An activity-based latent class modelling approach to assess the impact of hybrid working on travel demand in the Netherlands after COVID-19

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Short summary

After COVID some employees can continue to work from home or at their work location. This hybrid way of working can impact transport demand and traffic conditions. Current models can not fully capture mobility patterns caused by hybrid working. We developed a dedicated latent class hybrid working model to predict which individuals will choose to WFH and how frequently they will WFH and integrated it into an activity-based model. We illustrate the potential of the model by simulating travel demand in a metropolitan region in the Netherlands. The results show that under some scenarios, hybrid working can reduce mobility demand, but under other scenarios, these gains in work-home travel are lost by additional activities.
Keywords: activity-based, travel demand, hybrid working, latent class

1 Introduction

After the COVID19-pandemic, employees were allowed to continue to work from home partially (WFH) and partially at the office, thus providing a hybrid way of working. However, the level of impact of hybrid working on mobility patterns remains to be fully investigated.
Caldarola & Sorrell (2022) studied hybrid working in England and indicated that it leads to fewer commutes but does not necessarily reduce the distance employees travel. In the United States, the traffic worsened because of cuts in the transit network (resulting in less public transport) during the pandemic (Mack et al. (2021)) and more solo driving. The vehicle kilometres travelled in July 2020 were restored to 104% of pre-COVID levels in NYC (Wang et al. (2021)). A survey conducted in Melbourne, Australia also reported increased car usage post-pandemic (Currie et al. (2021)). In the Netherlands, 27% of hybrid workers are expected to WFH more often in the future, according to a study using the Netherlands Mobility Panel 2020 (de Haas et al. (2020)). A 2020 survey (Men$E$-team (2020)) by the Dutch Ministry of Infrastructure and Water Management shows a similar pattern. Both surveys have shown that people prefer to use cars, bikes and walk than pre-pandemic.
Since hybrid working potentially impacts transport demand and traffic conditions (Beck & Hensher (2022)), it is important to understand its role in mobility patterns. However, current traffic and transport models do not capture the extra activities that employees may do while working from home, which leads to inaccurate mobility assessments and traffic management, which may cause errors in decisions in congestion management and for large infrastructural investments.
Hybrid working may depend on many factors, e.g. the type of work, socio-demographic attributes, living/work locations, and employer's willingness to allow WFH. Since the decision to WFH is largely person-specific, it fits well with the domain of activity-based modelling (ABM), where detailed personal and household data is used to predict the daily activity and travel schedules. The schedule includes the individuals' mobility patterns, where and when they are carried out, and the travel modes.
The study by Cruz (2021) analysed the impact of COVID-19 on travel behaviours and in-home activities using ABM. However, the method used in that study has not yet fully integrated within an ABM and uses aggregated values for activity choices. These may underestimate the impact of hybrid working on people's destination choices, travel patterns and joint activities among household members. A case study by Wang et al. (2021) in New York City, using MATSim (Horni et al. (2016)), captured the preferences of WFH by updating the mode choice utility functions for the synthetic population and the travel schedules are modified to have the suitable WFH ratio based

on Dingel & Neiman (2020) and GTFS (General Transit Feed Specification) data to reflect its effect.
To the best of our knowledge, a dedicated ABM model determining the individual's choice of hybrid working is missing in the literature. In this paper, we fill this gap by initially applying latent class models and segmenting employees regarding their level of hybrid working, using empirical data from the Netherlands Working Conditions Survey (NWCS Hooftman et al. (2020)). The model aims to capture the heterogeneity of individuals and take gender, size of the company, work sector, household income, urbanization degree and age into account when creating latent segments of employees based on their decision to WFH.
Next, we integrate the latent class hybrid working model outputs into an existing ABM framework. The improved ABM model has the capability of evaluating the effect of hybrid working-related mobility patterns. To demonstrate the potential of our hybrid working decision model within ABM, we simulate the potential impact of hybrid working in an illustrative study in the Metropolitan Region Rotterdam The Hague (MRDH) in The Netherlands.
The remainder of this paper is organized as follows: Section 2 explains the construction of the hybrid working model using survey data, section 3 presents the estimation results, and the results of an illustrative example using the ABM model with the integrated hybrid working model. Finally, Section 4 presents the conclusions, discussion, and recommendations for future research.

