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A Methodology for the Evaluation of Street Functions Using Video Data: A Case Study on Speed Humps in Montreal

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Abstract

The direct observation of cars, pedestrians, cyclists, and other street users can be a viable method to evaluate the three main street functions, namely mobility, access, and place. However, a systematic procedure to evaluate the street functions is not evident in published work. Previously, a comprehensive framework for street functions and all users was proposed without any application. The aim of this research is therefore to develop a systematic methodology for collecting, pre-processing, and analyzing data on street users based on that comprehensive framework and to use it in a case study. In the proposed methodology, the trajectories and types of street users, their instantaneous speed, and direction of movement are automatically extracted from the collected videos using video analytics. These data are then analyzed in a new software tool, the Studio application, to derive street function evaluation indicators. The proposed method is applied to comprehensively assess the changes after speed hump installations in four residential streets in Montreal, Canada. The results demonstrate the value of direct street user observation and the proposed semi-automated method. The empirical results of the proposed method show that the speed of cars has decreased by 20-30% at all sites, while there have been significant changes in the flow and characteristics of vehicles, cyclists, and pedestrians in the study areas.

Keywords: street users; street functions; data collection; video analysis; indicator

1. Introduction

Streets play a particularly significant role in urban life. After home, school, and workplace, a part of the lives of city dwellers is spent on the streets, alleys, and public places. By street, here, we mean the roadway (i.e., roadbed for cars and public transit lane) and all its surrounding areas, including on-street parking areas, cycling facilities, sidewalks, planting zones, setbacks, and public squares (GDCI, 2016). Many urban residents may spend hours in a day in such environments, whether it be while on the way somewhere, shopping, entering/exiting a building, doing exercise, or

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simply watching the world go by. These uses relate to the three main functions of streets, namely *transit*, *access*, and *place*.

In other words, streets are not simply a set of public spaces developed for people to move from an origin to a destination (i.e., the transit or mobility function), urban streets also serve other *functions* including (for example Karndacharuk et al. (2013)):

- direct access to the adjoining buildings, facilities, and services which is known as the "access" function;
- and the "place" function where people use this public space for various physical activities (e.g., walking, jogging, playing, etc.) and social activities (e.g., chatting, attending street events, etc.).

In some streets the latter two functions are as crucial as, or even more crucial than, the mobility function (DfT, 2007). During the past decades, urban designers and transportation engineers have striven to make the streets a suitable environment for all potential users through various interventions and redesigns. These efforts have mostly focused on improving the facilities for active transportation (i.e., walking and cycling) and the safety for these vulnerable users. Yet, the impact of these efforts on the street functions is not systematically assessed. Though several indicator frameworks and audit tools have been proposed, most are based on the measurement of physical facilities and thus only reflect the potential street usage as opposed to the actual use. That is why the direct observation of street users is required. Since a small number of available frameworks rely on the direct observation of users and none covers all street users and functions, Sheikh-Mohammad-Zadeh et al. (2022) proposed a comprehensive framework to observe all street users and evaluate the three street functions. One of the challenges of direct user observation is the method of data collection in the real world. Past frameworks or audit tools usually adopt roadside manual methods for data collection which are limited and expensive. On the other hand, most of the available automatic methods, such as pneumatic tubes, inductive loops, and passive infrared, cannot collect the required data, especially regarding the activities that can occur in a given space.

Video data analysis is a relatively new data gathering technique in transportation that has the potential to address the aforementioned gaps. Accordingly, by taking advantage of video analytics, this paper aims to present a practical and cost-efficient methodology for data gathering and pre-processing, which is based on the comprehensive framework presented in (Sheikh-Mohammad-Zadeh et al., 2022). The framework is a conceptual structure devised for organizing the observation of street users. This paper also introduces a new open-source tool for analyzing the trajectories extracted from video data to derive relevant indicators. The data gathering, and analysis methodology proposed in this paper is applied to evaluate the impact of a traffic calming intervention on the use of residential streets in Montreal, Canada.

This paper is organized into six sections. The next section will discuss the background. Section 3 elaborates on the direct user observation framework and the methodology of data collection and indicator analysis. Section 4 presents the case study and empirical results. Section 5 provides a discussion on the empirical results. Finally, the conclusion and future works will be discussed in section 6.

2. Background

2.1. Methodologies for Street Evaluations Based on Direct User Observations

In the early twentieth century, the introduction of personal automobiles led urban planners and transportation engineers to design and manage the urban roadways around motorized vehicular movement (Hass-Klau, 2014). However, the many benefits to accommodating all road users and promoting sustainable modes of transportation (walking, cycling and public transit) are now widely recognized (Karndacharuk et al., 2014). Accordingly, in the past decade, many urban roads and streets have been re-designed, for example through space reallocation, to serve all users more safely (Hamilton-Baillie, 2008b). The question that arises here is about the extent to which the objectives of transportation managers and urban planners are achieved by such interventions or re-designs. For example, to what extent the provision of walking or cycling facilities promoted active transportation? To answer such questions, it is necessary to develop a consistent set of indicators to evaluate and compare the changes that happen due to interventions.

Prof. Allan B. Jacobs, known as “the ultimate student of the street” and the author of many classic books on cities, calls for engineers and planners to utilize direct user observation to study “what does and does not work in existing streets”, instead of adopting conventional traffic assumptions (Hamilton-Baillie, 2008a). Accordingly, it is necessary to observe the actual use of streets directly to assess the actual street use changes due to some interventions or changes in people’s lifestyles (e.g., due to the COVID-19 pandemic). However, the review conducted in (Sheikh-Mohammad-Zadeh et al., 2022) shows that a limited number of frameworks which evaluate street use are developed based on direct observations of users.

Furthermore, these frameworks mostly rely on manual methods for data collection. One or more observers typically record their observations on site manually during a limited period in the peak hours in compliance with pre-designed instructions or audit tools. Such methods have several limitations in terms of observation time, variety of observations, and validity. The use of modern observation methods such as video analysis can solve most of these problems. The video recording has many advantages such as not being easily detectable by road users, long periods of observation and the possibility to extract the required data in the office (Laureshyn, 2010).

In recent decades, numerous advances in cameras, image processing methods, and computer vision techniques have made video analytics a powerful and useful method for traffic monitoring and management. Buch et al. (2011) define video analytics as “computer-vision-based surveillance algorithms and systems to extract contextual information from video”. Nowadays, thanks to the developments in object detection methods and moving object tracking algorithms, video analysis procedures can provide microscopic data on all types of road users, including vehicles (Song et al., 2019), motorcycles (Espinosa et al., 2021), pedestrians (Preethaa and Sabari, 2020), and cyclists (Peixoto et al., 2020). Such data can be used in many applications like vehicle counting and classification (Arinaldi et al., 2018), road safety (St-Aubin et al., 2015; Navarro et al., 2022), extracting road users’ trajectories (Schönauer et al., 2012), accident detection (Ren et al., 2016), behavioral model calibration (Laureshyn, 2010), evaluation of the impact of an intervention or design (Karndacharuk et al., 2013; Batista and Friedrich, 2022), and traffic rule enforcement (e.g., automatic number plate recognition-ANPR for tolling purposes) (Buch et al., 2011).

The early methods for video analysis generally worked on detecting and tracking an entire vehicle, so they performed well on freeways where vehicles move in free flow. However, in congestion and under different daylight conditions, the results were not usually satisfactory. To address these issues, Coifman et al. (1998) proposed a feature-based tracking system. The proposed method was effective in partial occlusion of vehicles in congestion and in different conditions of lighting. This method detects the trajectories of vehicles which can then be used to characterize vehicular traffic. Later, Saunier and Sayed (2006) extended this method to intersections. In contrast to freeways in which vehicles have specific entrance and exit regions in videos, there are multiple entrance/exit regions in intersections. The proposed method in (Saunier and Sayed, 2006) addresses these challenges in analyzing the videos of such complex traffic situations.

Moving beyond tracking vehicles, Zangenehpour et al. (2015) proposed a method to extract the features of the moving object image box and classify the detected moving object to three types of road users, including cyclists, pedestrians, and vehicles. The appearance of the detected moving object in each frame and its associated speed are used to predict the type of the moving object. The results of this method showed high overall accuracy for identifying the type of road users in crowded intersections, especially for vehicles (Zangenehpour et al., 2015).

The feature-based method proposed by Saunier and Sayed (2006) for tracking moving objects in videos, as well as the method of automatic classification and identification of street user types in videos, are available in the open-source project *Traffic Intelligence*[1] at Polytechnique Montreal. In this paper, a part of the proposed methodology (i.e., video data preprocessing for tracking and identifying street users) is established based on the tools of this project.

Despite the various advantages, applying video-based traffic monitoring in urban areas is not as straightforward as using visual surveillance systems on highways. The variety and density of road users, the clutter in streets, different directions of vehicles in intersections and the narrow camera angle are some challenges that make the video-based traffic monitoring particularly challenging in the urban areas (Buch et al., 2011).

