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Modeling travel demand for dorm and non-dorm university students

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Abstract

This study presents a modeling approach for estimating travel demand at Hasselt University (Flanders, Belgium), where student residence patterns and sociodemographic characteristics play a crucial role. Travel mode choice models based on the Flemish household travel survey are combined with 2023 and 2025 GTFS datasets in order to assess how different public transport services influence student mobility patterns. Results show a slight difference in the mode shares which can have been caused by the use of stochastic processes. On the other hand, model results show clear behavioral differences between dorm and non-dorm students. Residential proximity significantly shifts preferences toward active modes, especially cycling and walking.

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Keywords: simulation; travel demand modelling; city scale; travel plan

1. Introduction - Aim

Applied research in transportation often relates to small study areas where city-scale models need to be deployed. Much effort is required to collect data that sufficiently describes the particular properties of the study area. This induces the need to apply project specific models which may make data preparation cumbersome and time consuming. Nationwide statistics are insufficient; they need to be augmented by locally relevant data. Such data can be retrieved in part by *web scraping* which is not sustainable for long term research because the structure and presentation formats on websites frequently change.

This paper describes which datasets and simulation models are used to estimate the travel demand generated by students of Hasselt University (UHasselt). Hasselt is a fairly small city containing two main education campuses hosting the university, two university colleges and several secondary schools (12 to 17 year old students). Parking is a problem at each campus. A relatively large fraction of the travel demand in the Hasselt region emerges from students, teachers and other university personnel (numbers for the year 2025: 8195 students, 740 PhD students, 1855 staff members. Source: <https://www.uhasselt.be/en/about-hasselt-university/facts-and-figures>).

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New facilities for (intercity and local) public transportation are under construction. Parking tariffs have been reformed and parking space is moved to the city border. In this context travel mode shares are estimated. We are interested in the timing and modal choice for trips from/to the respective campuses.

The following specific terms are used throughout the text:

specialization Identifies a specific type of diploma e.g. *Mathematics*

degree Identifies a subset of a specialisation e.g. *Bachelor Mathematics*

grade Identifies a study year in a degree e.g. *3-rd Bachelor Mathematics*

2. Related work

In [1] the number of daily trips to the Aristotle University in Thessaloniki campus generated by each faculty is assumed to be proportional to the number of students in the faculty. A simple linear regression based model on survey of 1% of students is used. The average number of daily trips for each student and employee is found to equal 2.26. Students seem to remain on campus for the full day. In addition, a model is presented to estimate the distribution of arrivals and departures over time-of-day. However, the paper does not explain neither the training data nor the training method.

[5] determine probability weight functions for the number of daily trips using particular modes by students at Old Dominion University in Virginia, US. The distance between the residence and the university is taken into account by considering on-campus, near-to-campus and farther-from-campus categories. Travel duration is ignored. The daily trip numbers are high (on-campus students: 6.24, near-campus: 5.34 farther-from-campus: 4.96) since walk between buildings on-campus was accounted for. Trip frequency is modelled by Poisson and negative binomial regression. ZIP (zero inflated Poisson) is used: first a binary logit determines whether making no trip is almost certain, then the number of trips is determined for other observations using the Poisson model. The residence situation (19% of students live on-campus, 15% live near-campus, 66% farther from campus) resembles the Hasselt situation. The authors do not consider the distribution over time-of-day.

Interestingly, [2] find that in Tehran students residing on campus perform less *activities* than off-campus students while [5] conclude for Old Dominion University in Virginia (US) that on-campus students do perform more *trips*. This may be due to different ways of counting and subtle differences in definitions.

The problem of dorm selection for a group of students is considered in [4]. Each student can belong to at most one group and a group contains at least one student. Groups are formed by the students. The group submits a ranking of a subset of preferred dorms. The paper first describes the admission criteria for individual students to dorms at Technion, Israel. The housing department considers groups as a whole considering the *merit* score and the *credit* score as aggregate group properties. All dormitories are assumed to consider a common ranking based on credit scores. The authors prove that a stable matching of student-groups to dormitories, does exist. The stated mathematically interesting *group assignment* problem is applicable only in very specific situations (not suited to our purposes).

