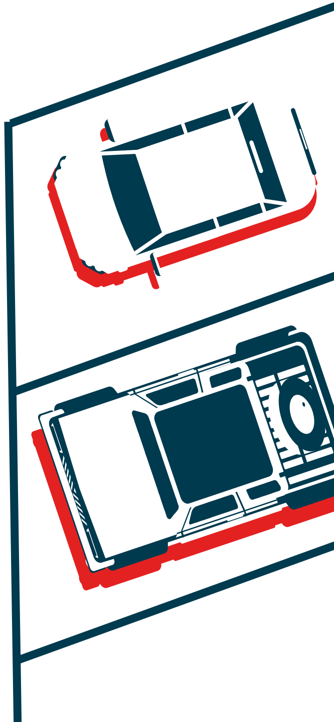


Fig. 20. Feature importance for tuned XGBoost in LTP occupancy prediction. Percentage gain of each feature representing relative contributions to the model over all trees.

AVAILABLE DATA - PB

- Online pre-bookings and their matched transactions;
    - Including start/end times of reservation, creation time, pre-booking product, actual parking visit arrival/departure times.
- Almost 40 000 pre-bookings with associated transactions between May 2022 and December 2023.
- Number of pre-bookings per day varies (weekends, holidays etc.).

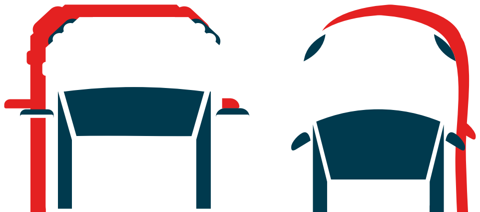


METHODOLOGY- PB

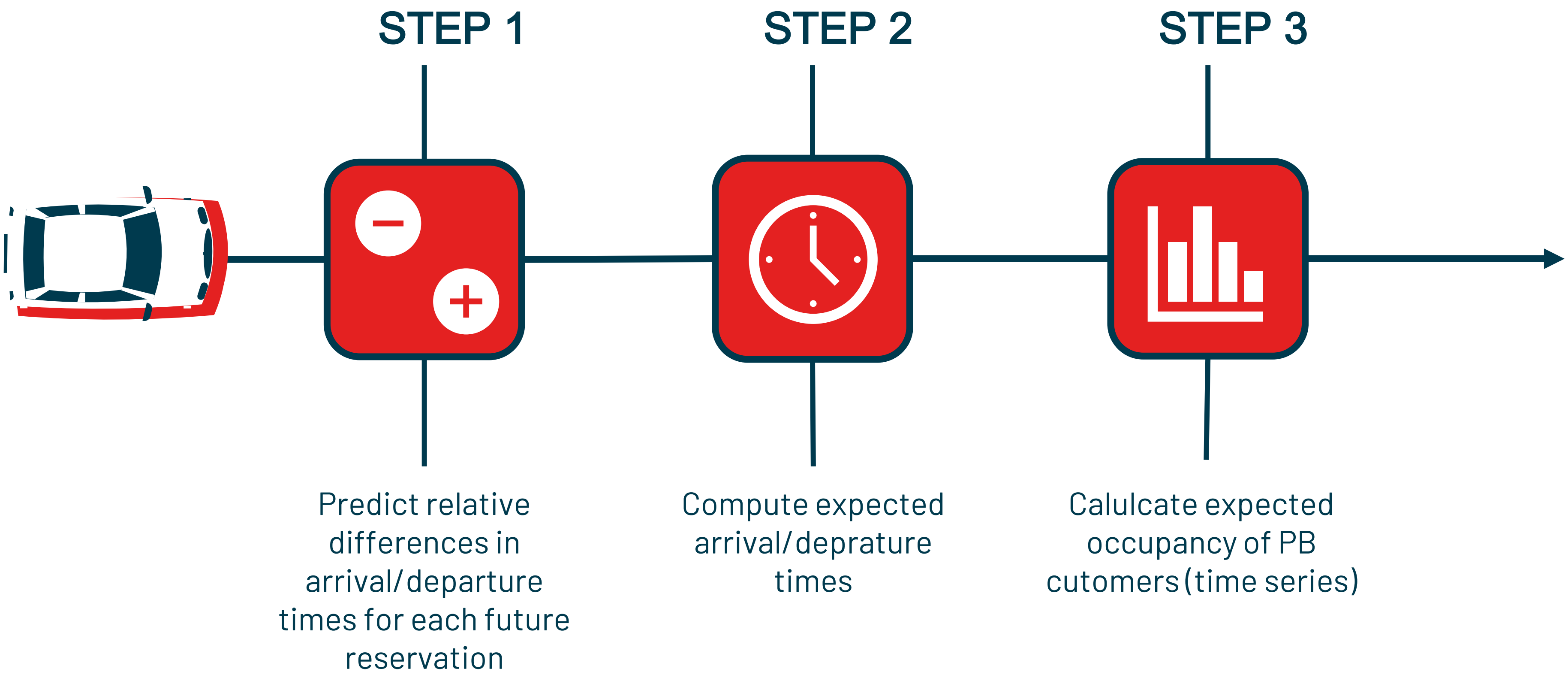
- Two separate regression models;
  - Model 1 predicts difference between actual and scheduled arrival time.
  - Model 2 predicts difference between actual and scheduled departure time.
- Regular retraining - rolling window approach monthly to adjust to changing trends.
- Using 6 different models for each case to find the most suitable one: linear regression, Lasso linear regression, Decision Tree regression, Random Forest regression, XGBoost regression, Support Vector regression.

	Name
Input	Booking lead time
	Product name
	Booking start month
	Booking start day of week
	Booking start season
	Booking start day period
	Booking end day period
	Booking duration
Output	Minutes difference to order arrival
	Minutes difference to order departure

Tab. II Variables overview - PB

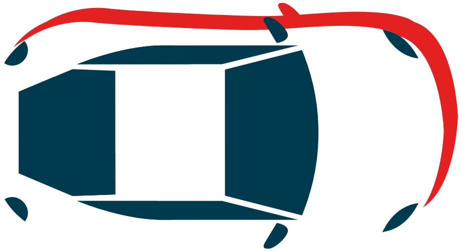


EVENT-CORRECTION FRAMEWORK



RESULTS – PB occupancy

- Arrival/departure differences regression models show limited stability across months.
- Best performing models used to predict differences in arrival (Random Forest) and departure times (XGBoost) for all test months.
- Reserved, actual and predicted occupancy times series calculated and compared.
- Currently on average daily there are **45.5 parking hours that are "lost"** (reserved parking spots unused).
- Assuming demand for parking spots, using the **event-framework would reduce the loss to 4.5 parking hours** creating potential to increase business revenue.



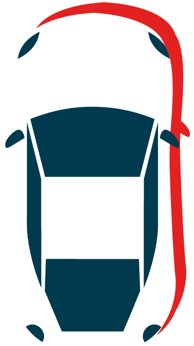
CONCLUSION

- LTP occupancy prediction highly successful using time series regression offering high accuracy and reliable forecast.
- Possible further feature relevance analysis and determining exact business potential.

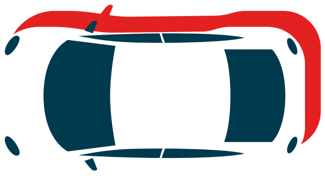
- PB time differences prediction models show limited stability across month individually.
- Event-correction framework offers high accuracy PB occupancy prediction, significant potential for the company and research in time series forecasting.
- Next steps in PB demand prediction should be further feature engineering and analysis of reasons of low performance (data quality, trends in customer behaviour etc.).

WHAT IS NEXT?

- Expanding to other facilities with different profiles.
- Automating the pipeline.
- Real life implementation
- And more questions to answer:
  - How to control inflow of customers without knowing how long they will stay for?
  - How long ahead should parking spots be reserved?
  - How to translate outputs into informed decision making and help parking hosts manage facilities?



THANK YOU



Universiteit Antwerpen
Faculteit Bedrijfswetenschappen
en Economie

Positioning of suitable locations for drop zones for free-floating forms of micromobility

Evi Rombouts

Under the supervision of Prof. Joris Beckers

Introduction

- **Evi Rombouts**
  - Business Engineering, University of Antwerp
    - Supply Chain Engineering
    - Major in Transport and Logistics
  - OMP: Supply Chain Consultant

- **Promotor: Prof. Joris Beckers**
  - Department of Transport and Regional Economics, University of Antwerp
  - Design of sustainable (urban) economic and transport networks in the context of the on-demand economy

Contents

Research Question

Start of the research: shared scooters

- **Negative public opinion**
  - “During working visits, if I even bring up the word “e-scooter”, you hear the public grunt like a herd of wildebeasts.”
- **Reasons**
  - **Unsafe**
    - Rather a problem for privately owned scooters
  - **Disorderly street scene**
    - “Leaving shared scooters behind on the sidewalk is a specific form of **illegal dumping**.”

Research question

- Where are **suitable locations** for **drop zones** for free-floating forms of micromobility?