[1] https://trafficintelligence.confins.net

2.2. Traffic Calming Studies

The high impact force in high-speed collisions cause serious damage, especially for pedestrians and cyclists (Yeo et al., 2020). Therefore, traditional traffic calming measures, including speed humps, speed bumps, curb extensions, chicanes, raised pedestrian crossings, etc. are usually applied to slow the speed of cars. Among these different measures, speed hump is the most common and economical traffic calming measure (Patel and Vasudevan, 2016). A speed hump is a rounded raised area on pavement spanning roadbed width with traverse distance of about 3.7 to 4.3 meters (12 to 14 feet) (ITE, 2018). Speed humps are usually made by rubber, thermoplastic materials, concrete, etc. (Pau and Angius, 2001) and applied to reduce the speed of cars in residential local streets and neighborhood collectors (ITE, 2018). Speed humps are aimed to decrease the average speed of cars between 20 and 25 percent (ITE, 2018) to improve the safety of pedestrians and cyclists (Samal et al., 2022).

Yeo et al. (2020) showed that the effect zone of speed reduction is ±30 meters from the speed humps where the number of crushes is limited with less severe injury. Although the speed humps are known to prevent drivers from speeding, they can cause undesirable experience to cyclists (Patel and Vasudevan, 2016), produce air and noise pollution (Clitan et al., 2017), decrease road capacity, and increase travel time (Samal et al., 2022).

There have been few studies on the impact of speed humps on traffic, primarily on their expected impacts on vehicular speed, and, to the best of the authors' knowledge, no integrated study on their impacts on street functions: what are the effects on the other road users - on the transit, access, and place functions of the street? Reduced vehicular speed might make the street more attractive and change the perception of safety, bringing more pedestrians to perform more activities or for a longer duration.

3. Methodology for Data Collection, Preprocessing, and Analysis

The conceptual framework proposed by Sheikh-Mohammad-Zadeh et al. (2022) underpins the methodology developed in this paper for collecting and processing video data to evaluate street use. Augmenting this comprehensive conceptual framework with practical data gathering methods and automatic analysis is necessary for the application of the framework to case studies with longer periods of observations than typically done manually.

The conceptual framework is designed to observe the movements and activities of all street users (e.g., motor vehicle, pedestrian, cyclist, public transit user, etc.) at the individual level based on two primitive spatial units, namely *screenlines* and *zones*. In this framework the attributes of all street users that *cross* a screenline or *enter*, *exit* or *dwell* in a predefined zone are observed in terms of transport mode (e.g., walking, driving, cycling, etc.), personal characteristics (e.g., age, gender, etc.), and the way that street users move (e.g., speed of vehicles, number of people in a group). Also, time (or time span) and place of the observation are logged for each observation. Finally, this framework provides a generic list of indicators (that can be derived from the direct user observations) to evaluate streets use in terms of the three functions (transit, access, and place).

In the conceptual framework proposed in (Sheikh-Mohammad-Zadeh et al., 2022), video analysis is recognized as a suitable method to collect the data required for the street use indicators. The methodology for collecting and processing video data is presented in this section, along with a new open-source tool for analyzing the information extracted from the collected video data. Figure 1 illustrates the steps of the data collection, preprocessing and analysis adopted in this paper.

Data collection is the first step of the methodology proposed in this paper. In order to collect the required video data, a single stationary visible-light camera at the top of a telescopic mast attached to a street light pole is sufficient to collect the required data. The position, height and viewing angle of the camera should be such as to cover the entire study area (i.e., street segment, intersection, or open space). The collected videos are then analyzed to observe the movements and activities of street users. In this paper, computer vision techniques have been adopted to automatically extract the trajectory, speed, and type of street users. To achieve this objective, the tools from the open-source *Traffic Intelligence* (TI) project, developed at Polytechnique Montreal (Jackson et al., 2013), are applied to detect, track, and classify most road users automatically. Video analysis requires several steps. It starts with the calibration of the camera view to be able to convert positions in the image to positions in the real world and compute traveled distances and speeds.

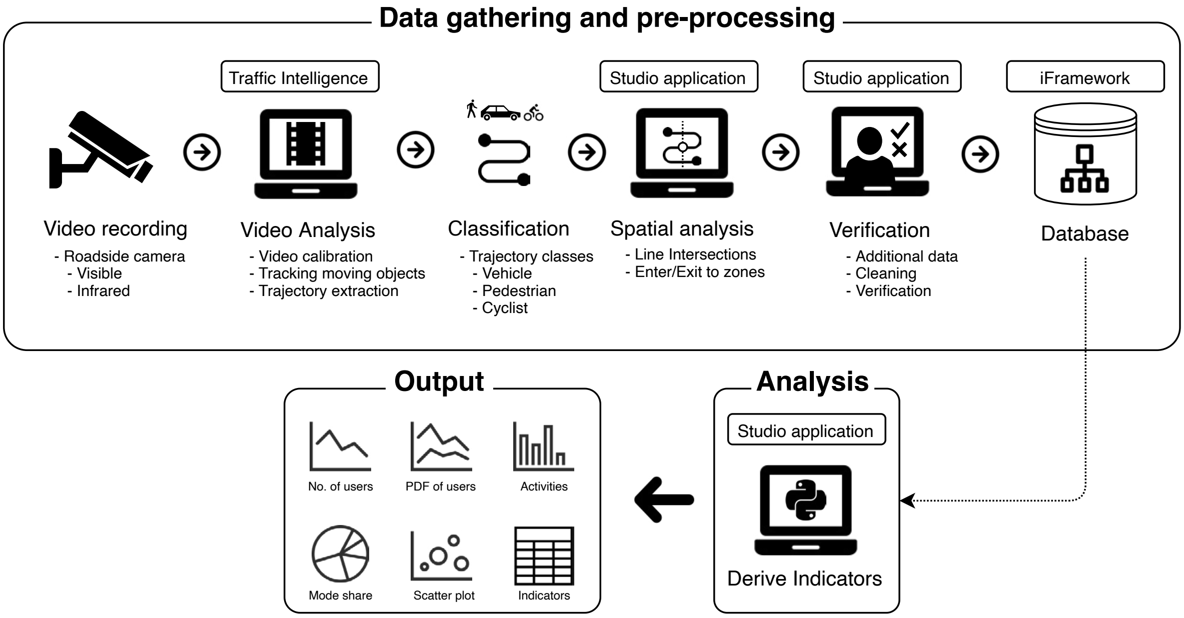


Fig. 1: Illustration of the methodology

After calibration, all collected videos are processed using the TI tools to detect and track all moving objects automatically; the result of this step is a set of trajectories associated with each detected moving object in the videos. In the next step, based on the appearance of the detected objects and their speed, the type of street user (e.g., car, pedestrian, cyclist, motorcycle) is automatically recognized.

The street use indicators require to define screenlines and zones of interest for the analysis. In this study, the screenlines are defined as perpendicular to the main flow of traffic and can be defined separately for each part of the street (e.g., sidewalk, road lanes) or as a single line crossing all parts. Screenlines are also added to count access to adjoining properties.

After defining the screenlines and zones, using the spatial analysis functions in the TI library, the location and time of intersection(s) of each trajectory and the predesigned screenlines are automatically identified. In addition, the direction of movement and instantaneous speed at the intersection point are calculated automatically. Also, the entry, exit, and stay of each street user in each predefined zone are calculated automatically. The results of these spatial analyses are used to detect the number of users, the location and time of each observation, the instant speed, and the number of entries and exits to each zone of interest.

Although most of the required information can be extracted automatically using discussed spatial analysis, some information like the road user characteristics and type of activities that are particularly challenging to be extracted automatically through video analysis. Therefore, by reviewing the videos, such information should be added manually to the road user trajectories, if needed. Also, at this stage, the extracted trajectories can be verified and cleaned. Finally, all this information is stored in a database developed based on the iFramework data model (Sheikh-Mohammad-Zadeh et al., 2022).

In order to perform some of the discussed tasks, a new application called *Studio* [2] (**St**reet **U**sers **Di**rect **O**bservation) is developed in this study. The Studio application is designed to create and manage the spatial observation units (lines and zones) and validate the trajectories extracted from videos. The last step in this process is to derive the desired indicators for each of the three functions. To this end, the required functions and tools are developed in the Studio application to derive the indicators, which are visualized through pre-defined plots.

[2] `https://github.com/Abbas-Shmz/StudioProject`

4. Case Study on Speed Hump Impacts

4.1. Data Collection and Preparation

To evaluate how speed humps affect street use and functions in the case study, video data were collected at four sites in residential streets in the Outremont borough of Montreal, Canada before and after the installations of speed humps in October 2019 and 2020 respectively. Unfortunately, it must be noted that the occurrence of the COVID-19 pandemic may have contributed to some of the observed changes in street use, along with the intervention and other unobserved factors.

Figure 2 shows the location of the four studied street segments (i.e., Champagneur, Stuart, Hartland, and Pratt between Avenue Van Horne and Lajoie) in the Outremont borough and the location of Outremont borough in Montreal Island. Outremont ranks as the third most walkable borough in Montreal by Walkscore.com (Score, 2022) and has a population of roughly 24,000 residents in 2018 (ARTM, 2020). Also, this borough is very suitable for biking and enjoys a very good public transport service including a subway (metro) station (Score, 2022). The authors' own calculations from GIS data (City of Montreal, 2019) show that streets, alleys, and sidewalks make up about 70 % of public spaces and 21 % of the total area of this borough. This pattern of public spaces being mostly streets is often found in urban areas (Lefebvre-Ropars et al., 2021; Hodges, 2019).