In [6] a comprehensive activity based travel demand model is developed based on survey data from 336 dormitory students. As an important feature the authors include the effects of class schedule, friends and roommates activities and indoor dormitory activities. A comprehensive 2-page questionnaire focusing on typical student activities (inside and outside of dorms), information on past and future exams and information about *supporting activities by friends* (e.g. shopping) is collected. The study area is Qazvin, Iran hosting 2500 students. The model consists of a sequence of 12 choice models in an hierarchy: up to two tours, each containing at most two activities. The mode for the trips in tours are determined by different choice models. The model choice order is: trip start time, duration, travel mode, travel destination. Standard and mixed logit models are used at each level in the model hierarchy. The best performing model is retained for each level resulting in an effective combination of submodels of several kinds. No synthetic population was generated: hence it is not possible to assess the effect of students on e.g. parking.

The effect of changes in *courses time-tables* on campus parking demand is investigated in [7]. The authors focus on (i) correlations between courses time tables and parking occupation, (ii) regression analyses to predict parking demand from time tables and (iii) optimization of courses time-tables in order to spread parking demand over time. Datasets used are: (i) course enrollment, (ii) facility information and (iii) campus parking lot survey. The authors do not assume

that students leave immediately after the courses. They use previously determined trip chaining patterns to decide how much time students spend on campus before and after courses (k-hours). The correlation between enrollment (number of students to be present on campus) and occupation of the student parkings peaks for $k=2$. For faculty staff parkings the correlation peaks for $k=4.5$ hours. Student and staff (linear) parking demand prediction models show high R^2 values (0.9897 and 0.9280 resp.). Finally, the classical constraints (room size, course duration, teacher availability, ...) in a course scheduling system are augmented by the predicted parking requirement to find a time-table that minimizes parking requirement peaks. The research applies to the University of Louisville, Kentucky, US (offered 3,032 courses, with a total course enrollment of 74,248 in the Fall Semester of 2016).

Most papers report on research that makes use of travel surveys to predict either the number of trips by students or a complete activity based demand model.

Our project constructs a synthetic student population using publicly available registration data by particular *degree*. Study-related activities and classroom locations are extracted from student rosters. We use the OVG¹ household travel survey records for students to build a mode choice model. For each student, a residence location is sampled and the travel mode for campus trips is predicted. The aim is to investigate how changes in two GTFS datasets affect students' mode choice, as well as how travel behavior differs between dormitory and non-dormitory students.

3. Data sources

The following main data sources have been used.

GTFS, OSM	Timetables for bus and train, road network to determine travel duration.
OVG	Household travel survey of which the subset of students is used to train a mode choice model.
FlemishStudRegister	Registrations of students in higher education (includes home municipality, domicile): this is an aggregated dataset published by the Flemish Government that lists for each (student domicile, home residence) municipality and each university the number of students registered by <i>degree</i> .
UnivRosters	Rosters published by the university: specify for each <i>level</i> the events (courses, lab sessions, excursions) to be attended by the students.
UnivRooms	List of university rooms: each room is mapped to a building and each building is mapped to (i) a campus, (ii) to the coordinates for the building main entrance and (iii) to a set of nearby parking lots.
StudentGroup	Set of students attending a particular course. In most cases such group is identified by the name of a course and the student <i>level</i> (e.g. "1-st Master Transportation Science".)
ResidAddresses	Dataset of residential addresses extracted from Flemish public data ²
StudentRooms	List of dorms (student rooms) specifying the street address, capacity and coordinates: taken from https://www.kotatlimburg.be/ik-zoek-een-kot/
UHasselt Data	The fraction of <i>dorm students</i> (residing in a student room) is only 0.3 (source: UHasselt student administration)

4. Components of the simulation

All results are determined for the roster of a particular date (e.g. 2025_Feb_17) because they heavily depend on UnivRosters and on GTFS timetables.