2 Methodology

The latent class hybrid working model has been developed as an activity-based model (ABM) component. To explain how this model interacts with an ABM framework, we use a specific framework called ActivitySim (Gali et al. (2008)). Using a population synthesizer (Snelder et al. (2021)), the ABM determines individuals' work or school locations, their level of hybrid working, and their daily activity patterns (DAP). Based on this information, the model predicts the number of tours an individual will undertake in a given day and the number of stops in each tour. This includes information about each tour's start time, duration, destinations, and modes. The trip mode chosen at this stage is considered the main mode. Next, our tour-based mode chain choice model determines the access and egress modes to generate a feasible trip mode combination for each tour (Zhou et al. (2023)).

Survey data

Data used to develop the models in this study are taken from NWCS (Hooftman et al. (2020)), a periodic survey carried out jointly by TNO and CBS and focusing on the labour situation among Dutch employees since 2003. It provides information on the working conditions, employability and health of a representative sample of the working population (age range between 15 and 75) in The Netherlands. Since the COVID-19, NWCS surveys added questions, amongst others, about employees' expectations of working from home. The survey from November 2021 has been adopted to reflect better people's opinions on the number of hours WFH at the time of the survey and in the future.
We have filtered out those respondents who did not complete their desired days of WFH in the future (post-pandemic), which resulted in 6359 respondents being used for latent class estimation. The sample distributions of several relevant socio-demographic and work attributes are explored (Figure 1).

Latent Class Cluster Analysis (LCCA)

We used LCCA (Vermunt & Magidson (2004)) to group individuals into different latent classes based on their responses to observed indicators (Molin et al. (2016)), which we call manifest indicators. The goal is to create latent segments based on the available data to maximize the homogeneity within the latent classes and the heterogeneity between clusters. Using the LCCA method, one can predict a probability of a respondent belonging to a particular class. We used Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) criterion, Chi-Squared and Log-likelihood ratio test as indicators to determine the best model fit (Oberski et al. (2013)). Furthermore, the LCCA models can incorporate covariates, which in this case are the socio-demographic characteristics of individuals. These covariates are used as additional predictors of class membership. This is based on the probability of observing a particular sequence of responses,