Methodology

Methodology

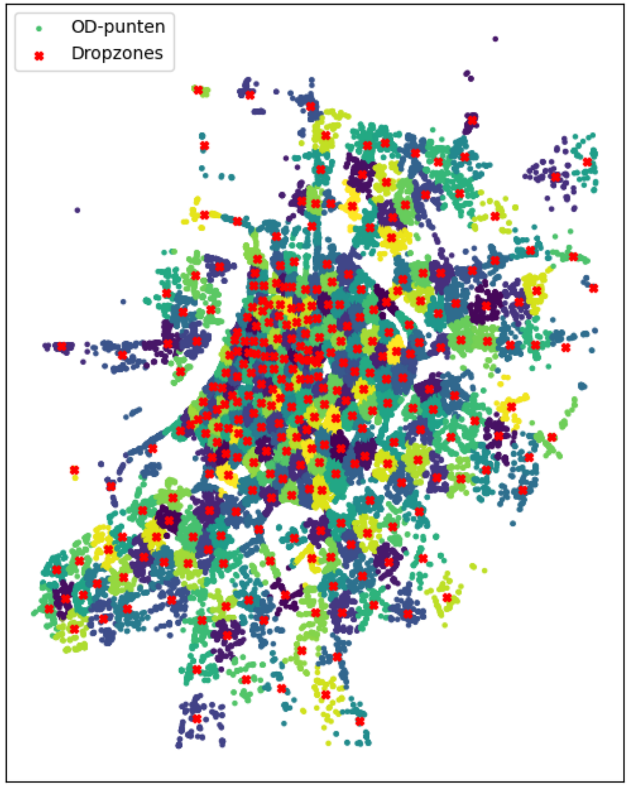
- **Data analysis**
  - Dataset:
    - Month **June 2022**
    - One of the shared scooter providers in **Antwerp**
- **2 location allocation methods**
- **Adjustment**

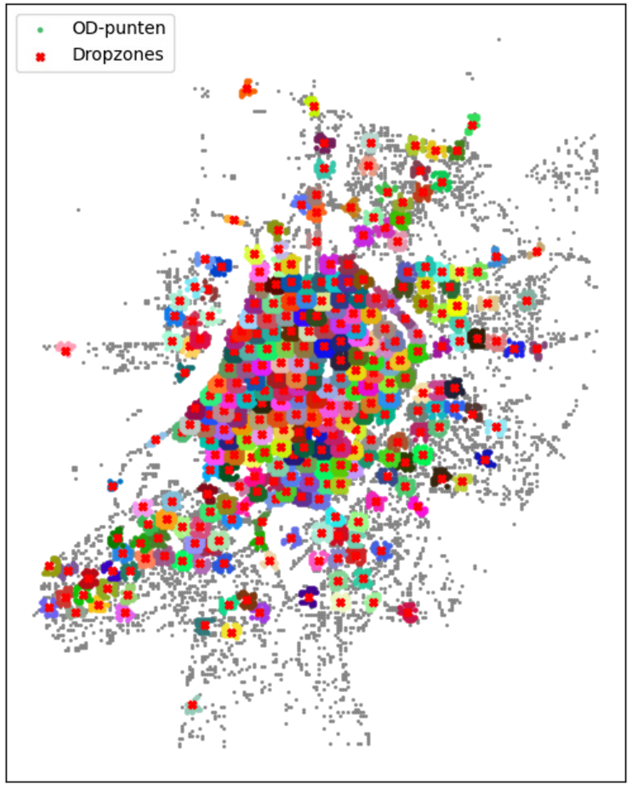
Methodology: optimization methods

- **2 location allocation methods:**
  - **K-means clustering**:
    unsupervised learning method
  - **Maximum coverage location problem (MCLP)**:
    optimization method

- **5 scenarios:**
  - Depending on the number of drop zones
    - 100, 200, 300, 400, 500

- Methods and situations assessed based on **performance indicators**



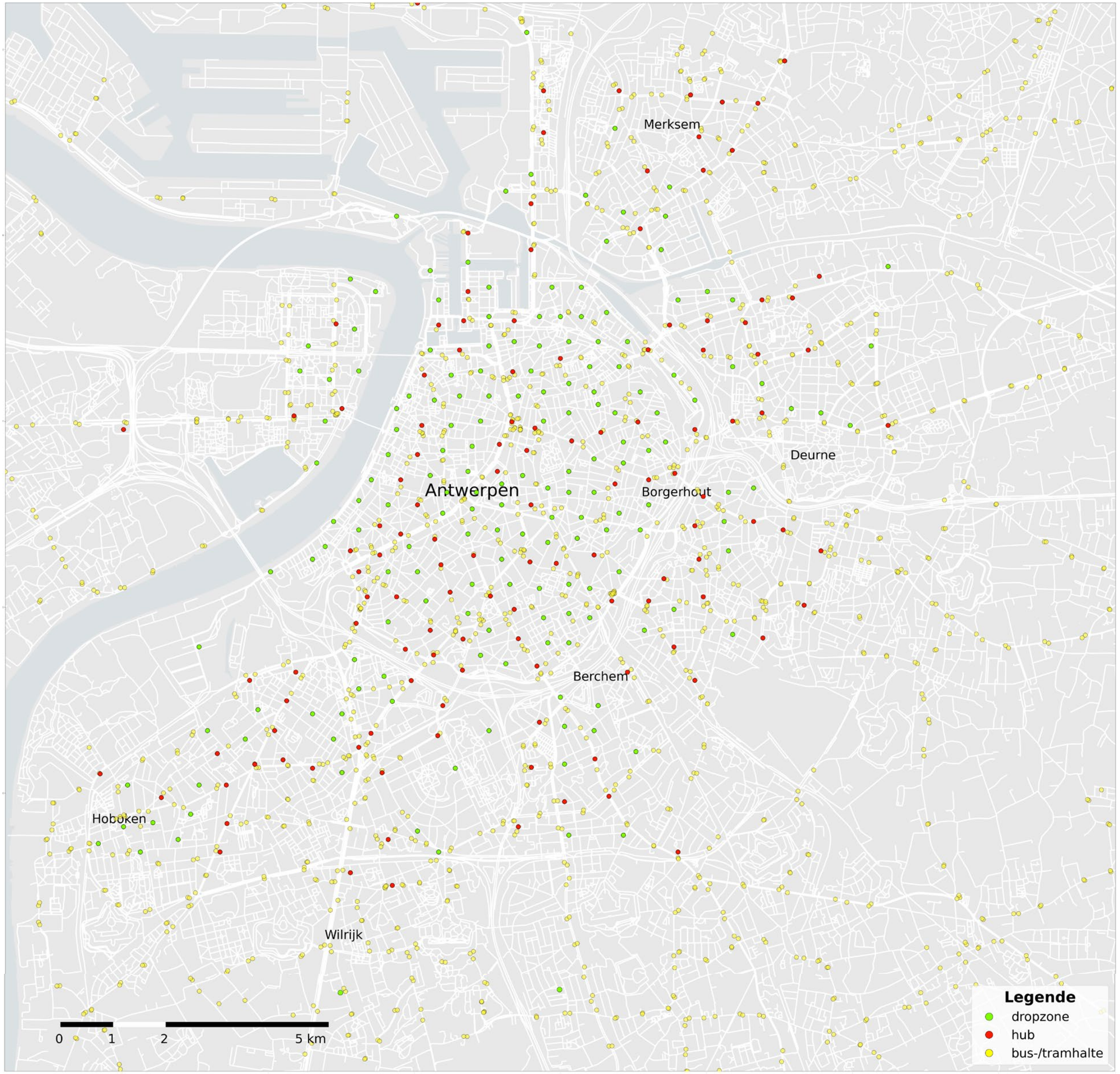


Methodology: adjustment

- Adjustment to the current **public transport** network

- **Why**?
  - Promoting multimodality
  - Multimodality facilitated by mobility hubs
- **2 scenarios**:
  - 50 meter radius
  - 100 meter radius

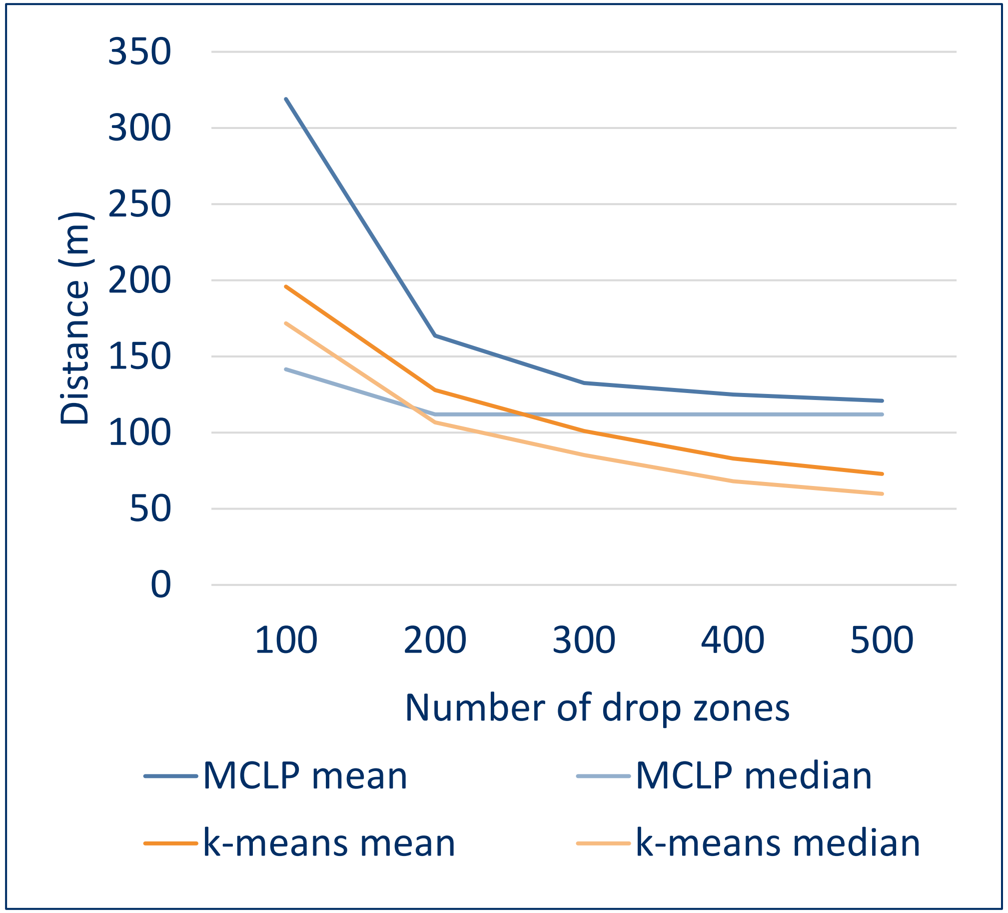
- How big is the impact on **performance indicators**?