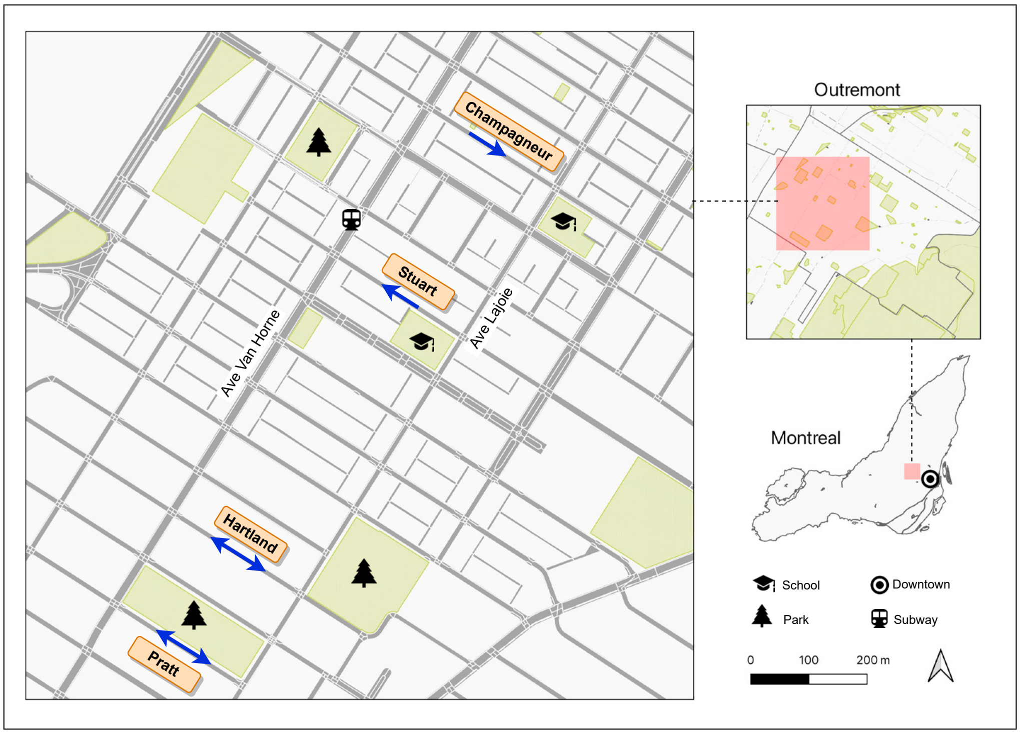
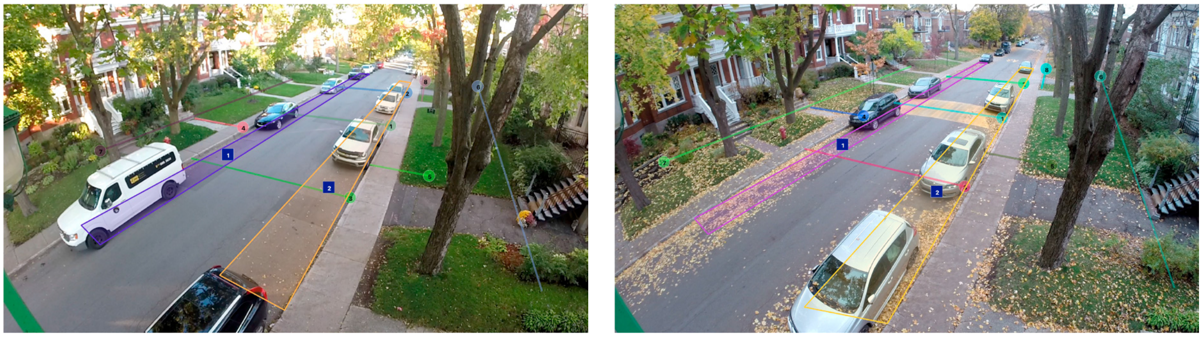


Fig. 2: Case study sites: the blue arrows indicate the direction of traffic

The selected streets in this study are completely residential (about nine meters in width) with two sidewalks on both sides, and on-street parking areas. The streets are selected so as to consider the different contexts in terms of traffic directions and proximity to facilities including schools, parks, and a subway station. In our study, two of the selected streets in the study site are one-way and the two other streets are two-way. As well, there is a school on one street and a park along another, and one of the streets is close to a subway station. As such, the streets are likely attraction points for pedestrians to reach those destinations. A video dataset of about 80 hours was collected on the four streets for one day on a working day before and after the installation of speed humps in October 2019 and 2020. For each street, considering the daylight and time of activities in the study sites, video data is available from 7:30am to 17:30pm for each session of data collection before and after the intervention.

All street user movements and activities are observed directly considering a set of predefined screenlines and zones. In this case, three screenlines on the roadbed (i.e., before, after, and over the speed humps) are defined to count the passing vehicles and measure their instantaneous speed at these three spots. Also, one screenline is drawn across each sidewalk to capture pedestrian (or cyclist) traffic. Further, to observe the access to the adjoining buildings, two more screenlines are defined along each sidewalk at the border of sidewalks and adjacent properties. In addition, two zones are defined to cover the on-street parking areas for counting the vehicles entering or exiting these areas. Figure 3 shows the predefined screenlines and zones depicted over two video images before and after the speed hump installation on Stuart Street.



(a) Before (October 2019) (b) After (October 2020)

Fig. 3: The screenlines and zones before and after speed hump installation on Stuart Street

Using the TI tools, the camera views are calibrated based on a local coordinate system in the real-world, and the road user trajectories are then extracted and classified automatically into vehicles, bicycles, or pedestrians. A sample of extracted trajectories are shown in Figure 4. The trajectories are then revised and cleaned manually, and the indicators are derived using the Studio tools. All the analysis and provided results including plots and tables are generated by the Studio project tools.

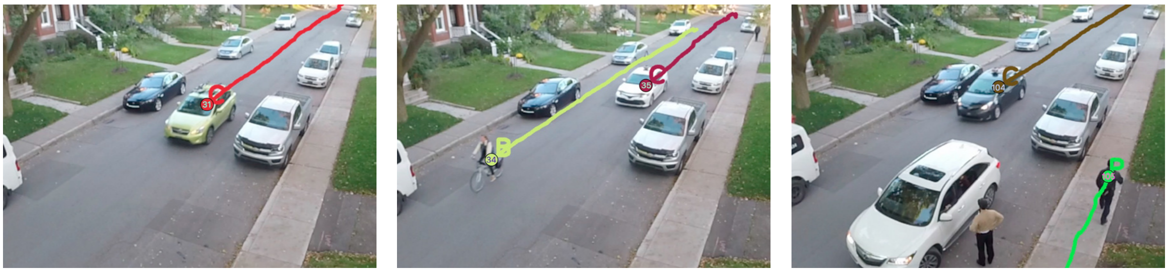


Fig. 4: A sample of extracted trajectories and identified cars, bikes, and pedestrians marked by C, B, and P, respectively.

4.2. Mobility

The instantaneous speeds and number of passing street users are the indicators presented here to evaluate the mobility function for three major street users, namely vehicles, pedestrians and cyclists.

4.2.1. All Transport Modes

Figure 5 shows how the transit function for each transport mode (motorized vehicles, pedestrians and cyclists) changed after the installation of speed humps. Also, given some streets are two-way, the vehicular flow in these streets is presented separately by lane. As shown in Figure 5, the flow of users in the streets is not the same in all studied sites. For example, while the number of cyclists decreased for three of the studied streets, it doubled on Champagneur Street. Looking at the share of different transportation modes, Figure 6 shows how active transportation modes have increased (as a proportion) on Hartland Street, while in other streets the mode share has not changed much.