¹ <https://www.vlaanderen.be/mobiliteit-en-openbare-werken/onderzoek-verplaatsingsgedrag-vlaanderen-ovg/onderzoek-verplaatsingsgedrag-vlaanderen-5-2015-2020>

² <https://opendata.bosa.be/download/best/openaddress-bevlg.zip>

4.1. Student group size - Student events timing and locations

The size of each StudentGroup is estimated from the FlemishStudRegister and the UnivRosters. Each UnivRosters item holds for a *grade* while FlemishStudRegister specifies numbers for *degrees*. A mapping (function) from *grade* to *degree* is established by enumeration and each ordered pair $\langle grade, degree \rangle$ is assigned a weight that specifies how individuals in a *degree* are distributed over the *grades*.

Each UnivRosters item specifies the *room* and the *teacher* as well as the *start* and *end* times for the event the students are expected to attend.

Each room maps to a building specification tuple $\langle identifier, campus, coordinatePair \rangle$. Each campus is mapped to a set of nearby parking lots.

4.2. Individual student residence

1. The FlemishStudRegister specifies the student's home municipality. The home address (where the student is domiciled) is sampled from a dataset of residential addresses. This dataset was created by downloading street addresses and coordinates from <https://opendata.bosa.be/download/best/openaddress-bevlg.zip>. Each address was labeled by a set of tags extracted from the corresponding label in OSM (OpenStreetmap). Residential addresses were used to sample home addresses.
2. In the *dorm decision* model, 30% of students are selected to reside in student dormitories. The number of dorm students was supplied by the student administration office. The probability of becoming a dorm resident is modelled as a function of the travel time by public transport between the student's registered domicile and their assigned campus. Students' registered domicile coordinates correspond to their sampled registered residential addresses. Campus locations are derived from the UnivRosters: each student is associated with a specific classroom, and these classroom identifiers allow us to determine the student's primary campus. Although students register with their family residence as their official address, many relocate when they begin their university studies. A substantial proportion choose to live in dormitories closer to the university to benefit from improved accessibility and shorter commute times. Others prefer dormitory housing for reasons related to independence from family or to participate more actively in campus activities and student life.

For this model, the origin coordinates correspond to students' registered residential addresses, while the destination coordinates represent their assigned campuses. Travel times by public transport between these two points were computed using the GraphHopper routing engine. These travel times serve as the key explanatory variable in the dormitory choice model, which is specified as a binary logit model distinguishing between dorm and non-dorm students. To estimate the parameters of this model, we impose the constraint that approximately 30% of students should be assigned to dormitories. Based on an assumption, a travel time threshold of 2000 seconds (0.55 hr) is associated with a dorm-residence probability of 0.01. Using these conditions, we obtain an alternative specific constant (ASC) and a travel time coefficient of -6.96 and 4.27, respectively. The estimated parameters confirm the expected relationship: as public transport travel time between a student's registered home address and their campus increases, the likelihood that the student chooses to live in a dormitory also increases. Figure 1 illustrates the spatial distribution of Hasselt University students across the Flemish region. Green points represent the domicile addresses for students who moved to a dormitory, whereas red points indicate those who remained at their registered residential addresses.