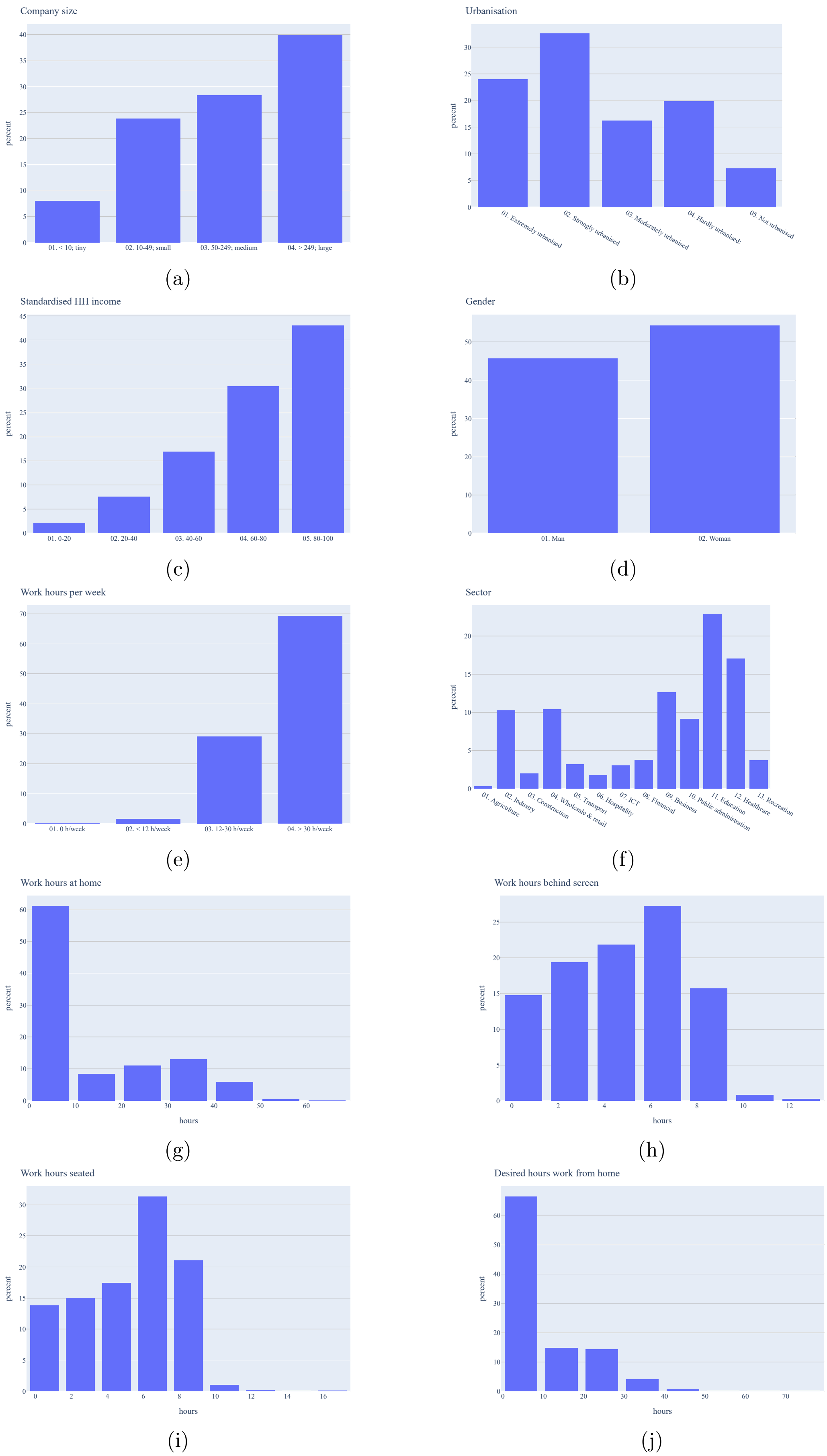

Figure 1: Distribution of several attributes

i.e. the response pattern, on the questions asked from the respondents.
This research is posited on the assumption that various groups exist in the population that have different approaches towards hybrid working, which are determined by working situations, e.g. less active work (such as sitting behind a desk) or being active at work or having the possibility to work at home (or at a distance from the employers' location) and socio-demographic covariates, e.g. age, gender, work sector, household income, urbanization degree and company size, number of contract hours per week or per month etc.

Hybrid working model within ABM

We have integrated a hybrid working component into our ABM framework using the outputs of the LCCA model described in Section 2. The membership likelihood function is used to predict which cluster each employee belongs to. The component also incorporates the probabilities of each hybrid working alternative from the LCCA model outputs and selects an alternative based on these probabilities. Once the hybrid working alternative is determined, the ABM uses a multinomial logit model (MNL) to predict individuals' daily activity pattern (DAP), including mandatory activities such as work or school and non-mandatory, and home activities.

3 Results

First, we show the LCCA results and then present the hybrid working outcomes integrated into the ABM model. We define different levels of hybrid working by the number of hours/week an employee could WFH in four ordinal categories: category 1 is the ones that can not WFH, which we call "No-hybrid". Category 2 is called "light-hybrid" for employees that WFH for less than 16 hours/week, category 3 is called "moderate hybrid", referring to those who WFH for 16 to 24 hours/week and category 4 is called "heavy hybrid" referring to those that WFH more than 24 hours/week.

LCCA model to determine hybrid working latent classes

The LCCA model was estimated from 1 to 6 classes, and based on the statistical criteria of Log-likelihood, BIC and AIC shown in table 1, we conclude that the 4 latent class model gives the best-fit.