Results

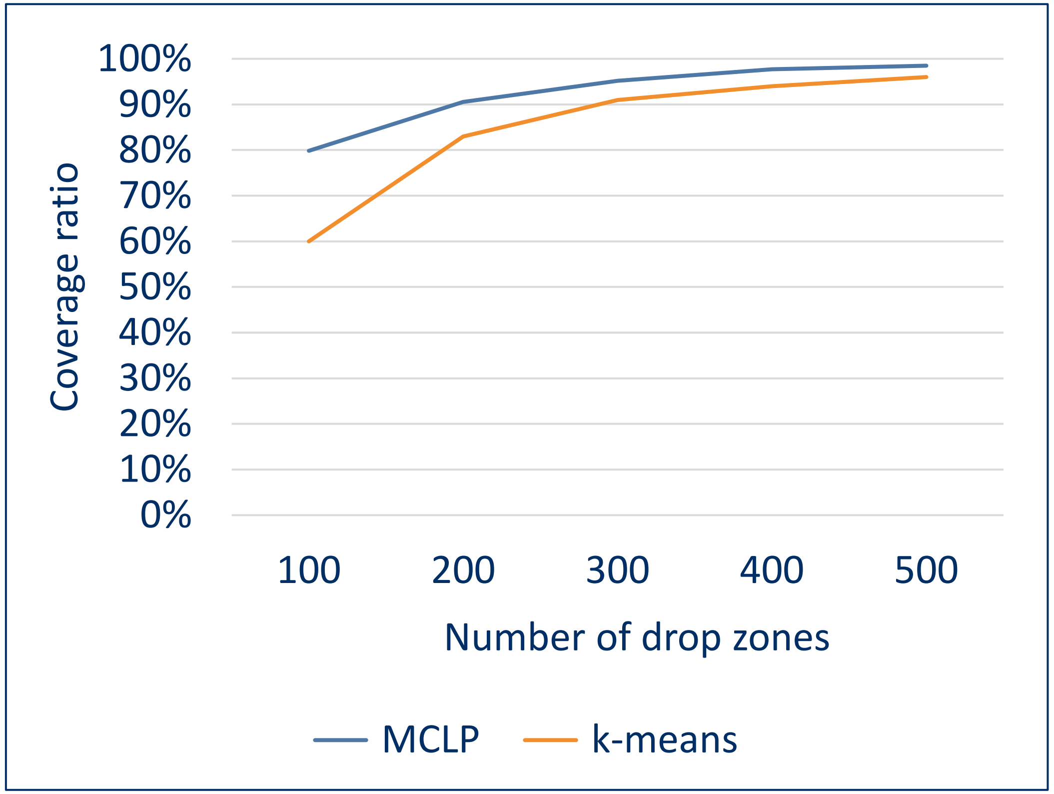
Location allocation models

- With respect to **distance**
  - Different mean and median progression
  - K-means distributed over the entire surface
  - MCLP mainly meets the demand in the center



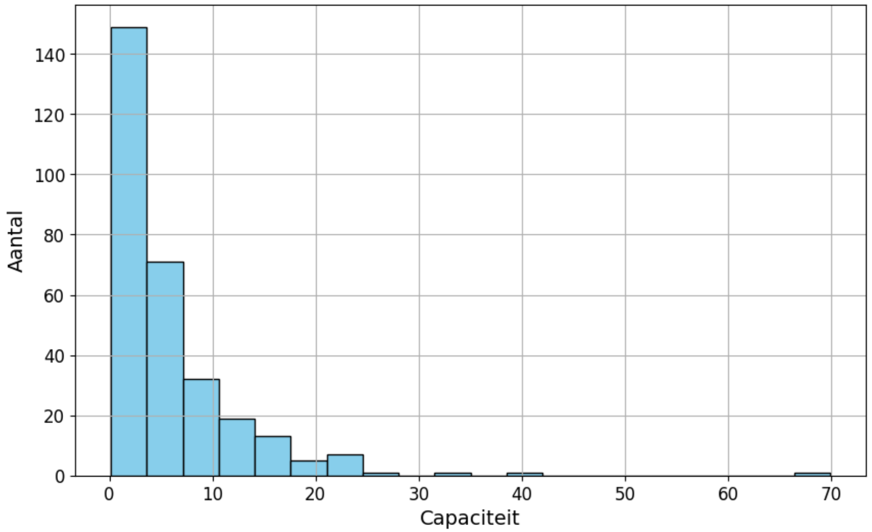
Location allocation models

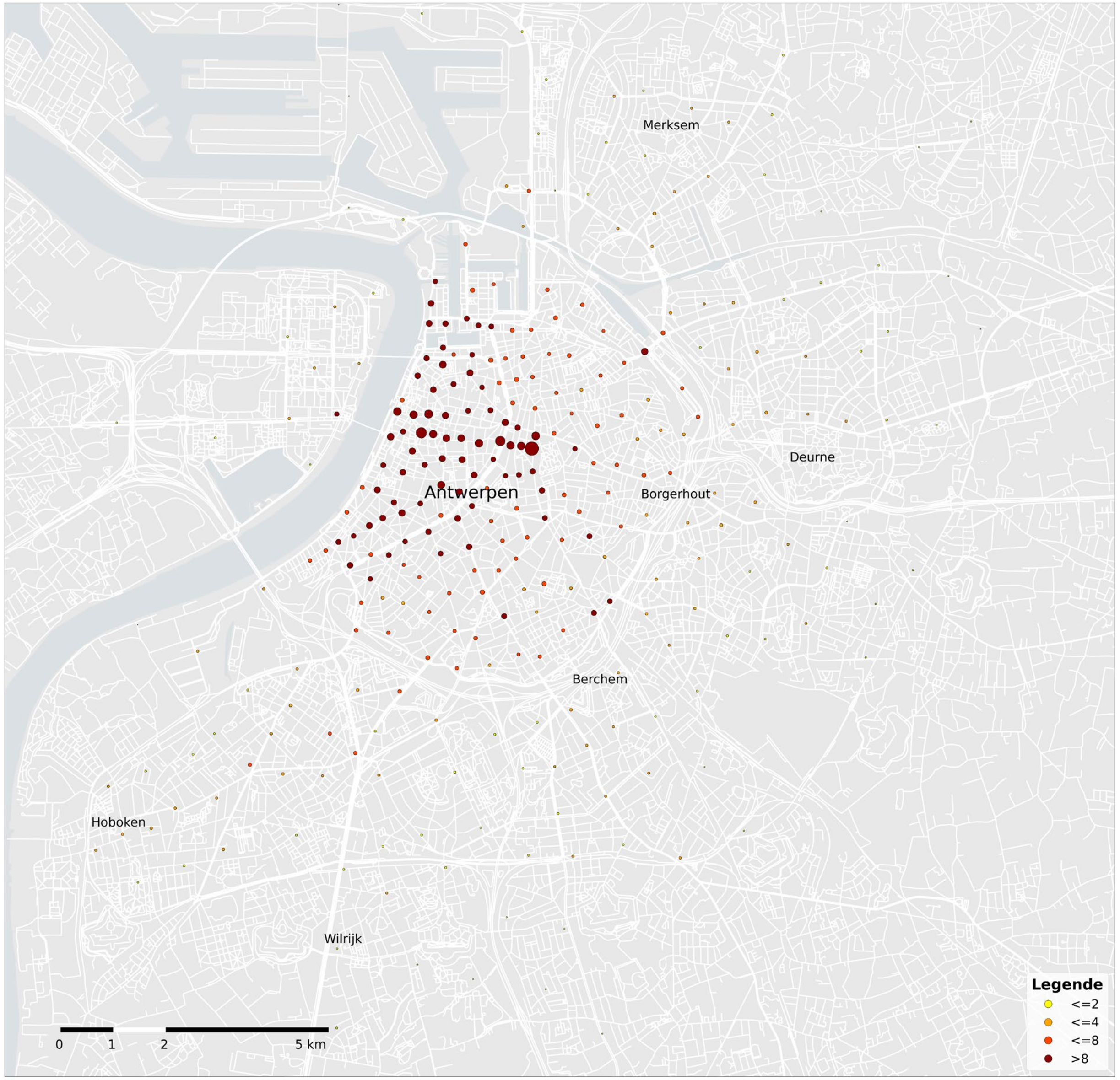
- Regarding **coverage ratio**
  - Both performing very well
  - MCLP doing better, but declining profits