3. The *student to dorm* allocation model selects a dorm for each dorm student by means of a probabilistic gravity model where the main campus for the student acts an attractor. The *attractivity* is proportional to $1/D^2$ with D the euclidean distance between campus and dorm. The allocation procedure is constrained by the dorm *capacity*. The spatial distribution of dormitories in Hasselt city (StudentRooms dataset) suggests that they are situated near university campuses. For each dormitory, the capacity is defined as the number of rooms, and we assume that each room is assigned to a single student. Consequently, if the number of students exceeds the total capacity of all dorms we apply over-sampling (assigning multiple students to a room). Students are processed

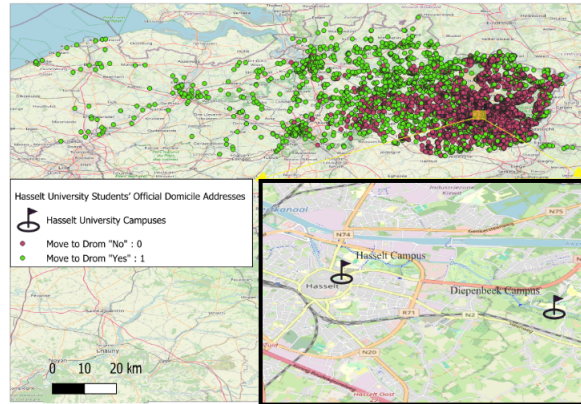


Fig. 1. Hasselt Students Spatial Distribution (Home addresses)

sequentially. Due to the use of a capacity retrained method this results in *first-come-first-serve* process. Therefore, the student set is initially shuffled. Figure 2 shows the final distribution of Hasselt University students after allocating 30% of the students to dorms.

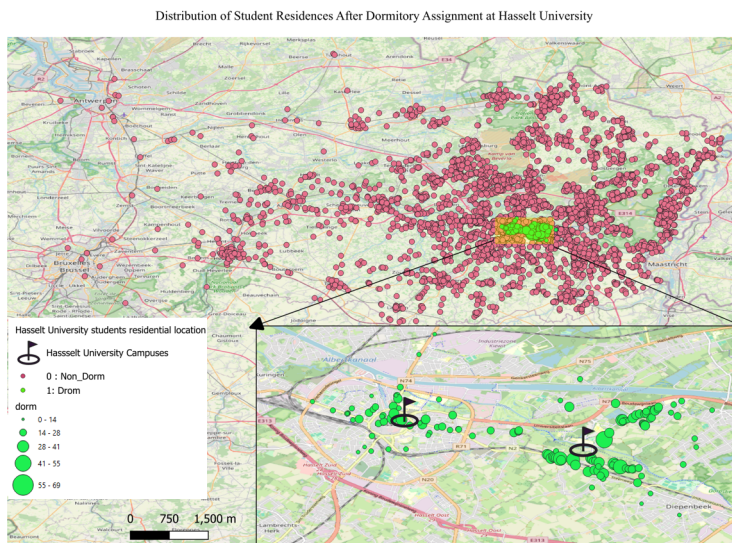


Fig. 2. Final distribution of Hasselt University students after allocating 30% of the students to dorms. Pink: Home residence non-dorm student. Green: dorm location..

4.3. Student travel mode choice

Data for this study were obtained from the (*Onderzoek Verplaatsingsgedrag Vlaanderen*) OVG household travel survey covering residents of Flanders, Belgium. The dataset comprises 34,380 trips, each accompanied by approximate origin coordinates, destination coordinates, and socio-demographic characteristics. These data provide the basis for modeling individual travel behavior.

The study focuses on modeling students' travel mode choices. For each student, a mode was predicted from five alternatives: (1) car (driver), (2) car passenger, (3) public transport, (4) walking, and (5) cycling.

The probability of selecting a particular mode is modeled using a multinomial logit model, and the model parameters were estimated using Python, Biogeme. The utility of each travel mode is a function of travel-related attributes and socio-demographic characteristics. Travel-related attributes include travel time per mode, calculated individually for each student from their domicile residence for non-dorm students and from dorm locations to campus for dorm students, using the GraphHopper routing engine. Socio-demographic attributes shown in Table 1 incorporated into the utility of each mode include (1) gender, (2) driver license possession, (3) personal status, and (4) living status.