Number of Classes	Log-Likelihood	BIC	AIC	Chi-square goodness of fit
1	-29081.89	58268.98	58187.89	32335.57
2	-23157.33	46638.7	46388.67	9335.125
3	-22139.75	44822.48	44403.51	5811.823
4	-21293.41	43348.72	42760.81	3113.202
5	-22576.24	46133.33	45376.47	5726.725
6	-27892.79	56985.37	56059.58	17234.99

Table 1: LCCA model fit statistics, 4 class model is selected

To estimate these LCCA models, we used 4 manifest variables and 6 demographic variables. The manifest variables are 1) the number of hours/week the employees worked at home (at the time of the execution of the survey Nov. 2021), 2) the number of hours/week the employees wished (i.e. desired) to work at home if things went back to normal and if they were able to choose, 3) the number of hours/day the employees worked behind a desk, 4) the number of hours/day the employees worked with a computer, tablet or laptop which had a screen. The socio-demographic variables used as covariates in the model were the following: 1) the size of the company the employee worked for, 2) the urbanisation level of the place of living of the employee, 3) total household income, 4) the number of work hours per week, 5) the sector to which the employee worked for, 6) the gender of the employee.
Figure 2 shows the percentage of employees among different manifest variables per latent class cluster. And Figure 3 shows percentages among different covariates per latent class.

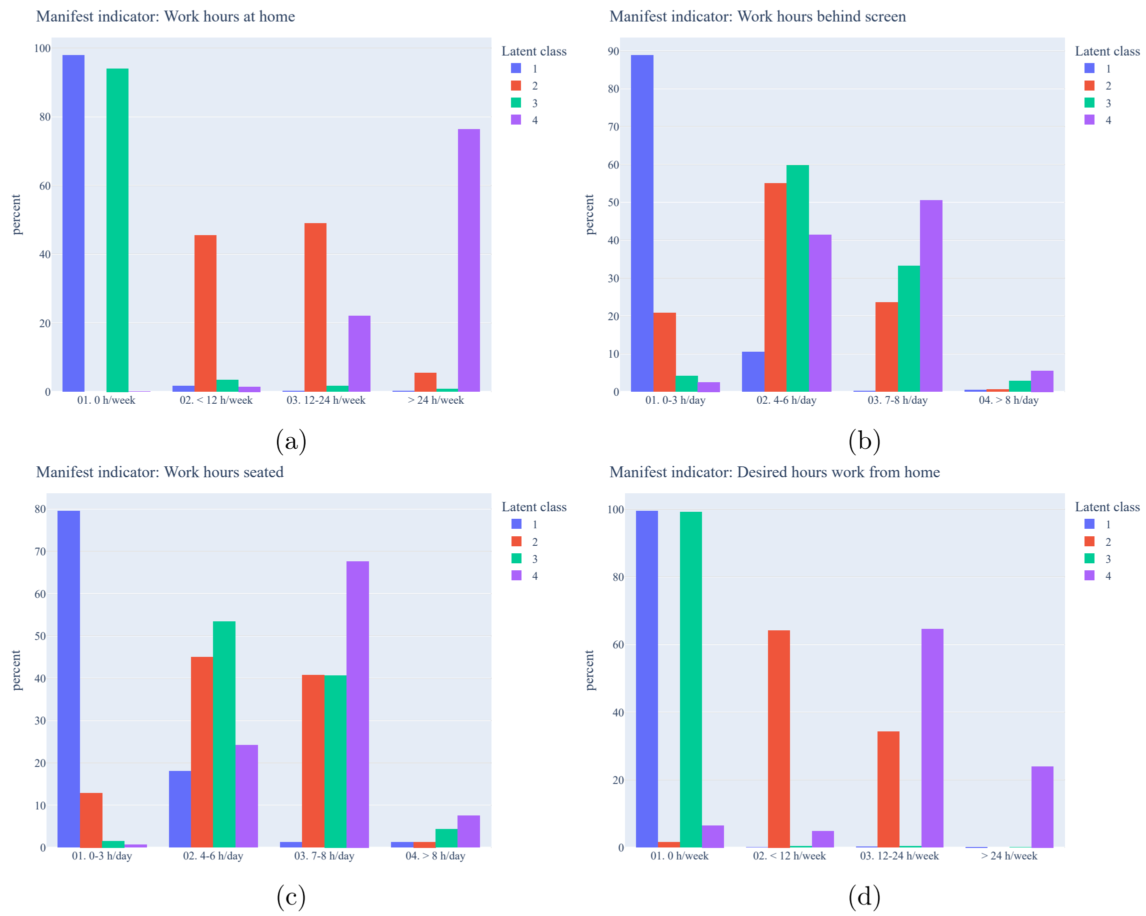

Figure 2: Distribution of manifest indicators of each latent class.