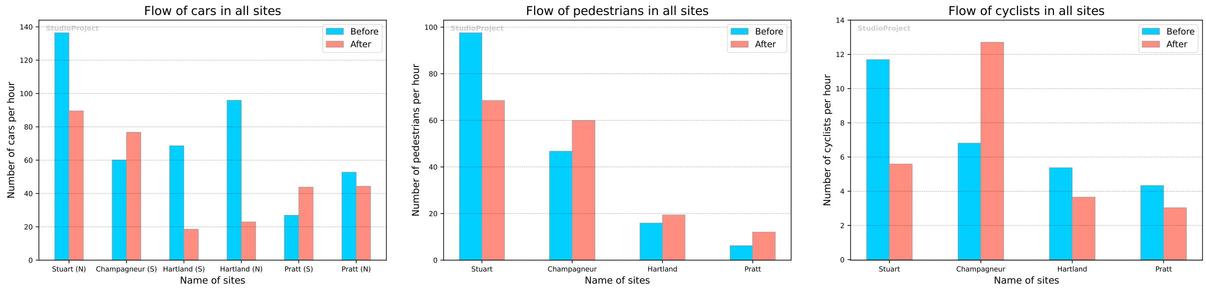


Fig. 5: Flow of street users before and after the speed humps installations

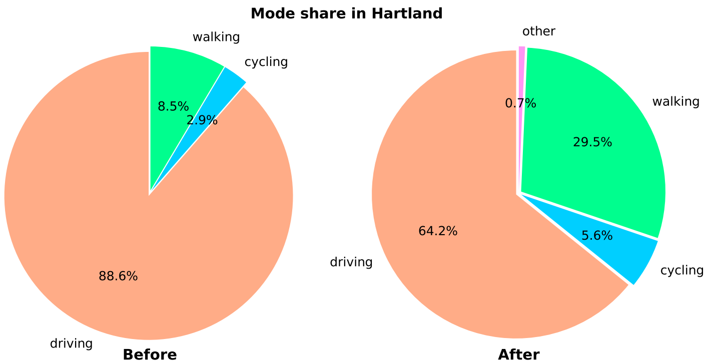


Fig. 6: Mode share comparison before and after speed hump installations at Hartland Street

Comparing the number of street users across all sites before and after the intervention shows that the change in street use was not the same in all sites. Figure 7 illustrates the number of observed cars, in 20 minutes intervals, before and after the speed hump installations. As Figure 7 shows, while in the morning peak-hour Hartland Street (North) had the highest number of cars across all sites in 2019, it sank to the lowest number at the same time in 2020. The number of pedestrians has not changed much between 2019 and 2020. On the other hand, the number of cyclists in Figure 8 shows decrease on Stuard and growth on Champagneur Street.

The probability density function (PDF) of observations made over time for the different street users is used to identify the peak-hours. Comparing the PDF in a before-after study can show changes in the temporal pattern of street use by different users. For example, Figure 9 shows that the peak hour for cyclists on Hartland Street has shifted from 09:00 in 2019 to 17:00 in 2020, while the peak hour for vehicles has remained unchanged.

4.2.2. *Vehicles*

One of the traditional measures of streets is motor vehicle transit, often valuing high speed and high volumes. This subsection presents a sample of related empirical results to demonstrate the capabilities of the proposed methodology. The presented plots show to what extent the vehicular traffic changed in the studied sites in terms of volume, empirical peak-hours, and speed. For example, as shown in plots of Hartland Street in the Figure 10, while the number of cars observed in 2019 and 2020 shows a noticeable drop (from 55 to 15 cars on average every 20 minutes), the PDF of the observations indicates that the peak-hours of vehicular flow are the less pronounced without any noticeable shift in time.

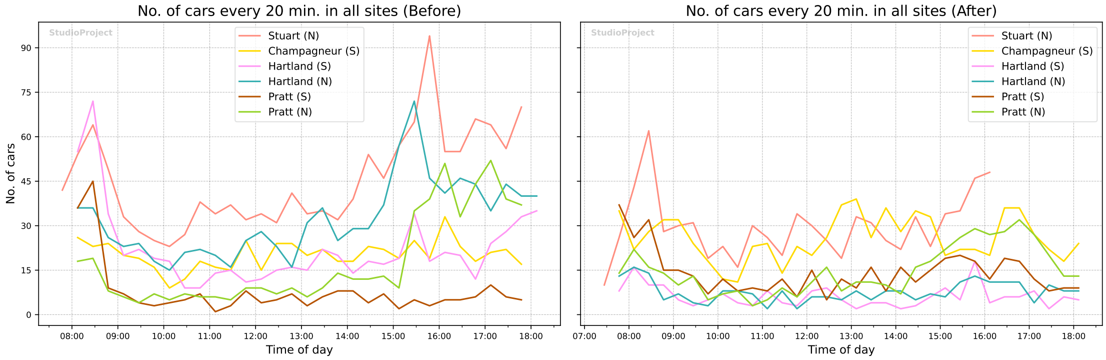


Fig. 7: Number of cars over time observed in all sites before and after the speed hump installations

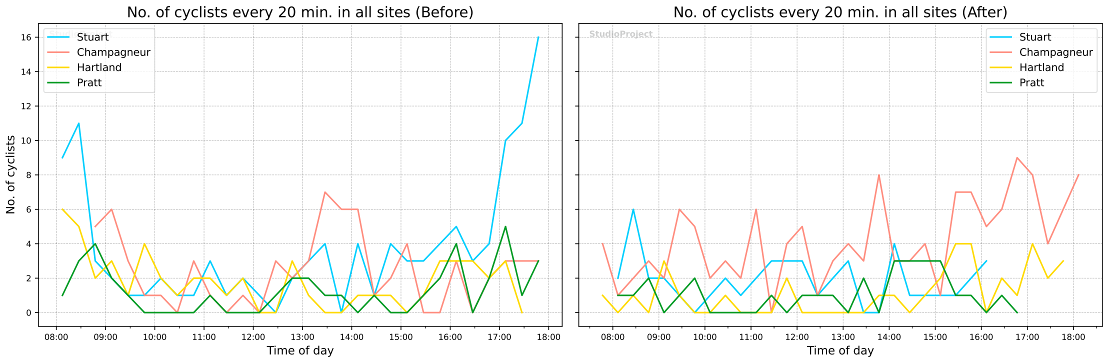


Fig. 8: Number of cyclists over time observed in all sites before and after the speed hump installations

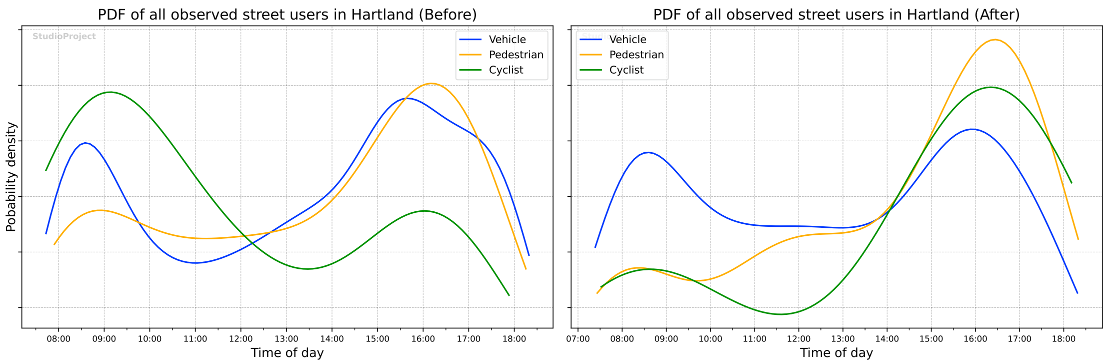
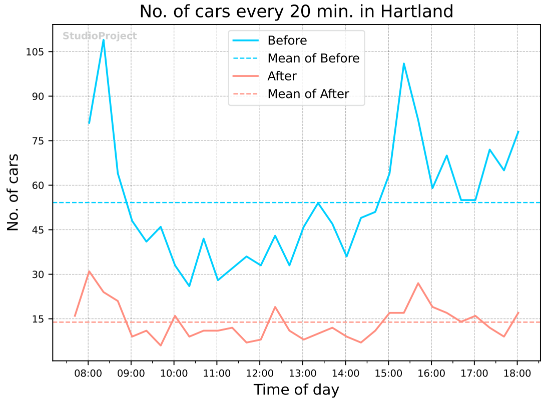


Fig. 9: Probability density function of street users over time before and after speed humps installation at Harland Street

Traffic calming measures (such as installing speed humps) are used to force car drivers to slow down. Figure 11 shows the vehicular speed change before and after the installation of speed humps in the studied sites: in all sites, the mean speed decreased by 20-30 % after the installation of speed humps, and the standard deviation was also reduced.

In addition to the plots and indicators presented in this section, the comparison of the number of cars observed in each lane on two-way streets (Figure A.16 and A.17), the types of observed cars (Figure A.18), and the numerical details of the observations (Table A.2) are shown in the appendix.



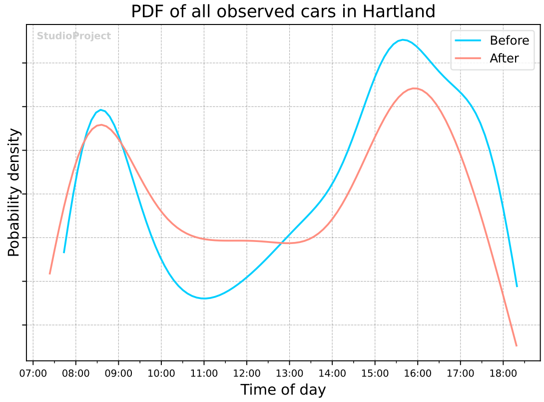


Fig. 10: Number of observed vehicles and probability density function of the observations at Hartland Street

4.2.3. Pedestrians

The number of observed pedestrians and the PDFs show different changes in the studied sites. For example, while the pedestrian flow on Champagneur Street has increased by 25 % and the number of pedestrians has doubled in the afternoon (see Figure 12), the pedestrian flow on Stuart Street has experienced a decrease of about 40 % (see Figure 6).