These variables allow the model to capture heterogeneity in mode preferences across different student profiles. For car travel time, we determined for each student the most visited building from the rosters, and for each building, we know the parking locations used by students and staff. Therefore, the total car travel time is defined as the in-vehicle travel time from the origin to the selected parking location, plus the egress time from the parking location to the building. The egress travel time may be covered by walking or by public transport (duration evaluated by means of GraphHopper).

$$\text{car}_{i,c} = T_{i,p(c)}^{\text{drive}} + T_{p(c),c}^{\text{egress}} \quad (1)$$

$$T_{p(c),c}^{\text{egress}} = \min(T_{p(c),c}^{\text{walk}}, T_{p(c),c}^{\text{PT}}) \quad (2)$$

- $T_{i,c}^{\text{car}}$ = Total car travel time for student i to campus c ,
 $T_{i,p(c)}^{\text{drive}}$ = Driving time from origin i to parking point $p(c)$,
 $T_{p(c),c}^{\text{egress}}$ = Egress time from parking $p(c)$ to campus c ,
 $T_{p(c),c}^{\text{walk}}$ = Walking time from parking to campus,
 $T_{p(c),c}^{\text{PT}}$ = Public transport time from parking to campus.

In this research two different GTFS datasets were incorporated: the 2025 GTFS (current schedule) and the 2023 GTFS. The intention behind using two datasets is to examine how changes in public transport supply influence students' mode choice decisions. By comparing these datasets, the model can capture the extent to which improvements or modifications in the transit network affect accessibility and, consequently, travel behavior.

Table 1. Attributes and Levels in the Travel Mode Choice Model

Attribute	Description / Levels
Travel time	travel time from origin to campus
Gender	Male / Female (<i>Reference</i>)
License possession	Yes / No (<i>Reference</i>)
Living status	<ul style="list-style-type: none"> • Living alone (<i>Reference</i>) • I live without a partner, with children • I live with my parents in a single-parent family • I live with my parents in a two-parent family • Not living alone (in a private household) • Cohabiting partners
Personal status	<ul style="list-style-type: none"> • Student • Other • Unemployed • Pensioner • Employed (<i>Reference</i>)

5. Results

Table 2, The estimated choice model is based on the OVG dataset which is applied here to predict the mode choice behavior of students. [3] stated that values of McFadden R^2 between 0.2 and 0.4 reflect extremely a good model fit, the estimated mode has $R^2 = 0.39$. Furthermore, the Bayesian Information Criterion (BIC) suggests that the selected model is the best of all runs of the models we tried, such that the lower BIC value implies a better fit model. The model demonstrates highly significant alternative-specific constants (ASCs) for all modes. Travel time coefficients are negative and highly significant across all modes, confirming that longer travel durations decrease the likelihood of choosing any option. Being male increases the probability of choosing a bicycle +0.279 and a car +0.302, while reducing the likelihood of choosing car passenger –1.05 and public transport –0.181. The presence of a driving license strongly shifts preferences toward car use +4.42, making it one of the most influential parameters in the model. Student status itself significantly affects choices: being a student increases the utility of cycling +0.0524 and public transport +0.465, while strongly discouraging car use –1.51. Other personal-status categories (e.g., employed, unemployed) do not affect the results in this application because the model is applied specifically to students, and therefore, all individuals share the same student status. Individuals from two-parent families have a higher preference for car and car-passenger modes compared with the reference category of living alone.

We used the parameters of this model to predict student mode choices for two different \GTFSdatasets, representing public transport conditions on 2023_December_04 and 2025_November_17. Our objective was to investigate how improvements in the public transport system influence student mode shares. As shown in Figure 3, the public transport share slightly decreases from 28.5% in 2023 to 27.55% in 2025, a reduction of only 1.05 percentage points. The overall mode pattern also shows only minor changes between the two model runs. Given the small magnitude of this difference, it is difficult to conclusively attribute any change to the public transport supply. It is important to note that mode choice depends partly on a stochastic term, and the observed variation may instead arise from random fluctuations in this stochastic component. To investigate this further, one could run the model multiple times with different random seeds to assess the robustness of the results. This analysis was beyond the scope of the current paper but could be explored in future work.