The description of each latent class is derived from the distribution of the manifest variables from figure 2. We see that latent classes 1 and 3 mainly include employees that have not reported WFH and additionally have no intention to WFH. This is mainly due to their work types. However, these 2 classes differ from each other when it comes to working hours behind the screen and seated. Workers of classes 2 and 4 are working +2 days per week from home and intent to keep WFH but slightly less than what they were already doing at the time of the survey (Nov 2021). Table 2 presents more features of each of the 4 classes and descriptions, together with the probabilities of each hybrid-working alternative per latent class.

Illustration example

In this section, we explore whether the hybrid working model leads to different travel behaviour. To do this, we run the entire ABM model for the MRDH region in the year 2022 with the integrated hybrid working component. We chose this year because the hybrid working survey was conducted at the end of 2021, which gives a reasonable prediction for 2022.

Input data

The MRDH region, located in the Netherlands, has an area of about 1130 km^2. The synthesized population of the region of MRDH is generated through a population generator based on data from the Dutch State Statistics (CBS) (Centraal Bureau voor de Statistiek (2020)). This synthesized population consists of 2,387,032 individuals spread over a total of 1,322,202 households. It includes characteristics such as age, vehicle ownership, education level, work sector, company size etc.
The second type of data is the land use from the V-MRDH 2.6 model (Schoorlemmer (2020)). It concerns the land use of 7,011 pre-specified traffic analysis zones (TAZ) in the Netherlands. Of these, 5924 TAZs are within the MRDH; see Figure 4. Each TAZ contains information such as the number of employment places (offices, shops, etc.), the number of education places (i.e., schools), the actual area of the TAZ and its urbanisation level (i.e., the population density), the number of paid and non-paid parking spots and the average hourly parking costs.