Another noteworthy point in the plots is the very low number of pedestrians on Pratt Street compared to other streets, which may be attributed to the proximity of the studied section to a park (refer to Figure 2) for two possible reasons: 1) people might be walking through the park, rather than along the sidewalk next to the road; 2) roughly half the number of households connect to the street that provides thus fewer origins or destinations of pedestrian trips. The number of pedestrians on this street has increased from one person every 10 minutes in 2019 to only two pedestrians in 2020, and the peak hour has shifted from the afternoon to the morning.

In addition to the plots discussed in this part, the number and percentage of the observed pedestrians by age and gender (Figure A.20 and Figure A.21 respectively), and the numerical details of the observations (Table A.3) are shown in the appendix.

4.2.4. Cyclists

Table 1 depicts the numerical details, generated automatically by the Studio application, showing the observation of cyclists over time in the Champagneur Street (one-way) before and after the speed hump installation in terms of six indicators. it shows cycling has increased overall and at each period of the day, although in varying amounts.

In addition, information on the number of cyclists over time (Figure A.22), as well as a graph of their age and gender (Figure A.23), are provided in the appendix.

4.3. Access

Considering that the streets in the case study of this paper were completely residential, the automatically extracted information only relates to people’s entry (or exit) into the nearby houses. Figure 13 shows the number of access to adjoining buildings on both sides of Champagneur Street.

4.4. Place

Figure 14 shows the number of observed activities per hour in 2020 compared to 2019. Based on this plot, the activity of people in the study sites has increased significantly at all sites. This is remarkable as there has been a drop in pedestrian flow at one site and the increases at the other sites are not commensurate with the increase in activities. Observing and recording the different types of activities can show how people are able to use the space. Figure 15 shows the types of activities over time at two sites before and after the speed hump installations. The plots reveal that the most frequent activity over the whole day is jogging in these residential streets.

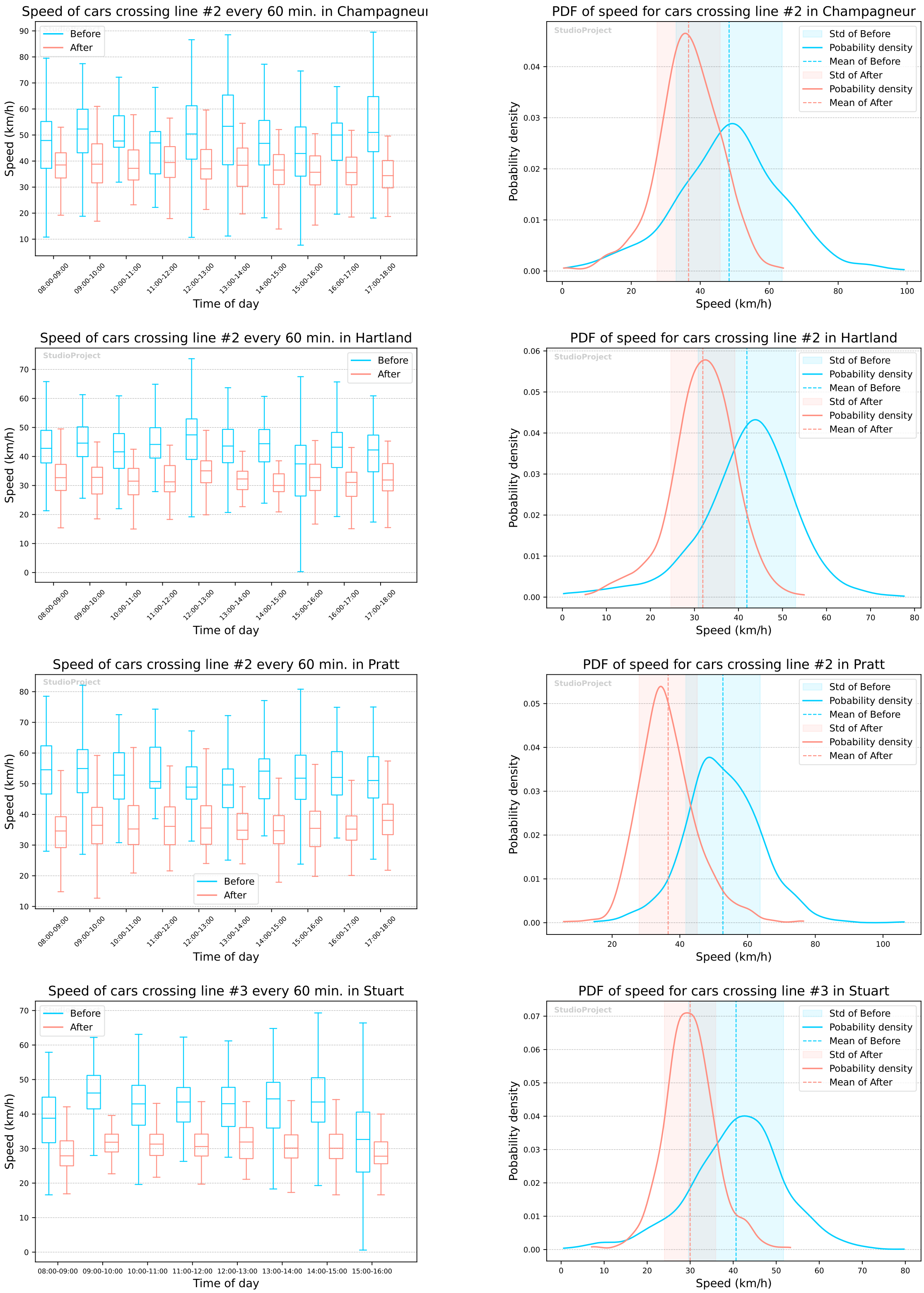


Fig. 11: Speed of observed vehicles over time and the probability density function of vehicle speeds before and after speed humps installation

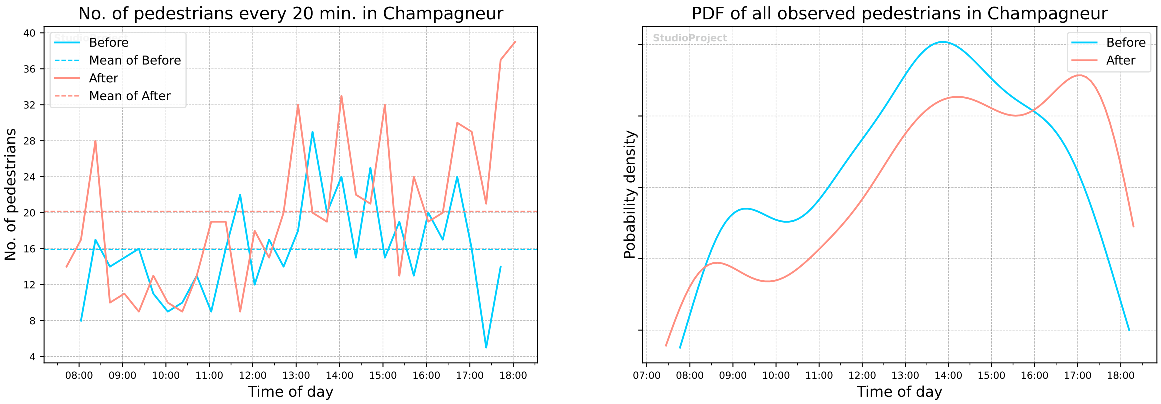


Fig. 12: Number of observed pedestrians and probability density function of vehicles before and after intervention at Champagneur Street

Before

	07:37 - 18:12	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all cyclists	72	16 (22.2%)	6 (8.3%)	22 (30.6%)	13 (18.1%)	13 (18.1%)
Flow of cyclists (bik/h)	6.8	8.0	3.0	11.0	6.5	6.5
Cyclists riding on sidewalk	24 (33.3%)	4 (16.7%)	1 (4.2%)	8 (33.3%)	6 (25.0%)	5 (20.8%)
Cyclists riding against traffic	21 (29.2%)	4 (19.0%)	1 (4.8%)	5 (23.8%)	3 (14.3%)	7 (33.3%)
No. of female cyclists	21 (29.2%)	7 (33.3%)	1 (4.8%)	5 (23.8%)	2 (9.5%)	4 (19.0%)
No. of children cycling	16 (22.2%)	0	1 (6.2%)	8 (50.0%)	6 (37.5%)	1 (6.2%)

After

	07:26 - 18:18	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all cyclists	138	18 (13.0%)	17 (12.3%)	24 (17.4%)	27 (19.6%)	37 (26.8%)
Flow of cyclists (bik/h)	12.7	9.0	8.5	12.0	13.5	18.5
Cyclists riding on sidewalk	22 (15.9%)	4 (18.2%)	3 (13.6%)	2 (9.1%)	2 (9.1%)	8 (36.4%)
Cyclists riding against traffic	39 (28.3%)	4 (10.3%)	5 (12.8%)	6 (15.4%)	8 (20.5%)	12 (30.8%)
No. of female cyclists	37 (26.8%)	5 (13.5%)	7 (18.9%)	5 (13.5%)	8 (21.6%)	8 (21.6%)
No. of children cycling	13 (9.4%)	1 (7.7%)	0	0	3 (23.1%)	3 (23.1%)