Location allocation models

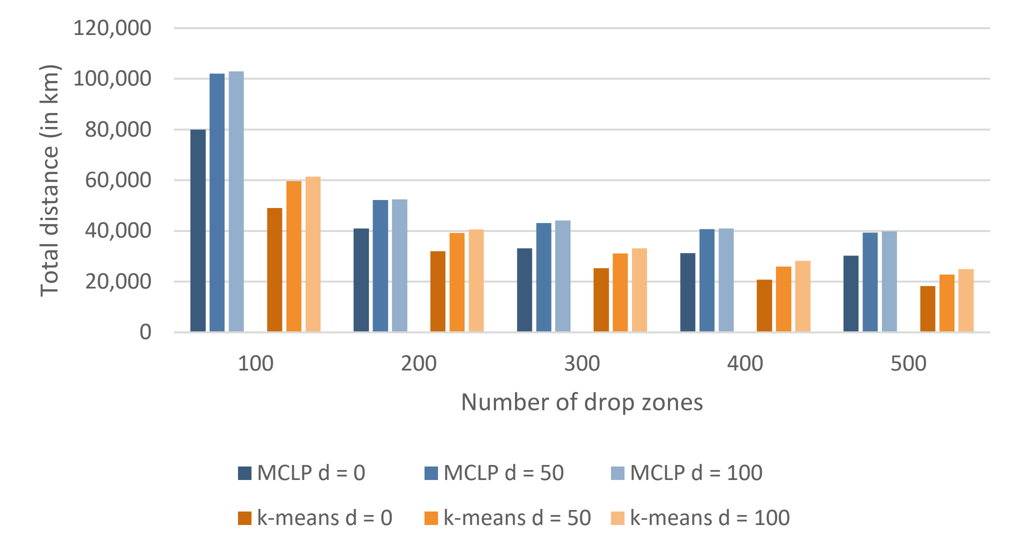
- At the level of **capacity**
  - **large differences** between center and outer edge
  - especially **challenges** with medium-sized drop zones in the center

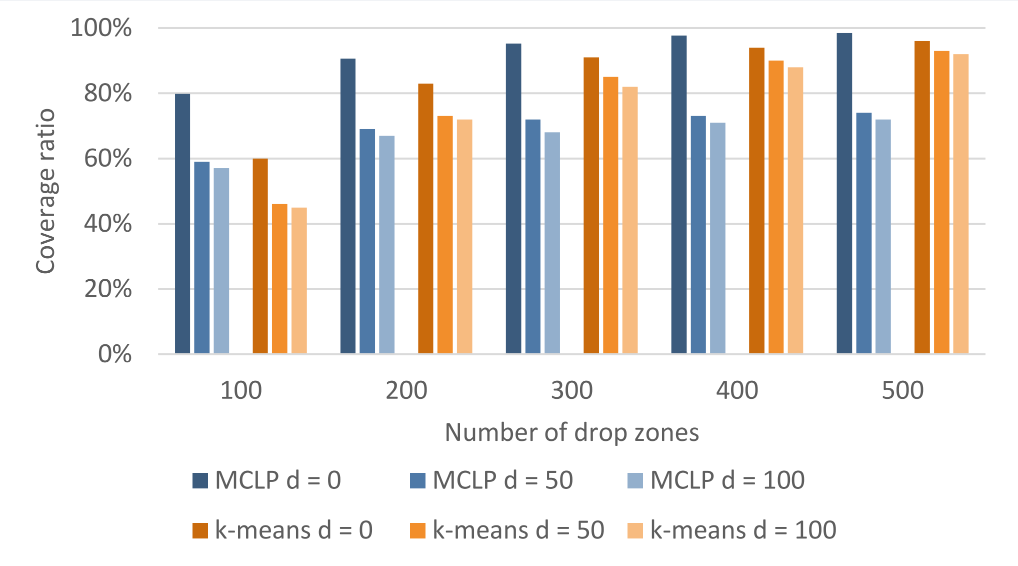




Adjustment to public transport

- These models **perform worse** at all levels
  - The differences become very small for a larger number of drop zones
- The **coverage ratio** drops sharply for **MCLP**
  - Possibly due to the grid
- There is surprisingly **little difference** between a radius of 50 and 100 meters
  - Busy points?