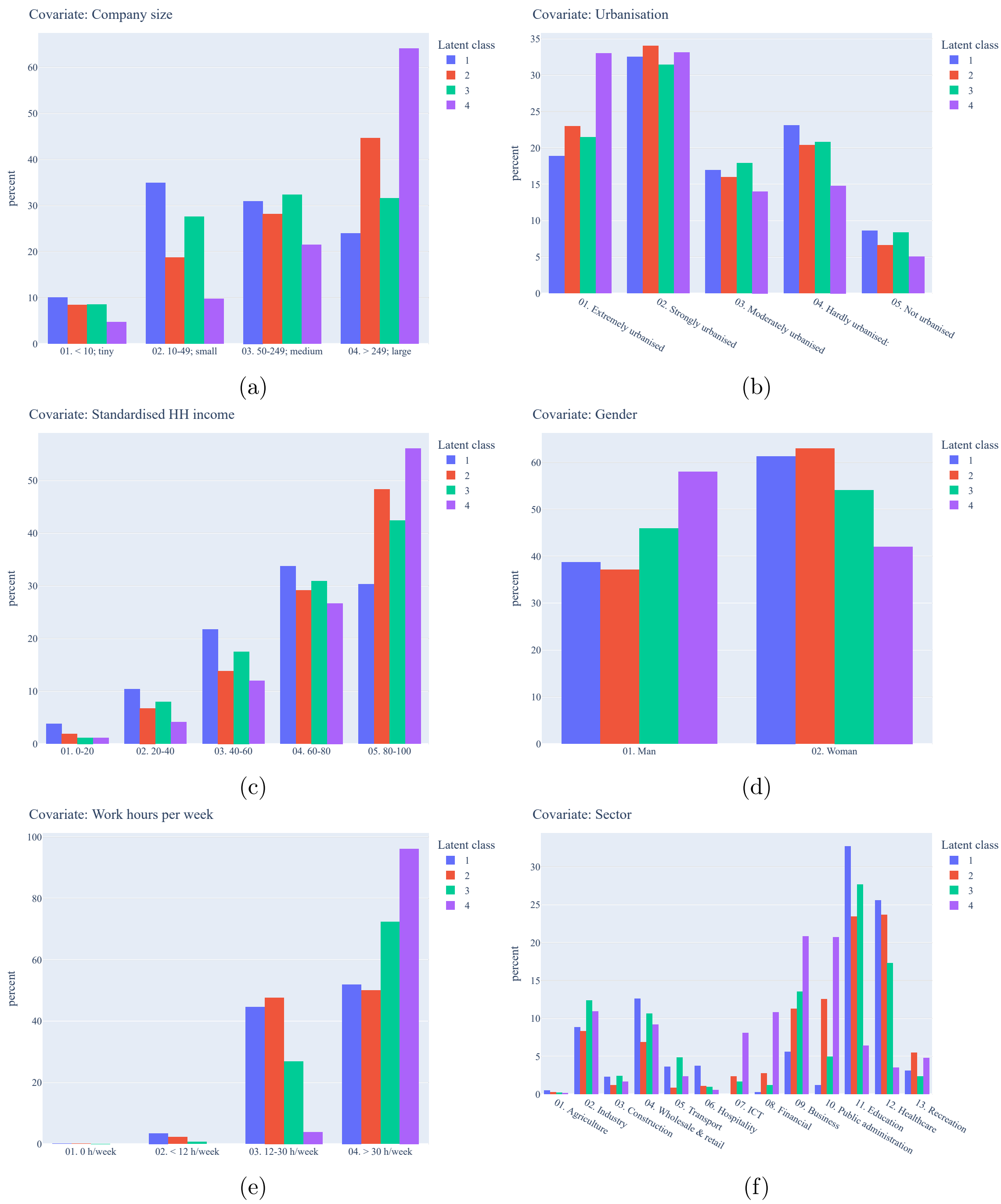

Figure 3: Distribution of covariates of each latent class.

The third type of input data concerns level-of-service data for each pair of TAZ's (origin-destination pair). For each possible pair and each of the seven unimodal travel modes (i.e. walk, bike, ebike, car, car-passenger, demand response transport and public transport (i.e., bus, metro, tram and train) that we consider, we generate travel time, cost, and distance for three different periods over the day (morning peak, evening peak, and off-peak).

Scenario description

The following three scenarios are considered::

1. The first scenario is the "Reference" which assumes that the transport system is not affected by the hybrid working since 2020.
2. The second scenario, "Hybrid working fix", allows people to choose to work sometimes at home and sometimes in the office. In this scenario, we assume that employees stay at home as much as possible and are not further mobile while working.

Class	Description	No-WFH	Light-WFH	Moderate-WFH	Heavy-WFH
1	very limited WFH, mainly working on-site limited screen & sit-work more active work types Female-dominated (61%) working in small to medium companies	99.39%	0.16%	0.27%	0.18%
2	light hybrid workers intention to WFH 2 or 3 days/week; female dominated relatively better-paid jobs in larger companies	4.22%	59.83%	35.95%	0.00%
3	very limited hybrid work mainly screen & sit-work (e.g. administrative) Working in relatively bigger companies	99.25%	0.31%	0.31%	0.12%
4	moderate to heavy WFH high behind screen & sit-work work mainly in large companies; intention to continue WFH $\geq$ 3 days/week male-dominated (58%)	6.02%	5.53%	64.01%	24.44%

Table 2: Description of latent classes and the corresponding probabilities of WFH for each latent class

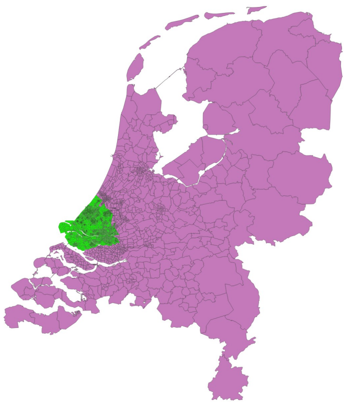

Figure 4: The Netherlands consists of 7011 TAZs, 5924 of which represent the MRDH region.