Difference

	07:37 - 18:12	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all cyclists	+62 [+86.1%]	+2 [+12.5%]	+11 [+183.3%]	+2 [+9.1%]	+14 [+107.7%]	+24 [+184.6%]
Flow of cyclists (bik/h)	+5.9 [+86.8%]	+1.0 [+12.5%]	+5.5 [+183.3%]	+1.0 [+9.1%]	+7.0 [+107.7%]	+12.0 [+184.6%]
Cyclists riding on sidewalk	-3 [-12.5%]	0 [0.0%]	+2 [+200.0%]	-6 [-75.0%]	-4 [-66.7%]	+3 [+60.0%]
Cyclists riding against traffic	+17 [+81.0%]	0 [0.0%]	+4 [+400.0%]	+1 [+20.0%]	+5 [+166.7%]	+5 [+71.4%]
No. of female cyclists	+15 [+71.4%]	-2 [-28.6%]	+6 [+600.0%]	0 [0.0%]	+6 [+300.0%]	+4 [+100.0%]
No. of children cycling	-5 [-31.2%]	+1 [+-%]	-1 [-100.0%]	-8 [-100.0%]	-3 [-50.0%]	+2 [+200.0%]

Table 1: Number of observed cyclists over time before and after speed humps installation at Champagneur Street

In addition to the provided plots, the number of observed people doing activities by age (Figure A.24) and gender (Figure A.25) in 2019 and 2020 are provided in the appendix.

5. Discussion

The issue in such experimental studies is to attribute the observed changes to the factors that may have caused them. As noted, this study is further complicated by the occurrence of the COVID-19 pandemic and the various public health measures put in place in Quebec starting in March 2020 and during the data collection period after the speed hump installation. Work and university courses were mostly remote in Montreal in fall of 2020, except for primary school.

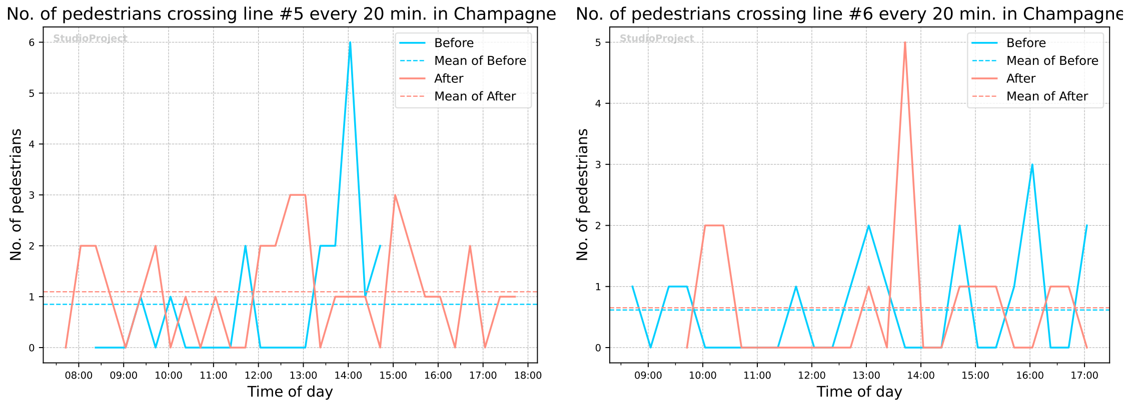


Fig. 13: Number of accesses to adjoining buildings in both sides of Champagneur Street

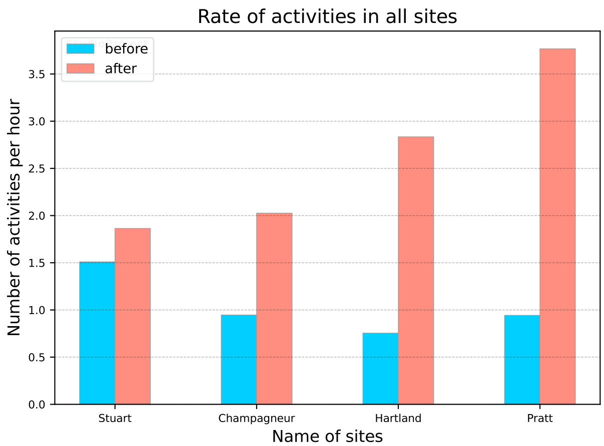


Fig. 14: Rate of activities in all sites

When reviewing the case study results, the decrease in car traffic can be attributed to the speed humps as well as work-from-home. It is unclear how this may have impacted pedestrian and cyclist traffic: pedestrian traffic dropped at only one site, which is the street leading directly to the metro station, where transit use was also drastically reduced at the time.

Regarding the main effect of speed humps on speed, the results are more conclusive. Although many studies demonstrate that the reduction in traffic during the pandemic was associated with speeding by drivers in many places (Lee et al., 2020; Tucker and Marsh, 2021; Hawkins et al., 2021), the study shows systematic reductions in speeds at all sites despite decreases in traffic flow (at Stuart and Hartland in both directions). The speed drops can therefore be reasonably attributed to the speed humps.

Regarding the place function, the considerable increase in activity rates cannot be attributed solely to either major factor. On the one hand, the decrease in car speeds, and in traffic on some streets, may have made the street more appealing for activities. On the other hand, people working from home during the pandemic could go out for activities at all times of the day, to take breaks during their day, which seems to be the case in the morning up to noon as observed in Figure 15.

Using video analysis to detect and track moving objects has some limitations. Accordingly, the proposed method in this paper has some limitations as well. The first limitation is identifying and tracking all individuals in very crowded environments. In such environments, identifying the number of people is associated with errors. Another restriction of the proposed method is the limitation of computer vision for automatic activity recognition (e.g., talking,

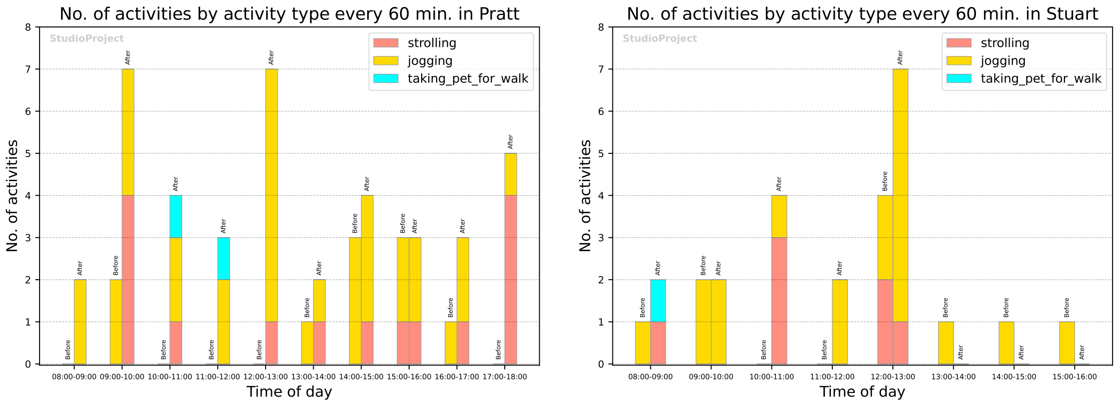


Fig. 15: Activity types over time before and after the speed hump installations at Pratt Street

strolling, eating, reading, etc.). Although identifying some activities such as jogging is possible to some extent based on the speed of movement, it is prone to error, because a person who is in a hurry may be identified as a jogger. In addition, recognizing personal characteristics such as age and gender is error-prone, both automatically and manually. Nevertheless, if such information is needed, it can be collected manually following the proposed framework, and the street function indicators can then be calculated automatically by adopting the developed tools in the Studio application.

The utilization of the proposed methodology for evaluating street functions provides several advantages to planners and decision-makers in the design, management, and regulation of streets that other one-function or one-mode approaches cannot. Through the observation of street users and their usage patterns, planners can better know how the street is being used by different users (equity issues), how an intervention impacts not just the target behavior (e.g., vehicle speed), but potentially other uses of the street (e.g., increased social interactions) and generally whether their initial goals are in effect fulfilled. It can help identify safety challenges, equity concerns, and determine the amenities that are in demand. These insights can contribute to creating streets that are safer, more accessible, and enjoyable for all user groups. Moreover, the observation of street users can aid planners and engineers in evaluating the effectiveness of designs, treatments, and interventions, and assist decision-makers in prioritizing investments in the streets based on the dominant street users and challenges identified. Overall, the application of this methodology can support evidence-based decision-making in street planning and management, leading to improved urban environments.