Figure 4 and Figure 5 illustrate clear distinctions in mode choice patterns between non-dorm and dorm students, reflecting the influence of residential location on campus mobility behavior. Among non-dorm students, motorized modes dominate: public transport 32.77%, car passenger, 26.48%, and car as driver 20.81%. Active modes such as walking and cycling each represent less than 20%, highlighting the long travel distances associated with off-campus residence. In contrast, dorm students who reside near the university campus exhibit a significantly different modal structure. Bike emerges as the most chosen mode 31.64%, followed by walking 24.29%, car as driver 17.89% and PT 16.05%, while a car passenger is comparatively low. These patterns suggest that proximity to campus encourages the adoption of active modes, particularly cycling and walking, while substantially reducing reliance on vehicles.

Table 2: Mode Choice Specific Parameters

Attribute	Value	Std.Err	t-test	p-value
ASC_BIKE2	2.59	0.176	14.7	0
ASC_CARP6	2.12	0.174	12.2	0
ASC_PT7	2.52	0.181	13.9	0
ASC_WALK1	3.11	0.182	17.1	0
b_dur_bicycle	-0.0532	0.00449	-11.8	0
b_dur_car	-0.0599	0.00584	-10.3	0
b_dur_carp	-0.0416	0.00566	-7.34	2.20e ⁻¹³
b_dur_foot	-0.0153	0.00202	-7.55	4.26e ⁻¹⁴
b_dur_pt	-0.0146	0.00221	-6.62	3.53e ⁻¹¹
b_driv_license_yes_bike	0.482	0.0744	6.48	9.19e ⁻¹¹
b_driv_license_yes_car	4.42	0.162	27.2	0
b_driv_license_yes_carp	-0.0588	0.0692	-0.85	0.395

Continued on next page...

Table 2 – Continued

Attribute	Value	Std.Err	t-test	p-value
b_driv_license_yes_pt	-0.580	0.0828	-7.00	2.58e ⁻¹²
b_male_yes_bike	0.279	0.0558	5.00	5.86e ⁻⁰⁷
b_male_yes_car	0.302	0.0463	6.52	7.07e ⁻¹¹
b_male_yes_carp	-1.05	0.0599	-17.5	0
b_male_yes_pt	-0.181	0.0746	-2.43	0.0153
b_student_bike	0.0524	0.157	0.333	0.739
b_student_car	-1.51	0.145	-10.4	0
b_student_carp	-0.766	0.167	-4.60	4.21e ⁻⁰⁶
b_student_pt	0.465	0.178	2.61	0.00894
b_other_bike	-0.234	0.120	-1.95	0.0512
b_other_car	-0.614	0.0988	-6.21	5.17e ⁻¹⁰
b_other_carp	0.0443	0.108	0.411	0.681
b_other_pt	-0.182	0.157	-1.16	0.247
b_Unemployed_bike	-0.393	0.136	-2.90	0.00373
b_Unemployed_car	-0.889	0.113	-7.83	4.88e ⁻¹⁵
b_Unemployed_carp	-0.249	0.135	-1.84	0.0659
b_Unemployed_pt	0.196	0.152	1.29	0.196
b_Pensioner_bike	-0.264	0.063	-4.19	2.84e ⁻⁰⁵
b_Pensioner_car	-0.697	0.0519	-13.4	0
b_Pensioner_carp	0.208	0.0626	3.32	0.000904
b_Pensioner_pt	-0.501	0.0889	-5.63	1.79e ⁻⁰⁸
b_without_a_partner_bike	0.341	0.152	2.24	0.0254
b_without_a_partner_car	0.605	0.126	4.81	1.51e ⁻⁰⁶
b_without_a_partner_carp	0.294	0.159	1.85	0.065
b_without_a_partner_pt	0.197	0.169	1.17	0.244
b_single-parent_family_bike	0.270	0.172	1.57	0.117
b_single-parent_family_car	0.440	0.141	3.12	0.0018
b_single-parent_family_carp	1.22	0.171	7.13	9.98e ⁻¹³
b_single-parent_family_pt	0.0326	0.190	0.171	0.864
b_two-parent_family_bike	0.477	0.156	3.06	0.00222
b_two-parent_family_car	0.636	0.133	4.77	1.86e ⁻⁰⁶
b_two-parent_family_carp	1.38	0.158	8.74	0
b_two-parent_family_pt	0.00287	0.182	0.0157	0.987
b_private_household_bike	-0.290	0.219	-1.32	0.186
b_private_household_car	-0.308	0.188	-1.64	0.101
b_private_household_carp	-0.475	0.255	-1.86	0.0626
b_private_household_pt	-0.681	0.270	-2.53	0.0116
b_Cohabiting_partners_bike	0.411	0.0786	5.23	1.68e ⁻⁰⁷
b_Cohabiting_partners_car	0.428	0.0631	6.78	1.22e ⁻¹¹
b_Cohabiting_partners_carp	0.965	0.0844	11.4	0
b_Cohabiting_partners_pt	-0.247	0.0969	-2.54	0.011
Rho-square-bar				0.39
AIC				56441.76
BIC				56879.85