3. The third scenario, "Hybrid working flex", assumes that people have the flexibility to arrange their working time while WFH. Employees may engage in other activities, such as shopping, picking up children, or walking/cycling, in addition to working from home.

Simulation results

We use the integrated ABM model described in Section 2 to simulate the three scenarios described in the previous section. Table 3 presents the indicators derived from the simulation results of each scenario. Additionally, Figure 5 shows the number of trips per trip purpose, and Figure 6 displays the departure time distribution of all trips.

In both hybrid working scenarios (Table 3), 73% of employees in the study area cannot WFH. This is not surprising, as not all types of work can be done remotely. However, this percentage is higher than the result reported by the NWCS survey (63.1%). This discrepancy could be explained by the fact that the synthesised population in the MRDH area has a lower income, works shorter hours per week, and lives in more densely populated urban areas than the main survey population. These factors may contribute to a higher percentage of people who cannot WFH in the MRDH area. Among those who can WFH, 8.1% choose to work less than 2 days per week, while 14.8% would like to WFH 2 or 3 days. Only 4.1% of employees would like to WFH more than 3 days per week.

In scenario 2, we saw on average a 3% decrease in the number of trips per person in a day. This decrease is expected because in this scenario we assumed people who WFH do not further adjust

Indicators	Reference	Hybrid Working Fix (% change w.r.t. reference)	Hybrid Working Flex (% change w.r.t. reference)
Hybrid working		no hybrid: 73% light hybrid: 8.1% moderate hybrid: 14.8% heavy hybrid: 4.1%	(The same as the 'Fix' scenario)
Tours p.p	1.132	1.096 (-3.2%)	1.138 (0.5%)
Trips p.p.	2.795	2.709 (-3.1%)	2.808 (0.5%)
Total trips	6,672,069	6,465,695 (-3.1%)	6,703,805 (0.5%)
Car kilometer traveled(million km)	15.962	15.495 (-2.93%)	15.912 (-0.3%)

Table 3: Indicators

their activity patterns. This reduction in trips leads to a significant decrease of 2.93% in the total car travel distance. However, there is no remarkable difference in the distribution of the departure time of the trips(Figure 6), which is not surprising since employees who do not work at home do not adjust their departure time in the model.
In scenario 3, employees still make fewer work-home trips but more other tours/trips, especially for groceries, visiting doctors (Figure 5) as they are more flexible during working hours. The total car travelled distance is higher than scenario 2 (see Table 3), which is justifyable since people may make non-work tours/trips during their work hours instead of staying home. However, it is still lower than that of the reference scenario, which can be explained by the fact that the non-work activity destinations are closer to their homes. The departure time shifts slightly towards off-peak hours since more non-work trips are made.
Overall, we conclude that the integrated ABM provides insights into the changes in travel behaviour.