6. Conclusion

The main objective of this paper was to propose a methodology to systematically evaluate the street functions based on the direct observation of street users and to apply it to a before-after study of speed humps. One of the challenges of direct user observation is the high cost and limitations of manual methods, as well as insufficient information in other methods such as pneumatic tubes and inductive loops. The methodology proposed in this article has the possibility to automatically track and store the trajectories of all street users for a long period of time (not only in the peak hours) during the day (and even at night). Automatic detection of the user types (e.g., cars, cyclists, pedestrians) is another advantage of the proposed method. For data collection in the proposed method, there is no need to install any special equipment except a camera, so it is a cost-effective method. In addition, the analysis tools required in this method are all open-source and available for free. Automatic capturing of the speed and movement direction of all users is another advantage of the proposed method. After extracting the information from the collected videos, the indicators related to the street functions can be calculated automatically by applying the developed tools.

Using the proposed method, the impact of speed humps on street use has been studied in four streets. The results show that significant changes in the flow and characteristics of vehicles, cyclists, and pedestrians in the study areas, which can be attributed to the intervention or other factors. More importantly, we measure a consistent decrease in the speed of cars by 20-30% at all sites, regardless of the changes in motorized traffic. Finally, there is also a systematic increase in pedestrian activities in all streets, regardless of changes of pedestrian traffic.

The application of this methodology can support evidence-based decision-making in street planning and management, leading to improved urban environments for all users and uses.

For future work, in the continuation of this research, it is intended to apply the framework and method proposed for the data collection on different case studies, such as pedestrianized streets, bicycle paths, etc., to identify the possible limitations of the proposed method.

Acknowledgement

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All the diagrams in this paper were prepared using *Diagrams.net* and its provided icons, a free and open-source graph drawing software developed by JGraph Ltd. Also, some icons are designed by Freepik from Flaticon.

Appendix A. Supplementary empirical results

In this appendix supplementary empirical results are provided for street functions in the case study.

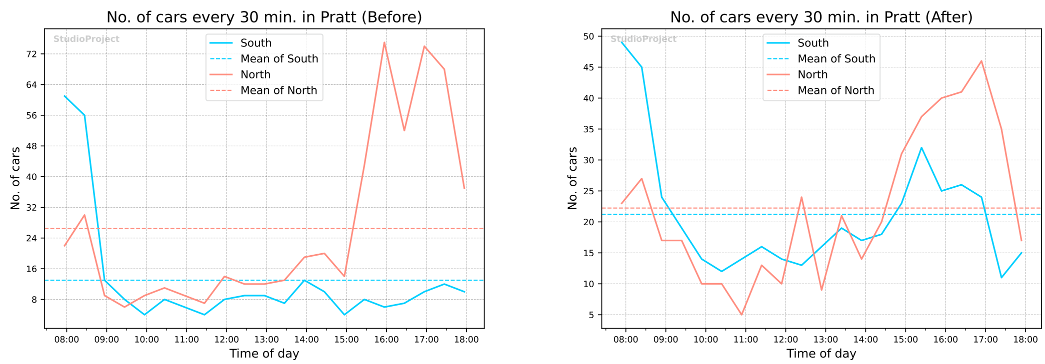

Fig. A.16: Number of vehicles in two-way streets by direction before and after speed humps installation

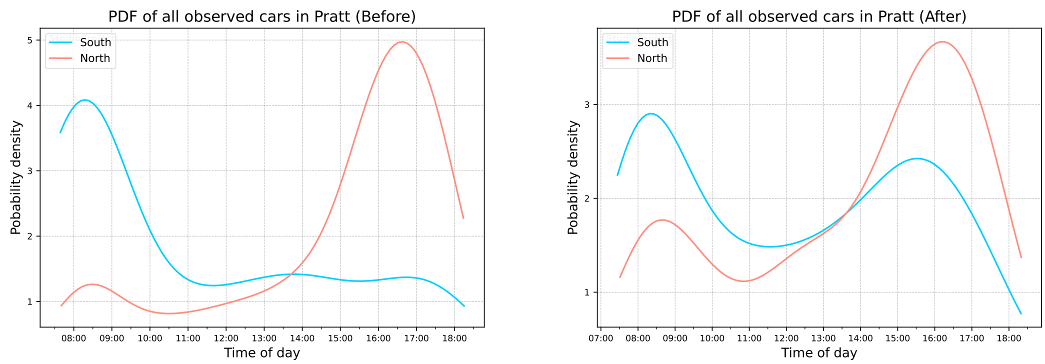

Fig. A.17: Probability density function of vehicles in two-way streets by direction before and after speed humps installation

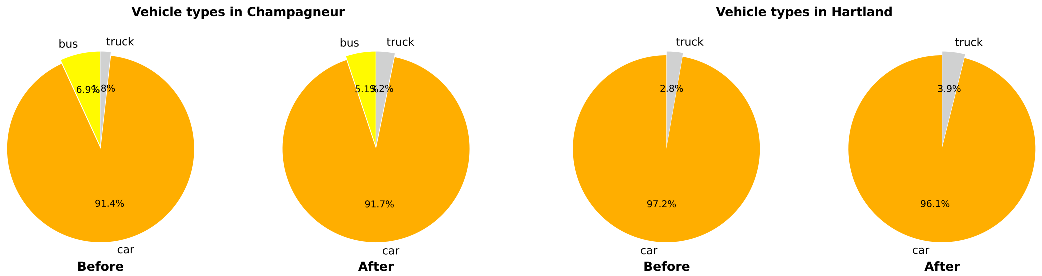

Fig. A.18: Observed vehicle types before and after speed humps installation

Before	07:37 - 18:12	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all vehicles	635	126 (19.8%)	96 (15.1%)	124 (19.5%)	129 (20.3%)	128 (20.2%)
Flow of all vehicles (veh/h)	60.1	63.0	48.0	62.0	64.5	64.0
Speed: average (km/h)	44.9	44.9	43.4	47.7	41.1	45.6
Speed: std (km/h)	14.6	14.6	12.0	14.8	14.5	15.5
Speed: median (km/h)	45.4	45.8	43.5	47.4	41.2	46.6
Speed: 85th percentile (km/h)	60.2	59.3	55.5	63.8	55.9	60.0

After	07:26 - 18:18	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all vehicles	833	155 (18.6%)	109 (13.1%)	182 (21.8%)	160 (19.2%)	160 (19.2%)
Flow of all vehicles (veh/h)	76.7	77.5	54.5	91.0	80.0	80.0
Speed: average (km/h)	36.6	37.6	39.2	37.6	34.9	34.2
Speed: std (km/h)	9.6	10.4	9.5	9.9	9.7	9.2
Speed: median (km/h)	37.2	38.4	39.2	37.9	35.7	34.8
Speed: 85th percentile (km/h)	46.4	47.7	48.9	47.6	44.9	44.0

Difference	07:37 - 18:12	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all vehicles	+180 [+28.3%]	+29 [+23.0%]	+13 [+13.5%]	+58 [+46.8%]	+31 [+24.0%]	+32 [+25.0%]
Flow of all vehicles (veh/h)	+17.0 [+28.3%]	+14.5 [+23.0%]	+6.5 [+13.5%]	+29.0 [+46.8%]	+15.5 [+24.0%]	+16.0 [+25.0%]
Speed: average (km/h)	-8.4 [-18.7%]	-7.3 [-16.3%]	-4.2 [-9.7%]	-10.1 [-21.2%]	-6.2 [-15.1%]	-11.4 [-25.0%]
Speed: std (km/h)	-4.9 [-33.6%]	-4.2 [-28.8%]	-2.5 [-20.8%]	-4.9 [-33.1%]	-4.8 [-33.1%]	-6.3 [-40.6%]
Speed: median (km/h)	-8.3 [-18.3%]	-7.4 [-16.2%]	-4.3 [-9.9%]	-9.5 [-20.0%]	-5.5 [-13.3%]	-11.8 [-25.3%]
Speed: 85th percentile (km/h)	-13.7 [-22.8%]	-11.6 [-19.6%]	-6.6 [-11.9%]	-16.2 [-25.4%]	-11.0 [-19.7%]	-16.0 [-26.7%]

Table A.2: Numerical details of the observed vehicles in Champagneur

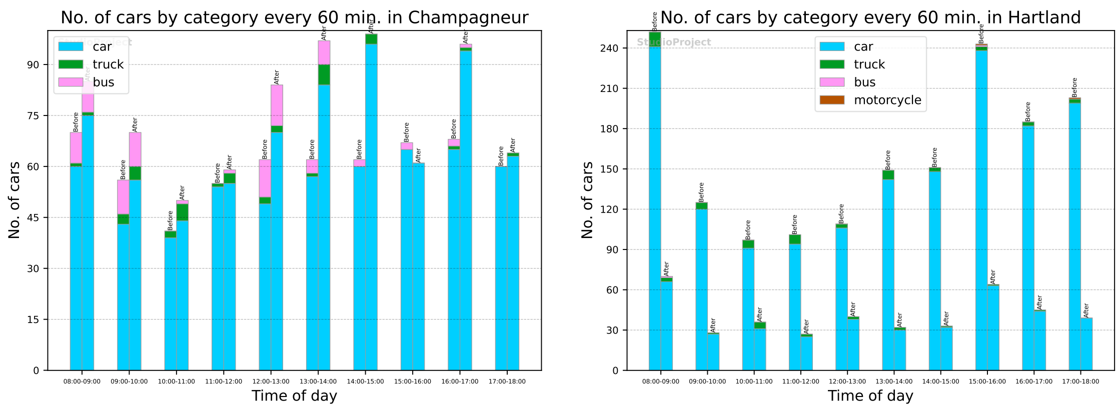

Fig. A.19: Number of vehicles by category before and after speed humps installation