Conclusion

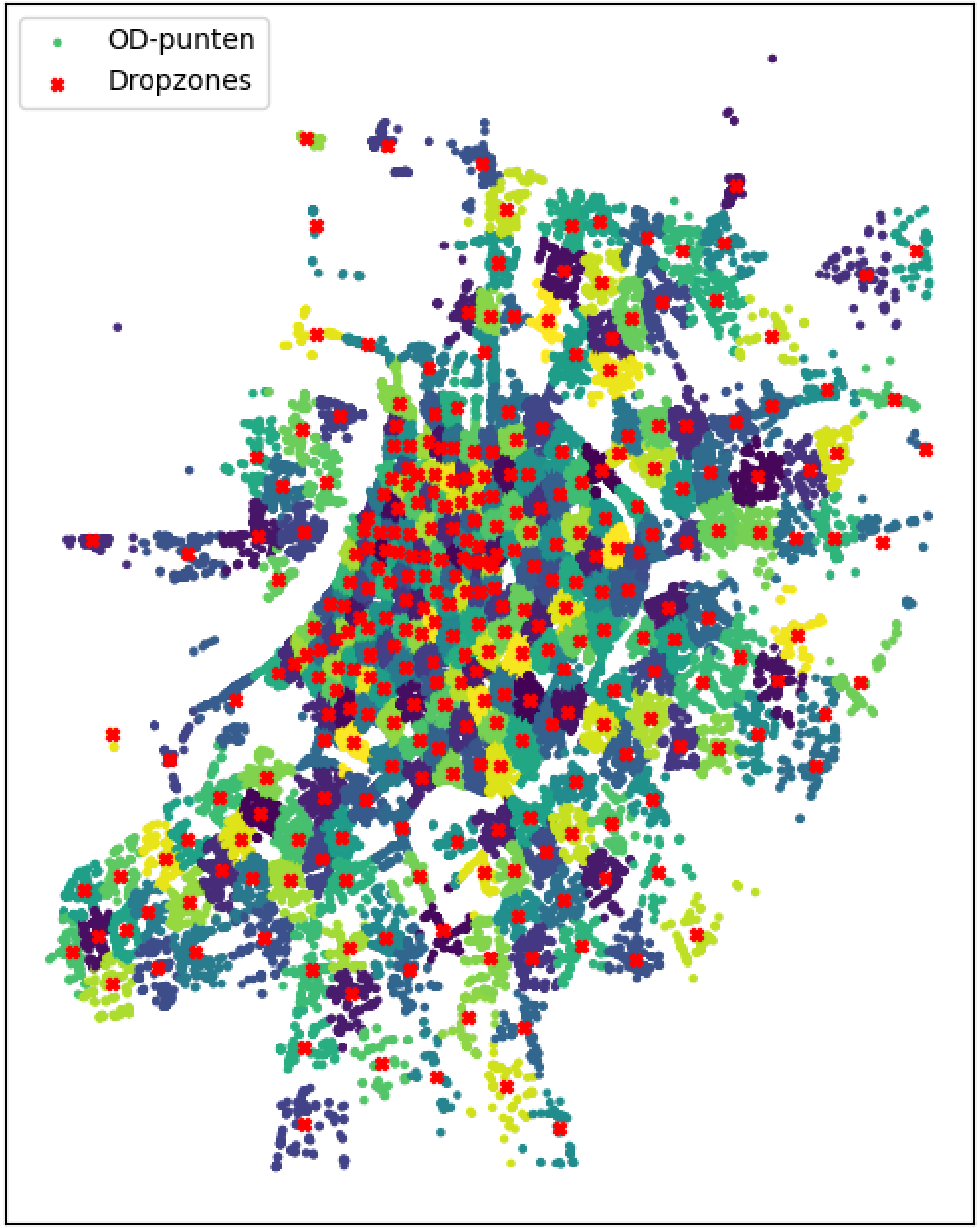
Conclusion

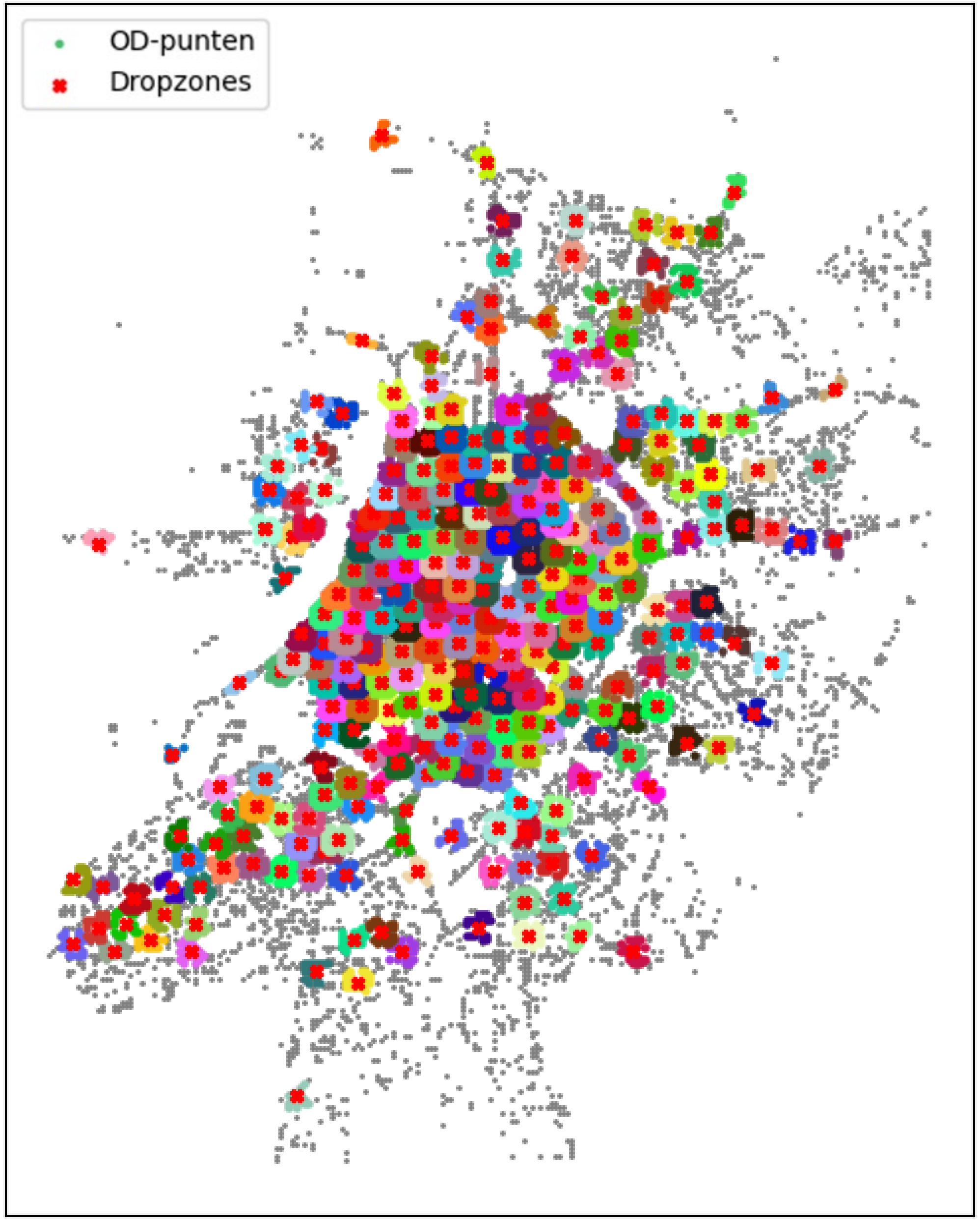
- **Optimization methods:**
  - K-means clustering and MCLP **each have their strengths**
    - Intrinsic differences are reflected in results
  - **Marginal benefits decrease** for the number of stops
    - Ideal scenario depends on preferences of the city government and providers
      - Redistribution, space on the street
  - **Capacity** is a **point of attention** in both models
    - Adjustments will have to be made for this
- Adjustment to **public transport:**
  - Performance indicators are lower
  - MCLP performs worse (due to grid)

Recommendations for future research

- **Optimization models:**
  - Capacitated MCLP
  - Run K-means multiple times
- **Representativeness:**
  - Integrate data from a longer period across different providers
- Integration of the **entire mobility system**

Questions?


OD-punten
Dropzones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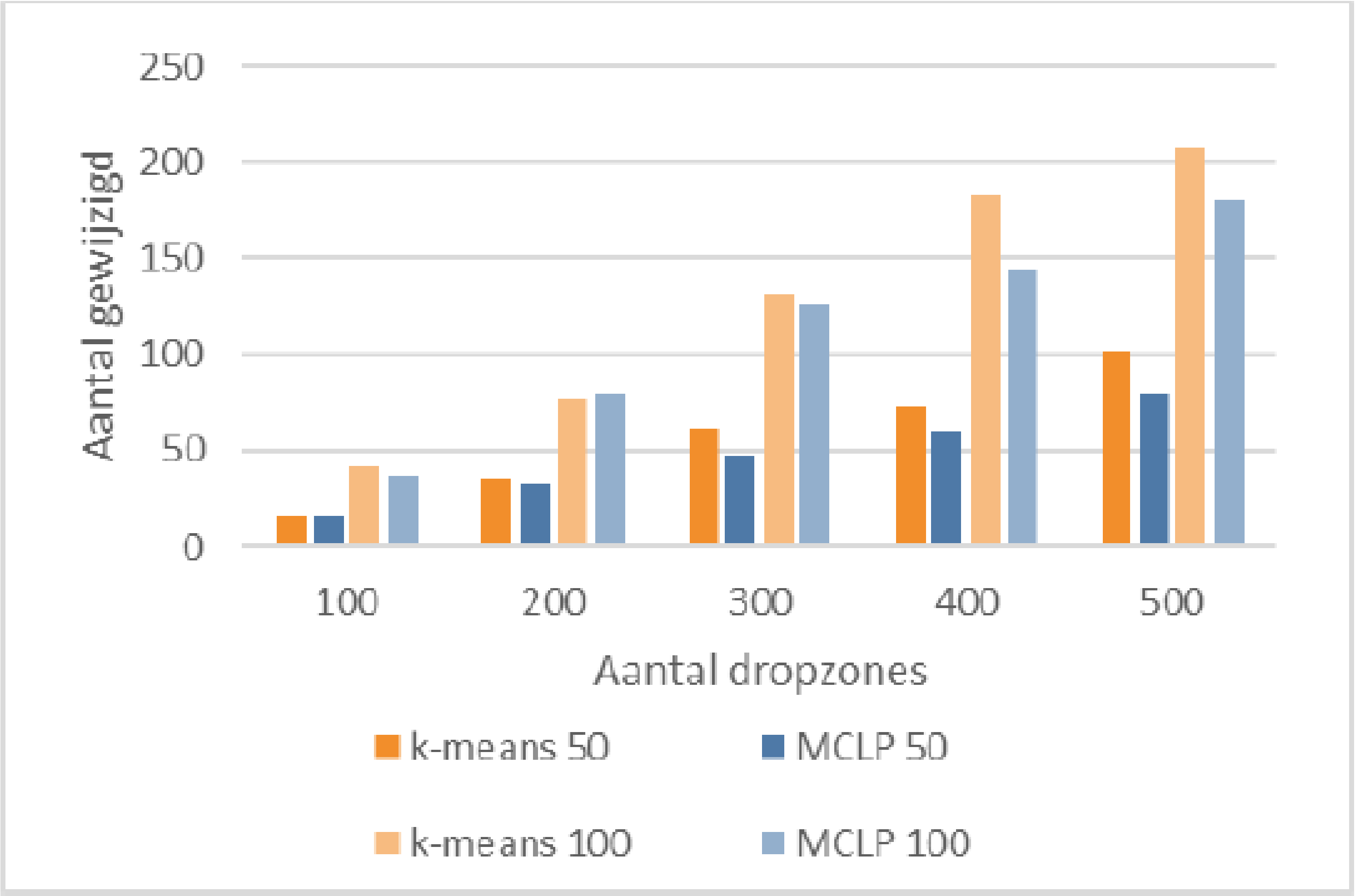


Grafiek 12 - Aantal multimodale locaties

STORIES OF AGING AND ACCESS

Exploring Capabilities and Challenges of Accessibility for urban Elderly through Microstories

Laura Drechsel

STUDIO BEREIKBAAR

TU Delft

Outline

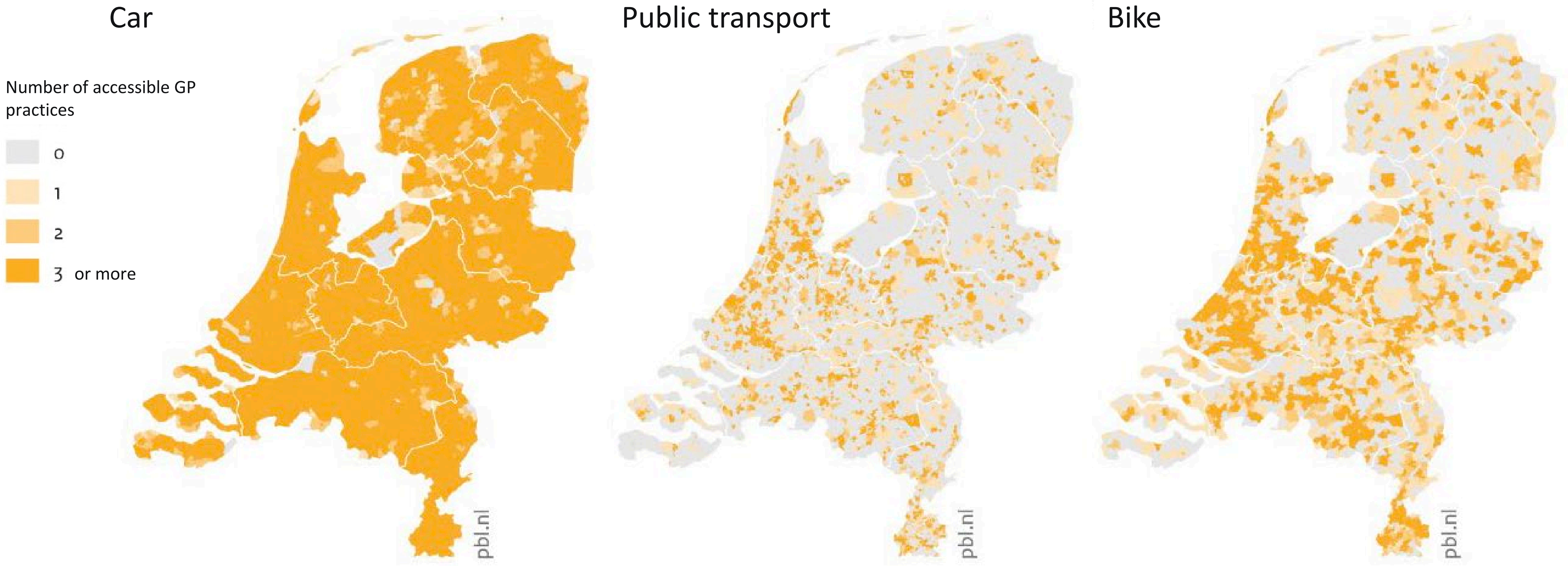
+ Inspiration
+ Method
+ Capabilities and barriers
+ Policy implications
+ Conclusion