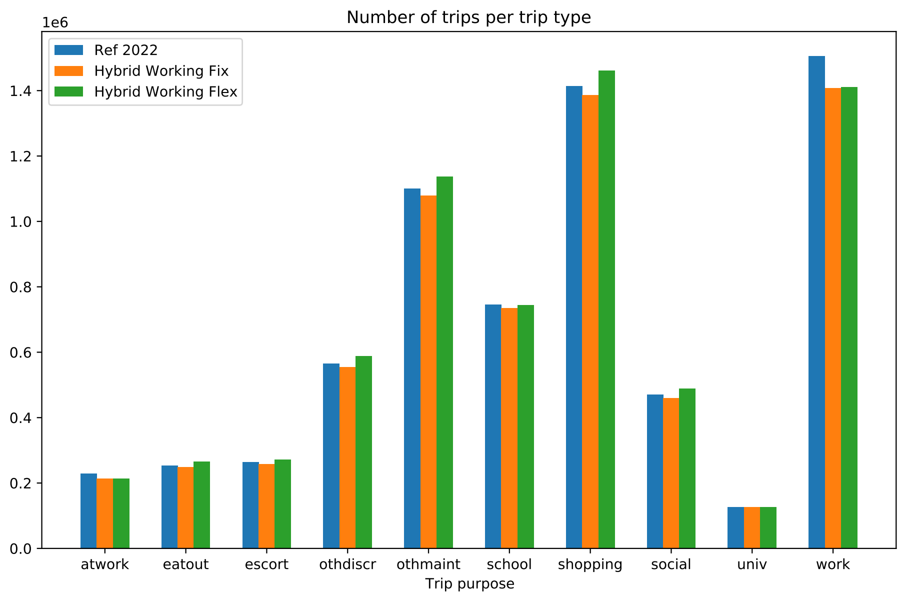

Figure 5: Number of trips per trip purpose

4 Conclusions and discussion

In this study, we used empirical data to develop latent class clusters of employees based on their hybrid working levels. Our analysis showed that several factors, such as company size, urban area type, household income, weekly working hours, work sectors, and gender, play a crucial role in people's choice of hybrid working. The developed hybrid working model was then integrated into

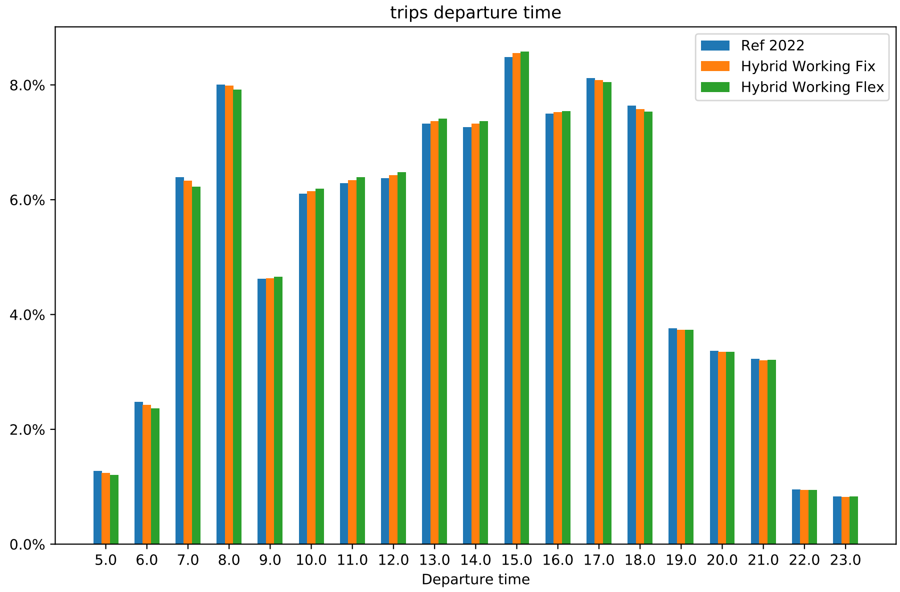

Figure 6: Distribution of trip departure time

an ABM framework and applied to a synthesised population of the MRDH region. In the scenario where we assumed employees do not further travel during the day while they WFH, we saw a 2.93% reduction in car travel distance. We conclude that hybrid working has the potential to reduce the total travel demand. And policies regarding the departure time, especially during peak hours, could be explored to make further improvements on the travel demand.

In the scenario in which people who WFH are allowed to be flexible in doing other activities, the car travel distance is hardly reduced, because of an increase in shopping and other maintenance trips due to hybrid working. We conclude that this way of hybrid working (i.e. scenario 3) could positively and negatively affect travel demand. On the one hand, fewer work trips could reduce traffic congestion during peak hours. On the other hand, more non-work trips could increase overall travel demand, increasing traffic congestion during off-peak hours.

As the trend towards hybrid working is expected to continue, it is important to develop better models to evaluate its impact on cities and urban areas and inform policy decisions. In this regard, we recommend that future research focuses on calibrating the mode choices while accounting for hybrid working. Such updates could provide a more accurate representation of the impact of hybrid working. In addition, we recommend surveys to add questions about employees' mobility patterns while they work at home. Including this information in the model can increase the accuracy of the whole ABM model.

Notably, there is no significant difference in the distribution of departure times of trips. This could imply that travellers not working from home are not adjusting their departure times, which could be a potential area for further exploration in future studies.

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