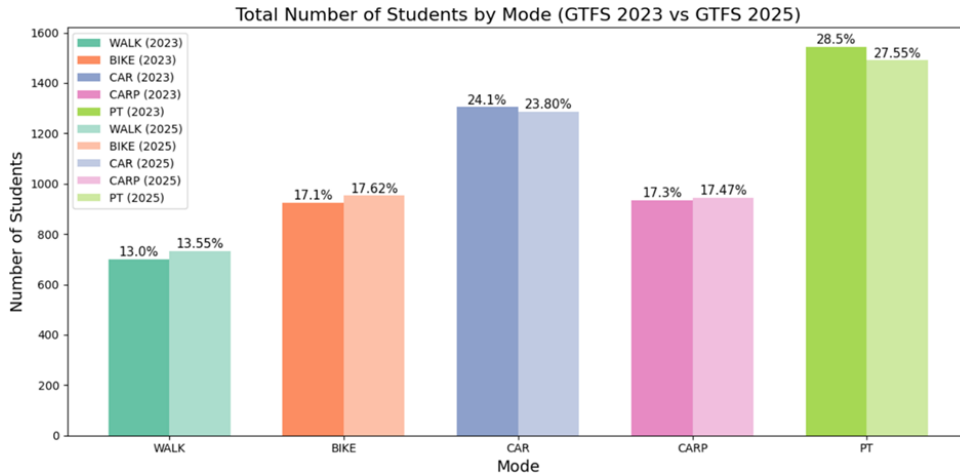


Fig. 3. Mode Choice Distribution of All Students Considering GTFS 2023 vs GTFS 2025