Inspiration

A (typical?) way to measure accessibility

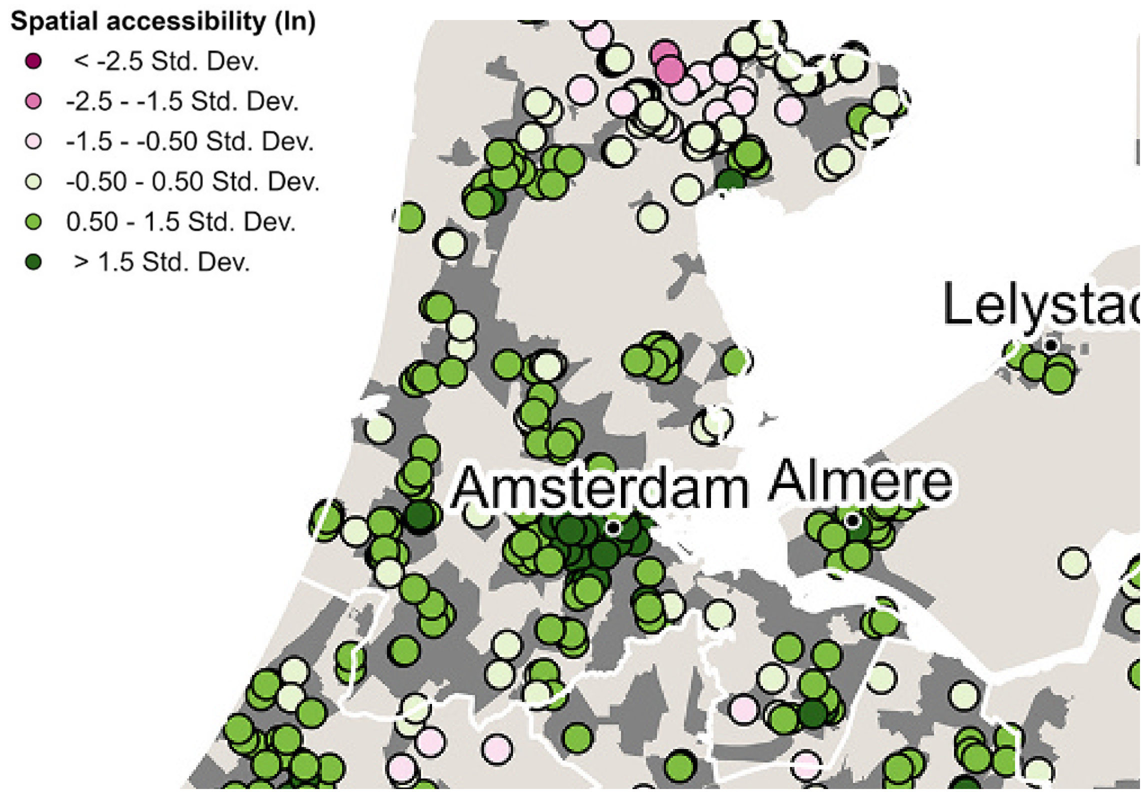
"A common […] ***strategy for understanding transport poverty*** *is to* ***measure and compare the accessibility of*** *these* ***activities*** *for different groups and areas."*

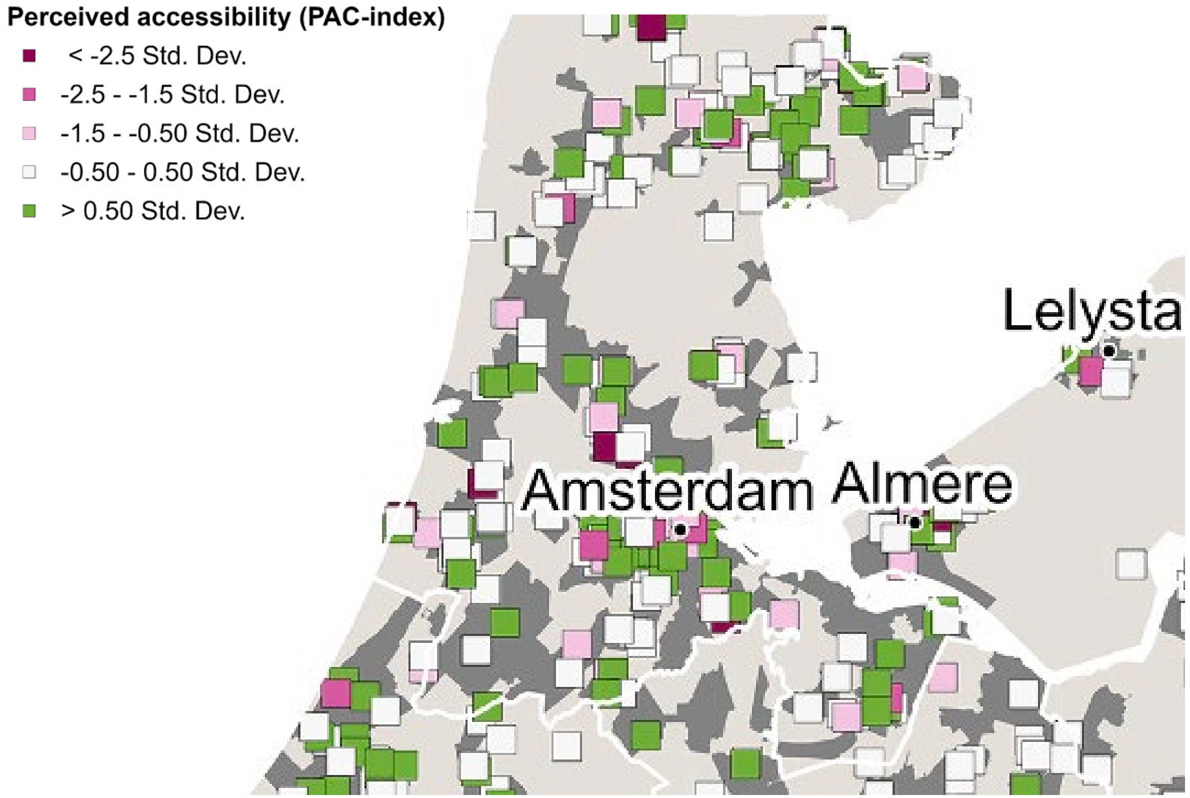
PBL-Rapport TOEGANG VOOR IEDEREEN? Een analyse van de (on)bereikbaarheid van voorzieningen en banen in Nederland
Bastiaanssen en Breedijk, 2022



Source: ZorgkaartNederland; adapted by PBL

Aged 67+: accessibility GP practices per transport mode within 15 minutes travel time, 2021





Perceived accessibility and residential self-selection in the Netherlands
Pot, Koster, Tillema, 2023

Spatial distribution of (a) spatial accessibility and (b) perceived accessibility