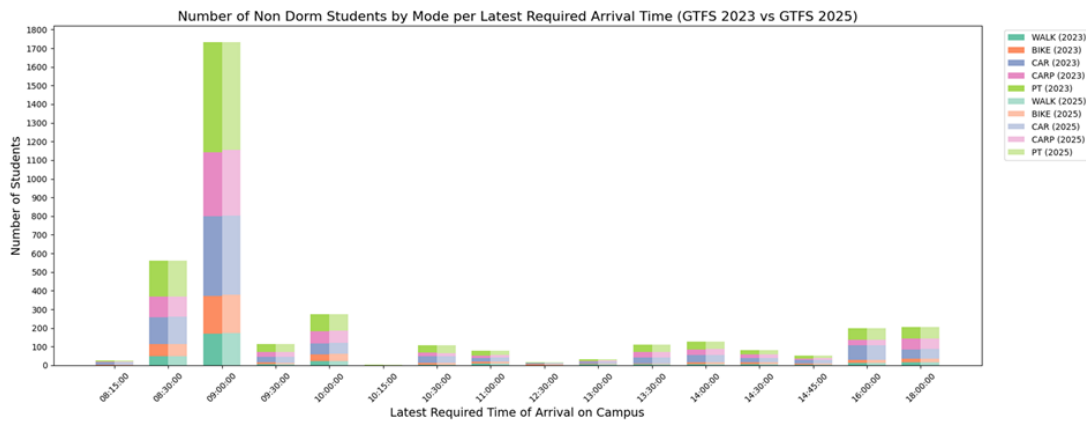


Fig. 4. Mode Choice Distribution of Non-Dorm Students by Latest required Time of Arrival on campus

6. Discussion

The situation in the study area evolves fast. The number of students grew in 2025 12% w.r.t. 2024³. The structure of the road network has severely changed by the introduction of satellite parkings and bicycle streets (bicyclists have highest priority and cannot be overtaken by cars). Public transport PT schedules, described in GTFS data, are also updated periodically. For this study, we used the student roster for 2025. To predict individual mode choices, we applied different GTFS datasets. Although the training data from OVG dates back to 2018 reflecting earlier student behaviors we still observe notable differences in mode choice patterns between dormitory and non-dormitory students. These differences are influenced by residential location: dormitory students live closer to campus and therefore show a higher preference for active modes, such as walking and cycling, whereas non-dormitory students tend to rely more on motorized modes.

Acknowledgements

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³ <https://www.uhasselt.be/nl/over-uhasselt/actueel/opnieuw-sterke-stijging-aantal-inschrijvingen-aan-uhasselt>

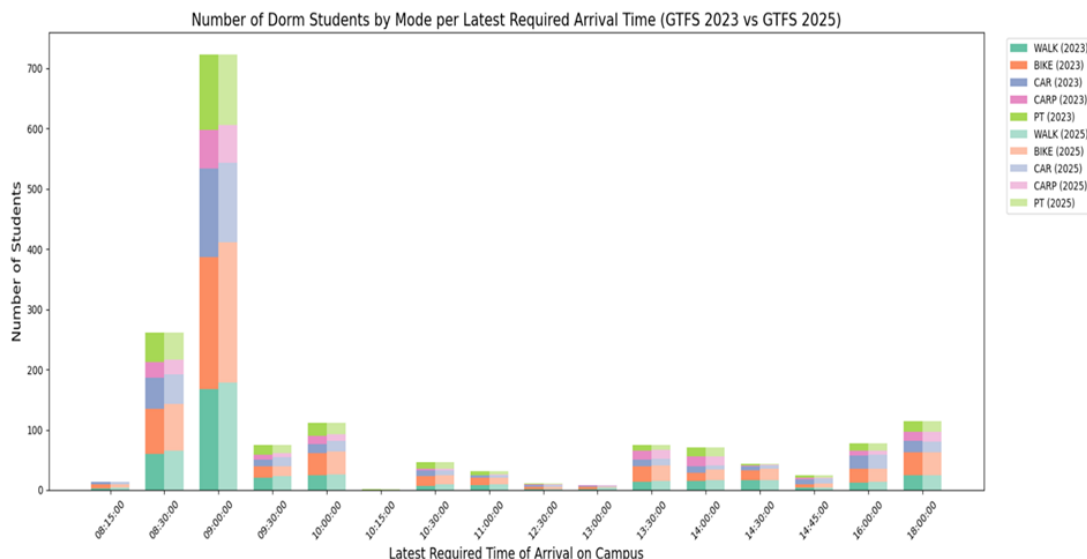


Fig. 5. Mode Choice Distribution of Dorm Students by Latest required Time of Arrival on campus

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