… a little round-up

Accessibility analysis for elderly so far …

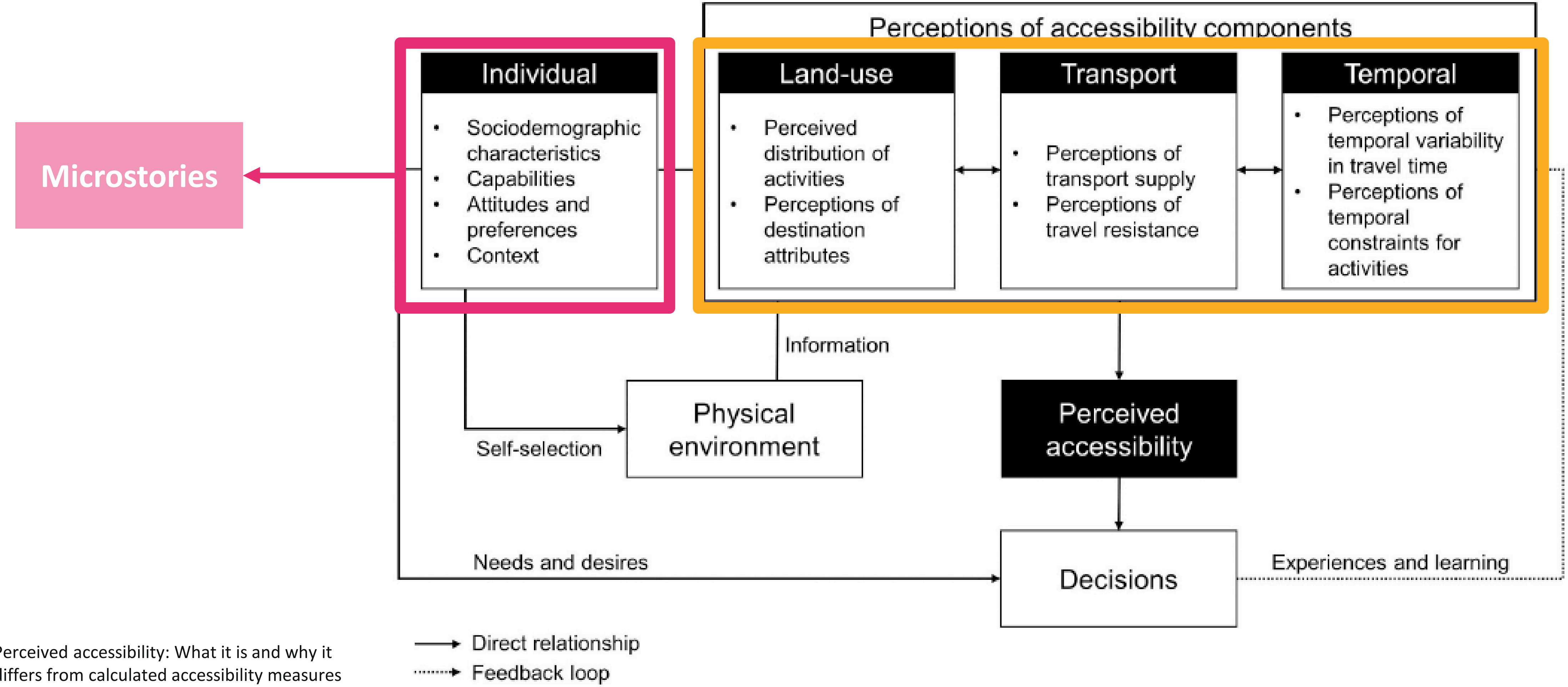
sees elderly as homogeneous group of 65-year-olds and older,

mostly focuses on health care facilities as destinations,

and is inconsistent with thresholds, but almost all of them centre around travel time.

At the same time, **this calculated accessibility** seems to have quite a **mismatch with how people themselves perceive accessibility**

What are we missing when we measure accessibility?



Perceived accessibility: What it is and why it differs from calculated accessibility measures based on spatial data
Pot, Van Wee, Tillema, 2021

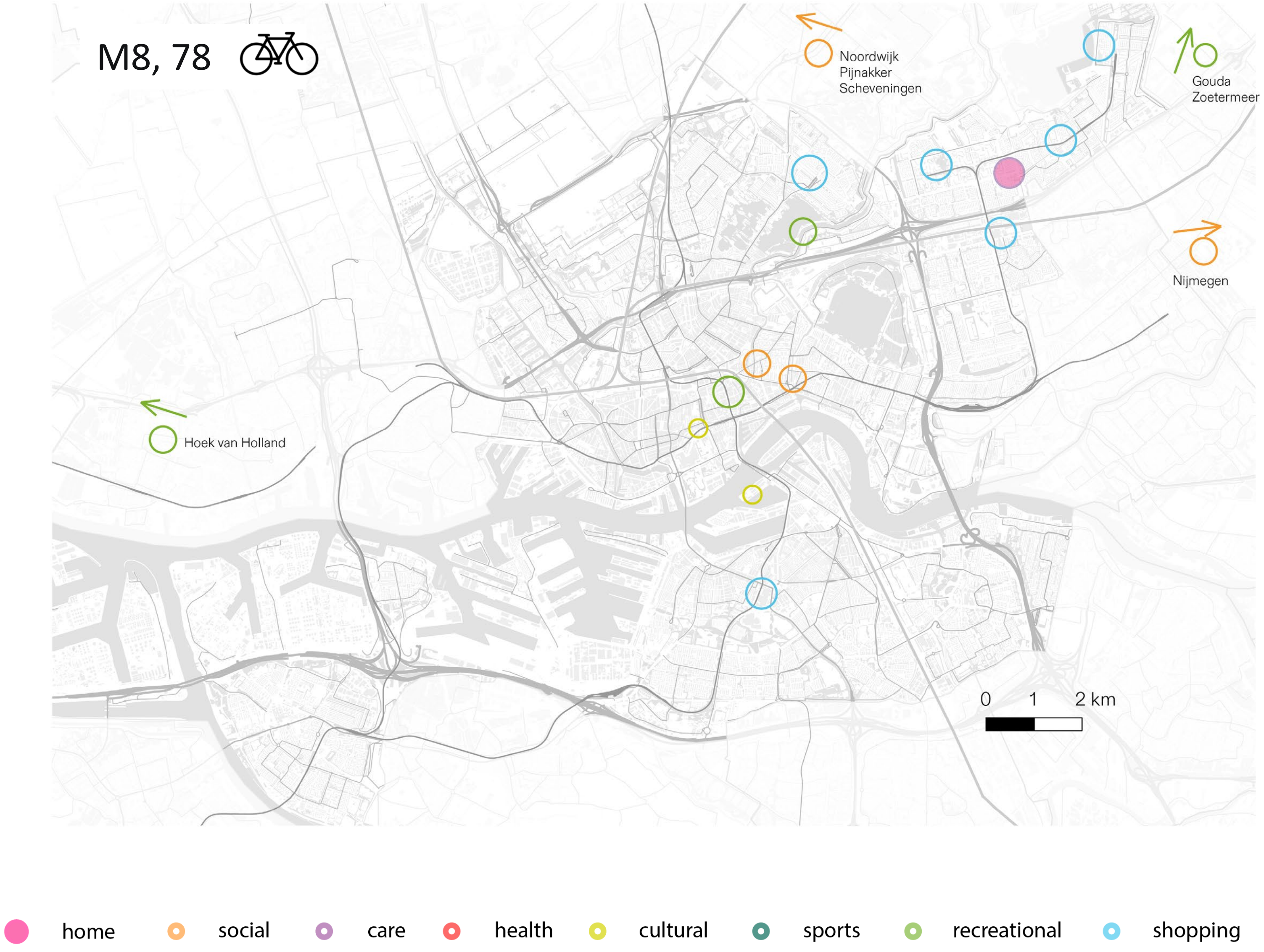
Method

The interviews

Respon-dent	Age	Gender	Partner [a]	Neighborhood	Interview time [m]	Map [b]	Rollator	STS[c]	Private mode available
M1	90	Male	-	Centrum	45	B.1	x	x	-
M2	90	Male	-	Centrum	40	B.2	-	-	-
M3	82	Male	x	Centrum	40	B.3	-	-	-
M4	67	Male	-	Zuidwijk	47	B.4	-	-	Bike
M5	71	Male	x	Hillegersberg	40	B.5	-	-	Bike, Car
M6	71	Male	o	Delfshaven	19	B.6	-	-	Car
M7	91	Male	-	Delfshaven	15	B.7	-	-	-
M8	78	Male	o	Ommord	26	B.8	-	-	Bike
W1	77	Female	-	Oud-Charlois	45	B.9	-	-	Car
W2	69	Female	-	Kralingen	48	B.10	x	o	-
W3	80	Female	-	Centrum	16	B.11	x	x	-
W4	69	Female	-	Centrum	40	B.12	-	-	Shared Car
W5	77	Female	-	Oud-Charlois	29	B.13	x	o	Bike
W7	73	Female	-	Schiebroek	35	B.14	-	-	Bike
W8	83	Female	o	Carnisse	17	B.15	-	-	Bike, Car [d]
W9	72	Female	o	Ommord	20	B.16	-	-	Bike

[a] x - having a partner; o - having and living with a partner
[b] maps can be found in appendix B
[c] x - eligible but no use; o - eligible and using it
[d] as a passenger with partner

Capabilities and barriers



Health as a critical factor:
Declining health can limit mobility and reduce the number of activities an individual can engage in.

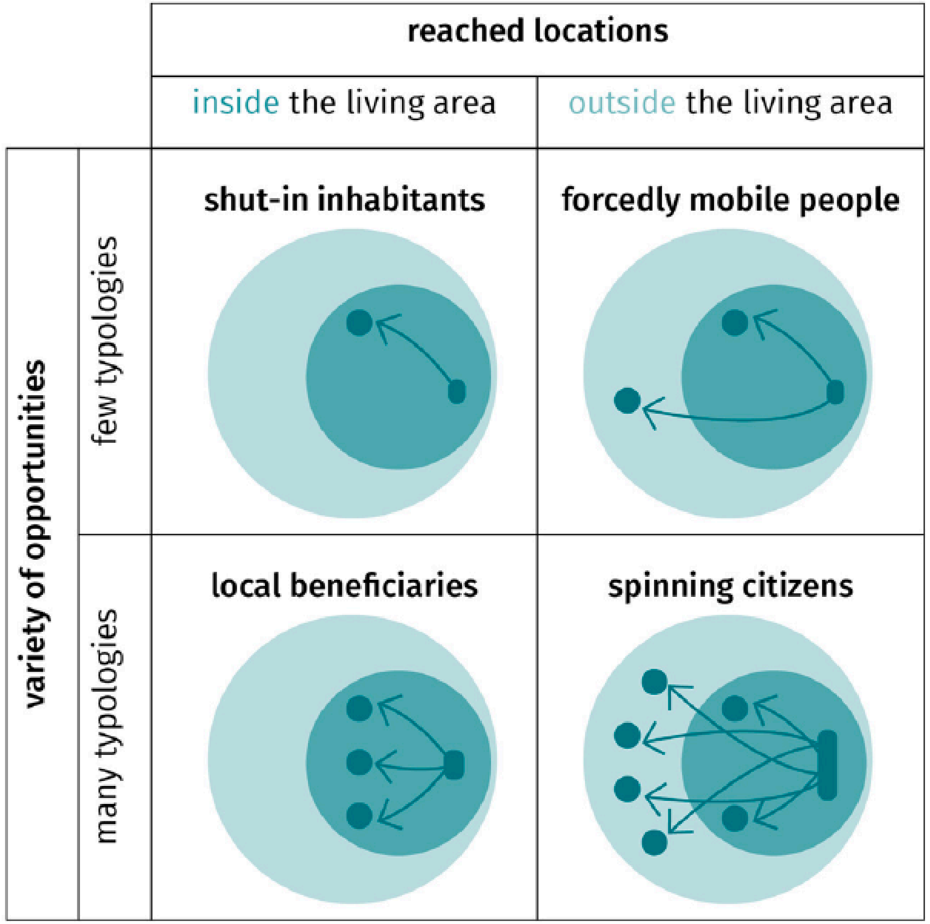
Adaptation:
Elderly individuals often adapt through a reduced number of activities or a smaller movement radius.

Health as a critical factor:
Declining health can limit mobility and reduce the number of activities an individual can engage in.

Adaptation:
Elderly individuals often adapt through a reduced number of activities or a smaller movement radius.

Mobility profiles

Vecchio (2020) in his microstories identified different mobility profiles



Microstories of everyday mobilities and opportunities in Bogotá: A tool for bringing capabilities into urban mobility planning
Vecchio, 2020

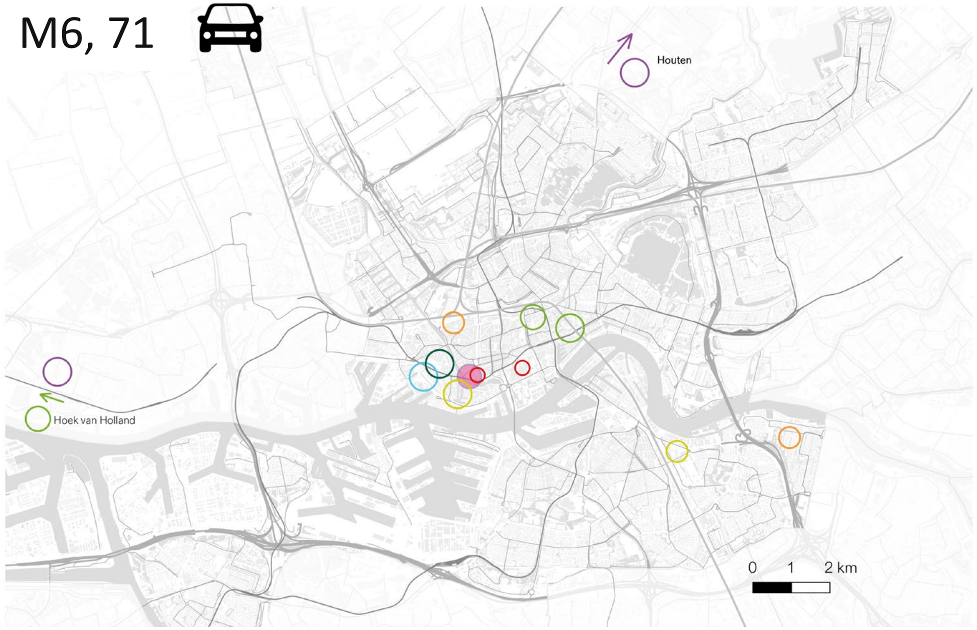
M1, 90

shut in inhabitant - because of age and physical disability

W2, 69

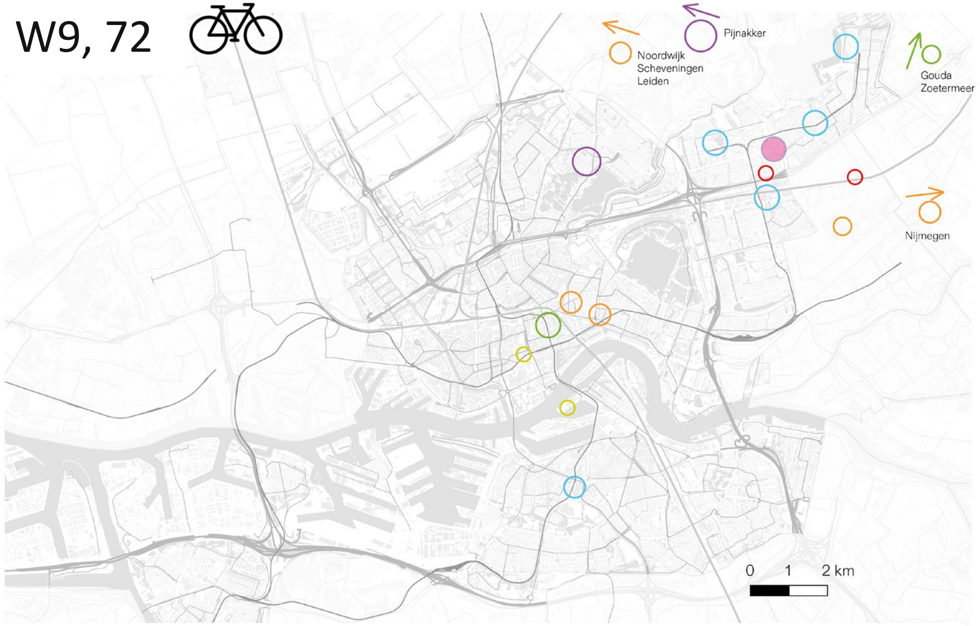
forcedly mobile person (with disability) because of care tasks

M6, 71



local beneficiary living in Delfshaven

W9, 72

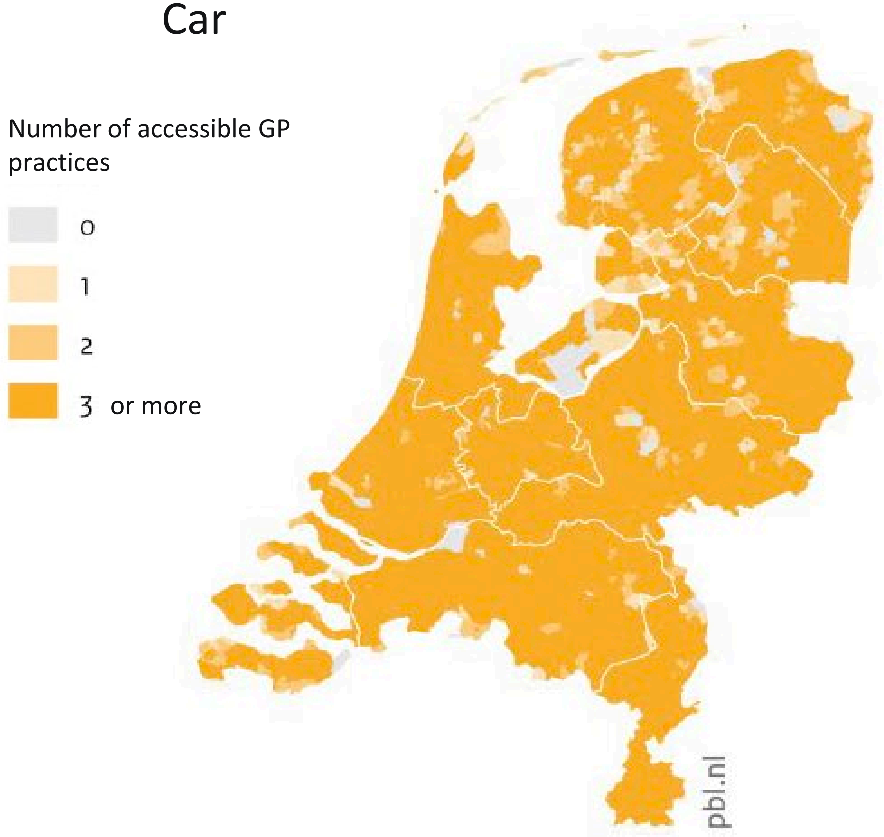


spinning citizen living in Ommord

Policy implications

… does it always make sense to focus on time and health care facilities?

Car



Public transport

Bike

Source: ZorgkaartNederland; adapted by PBL

PBL-Rapport TOEGANG VOOR IEDEREEN? Een analyse van de (on)bereikbaarheid van voorzieningen en banen in Nederland
Bastiaanssen en Breedijk, 2022

Conclusion

Accessibility for urban elderly …

“the elderly” does not exist - diverse capabilities and barriers

Health and predictability are key factors for accessibility capabilities

Categorization by mobility types

THANK YOU!

STUDIO
BEREIKBAAR

TU Delft

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