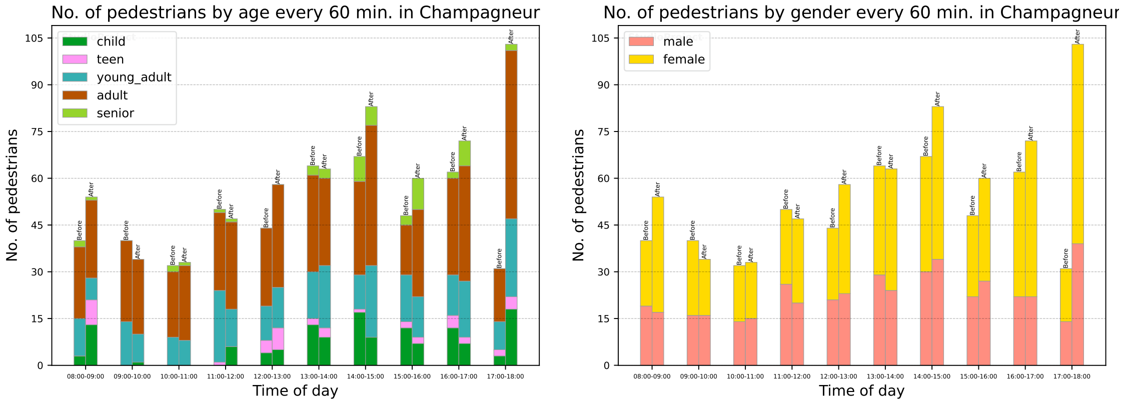

Fig. A.20: Number of observed pedestrians by age and gender over time before and after speed humps installation

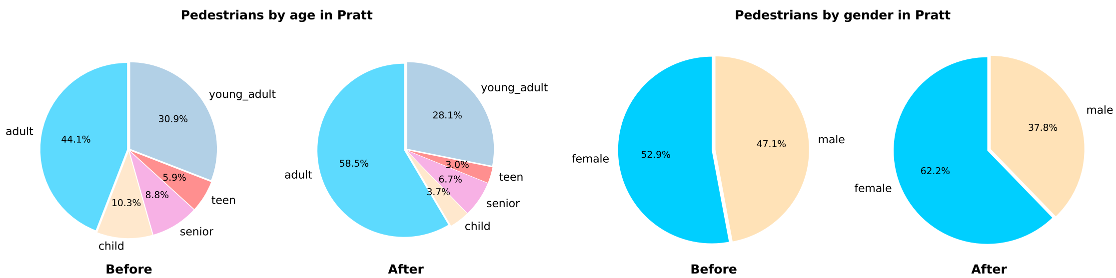

Fig. A.21: Age and gender of observed pedestrians before and after speed humps installation

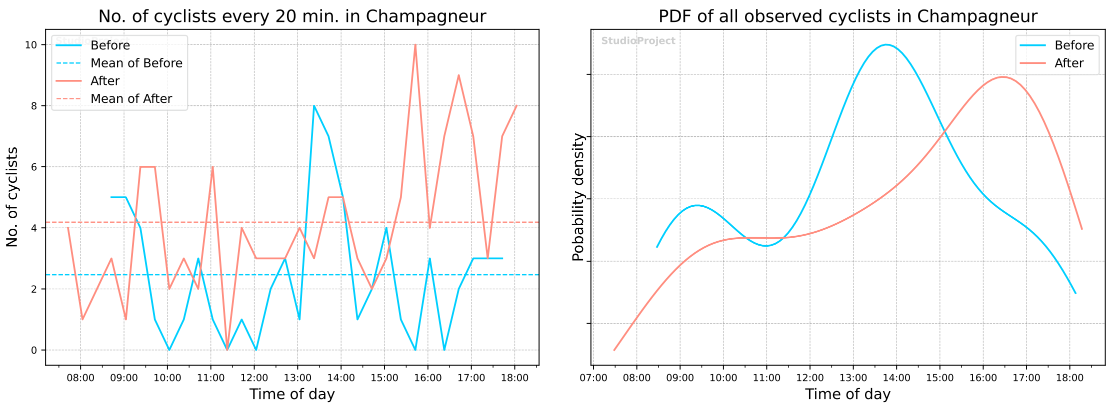

Fig. A.22: Number of observed cyclists and probability density function of vehicles before and after intervention

Before

	07:43 - 18:19	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all pedestrians	169	32 (18.9%)	22 (13.0%)	26 (15.4%)	30 (17.8%)	50 (29.6%)
No. of females	95 (56.2%)	18 (18.9%)	9 (9.5%)	15 (15.8%)	20 (21.1%)	27 (28.4%)
No. of males	74 (43.8%)	14 (18.9%)	13 (17.6%)	11 (14.9%)	10 (13.5%)	23 (31.1%)
No. of children	24 (14.2%)	3 (12.5%)	0	2 (8.3%)	1 (4.2%)	16 (66.7%)
No. of elderly people	9 (5.3%)	5 (55.6%)	1 (11.1%)	0	0	3 (33.3%)
No. of people with pet	8 (4.7%)	0	3 (37.5%)	2 (25.0%)	0	2 (25.0%)
No. of disabled people	0	0	0	0	0	0
Flow of pedestrians (ped/h)	15.9	16.0	11.0	13.0	15.0	25.0
No. of all groups	133	26	21	21	25	33
No. of groups with size = 1	109	20	20	18	22	23
No. of groups with size = 2	13	6	1	1	1	4
No. of groups with size = 3	10	0	0	2	2	5
No. of groups with size > 3	1	0	0	0	0	1
People walking on roadbed	4 (2.4%)	0	0	1 (25.0%)	1 (25.0%)	1 (25.0%)

After

	07:23 - 18:19	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all pedestrians	211	24 (11.4%)	27 (12.8%)	30 (14.2%)	36 (17.1%)	72 (34.1%)
No. of females	105 (49.8%)	13 (12.4%)	12 (11.4%)	17 (16.2%)	19 (18.1%)	35 (33.3%)
No. of males	106 (50.2%)	11 (10.4%)	15 (14.2%)	13 (12.3%)	17 (16.0%)	37 (34.9%)
No. of children	29 (13.7%)	3 (10.3%)	1 (3.4%)	0	10 (34.5%)	7 (24.1%)
No. of elderly people	15 (7.1%)	2 (13.3%)	1 (6.7%)	2 (13.3%)	3 (20.0%)	7 (46.7%)
No. of people with pet	16 (7.6%)	1 (6.2%)	2 (12.5%)	1 (6.2%)	5 (31.2%)	5 (31.2%)
No. of disabled people	1 (0.5%)	0	0	0	0	1 (100%)
Flow of pedestrians (ped/h)	19.3	12.0	13.5	15.0	18.0	36.0
No. of all groups	160	20	21	26	30	50
No. of groups with size = 1	117	17	15	22	26	31
No. of groups with size = 2	36	2	6	4	2	17
No. of groups with size = 3	6	1	0	0	2	1
No. of groups with size > 3	1	0	0	0	0	1
People walking on roadbed	6 (2.8%)	0	2 (33.3%)	1 (16.7%)	0	2 (33.3%)

Difference

	07:43 - 18:19	08:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 18:00
No. of all pedestrians	+29 [+17.2%]	-8 [-25.0%]	+5 [+22.7%]	+4 [+15.4%]	+6 [+20.0%]	+22 [+44.0%]
No. of females	+6 [+6.3%]	-5 [-27.8%]	+3 [+33.3%]	+2 [+13.3%]	-1 [-5.0%]	+8 [+29.6%]
No. of males	+23 [+31.1%]	-3 [-21.4%]	+2 [+15.4%]	+2 [+18.2%]	+7 [+70.0%]	+14 [+60.9%]
No. of children	-2 [-8.3%]	0 [0.0%]	+1 [+-%]	-2 [-100.0%]	+9 [+900.0%]	-9 [-56.2%]
No. of elderly people	+6 [+66.7%]	-3 [-60.0%]	0 [0.0%]	+2 [+-%]	+3 [+-%]	+4 [+133.3%]
No. of people with pet	+8 [+100.0%]	+1 [+-%]	-1 [-33.3%]	-1 [-50.0%]	+5 [+-%]	+3 [+150.0%]
No. of disabled people	+1 [+-%]	0 [-%]	0 [-%]	0 [-%]	0 [-%]	+1 [+-%]
Flow of pedestrians (ped/h)	+2.8 [+17.6%]	-4.0 [-25.0%]	+2.5 [+22.7%]	+2.0 [+15.4%]	+3.0 [+20.0%]	+11.0 [+44.0%]
No. of all groups	+20 [+15.0%]	-6 [-23.1%]	0 [0.0%]	+5 [+23.8%]	+5 [+20.0%]	+17 [+51.5%]
No. of groups with size = 1	+5 [+4.6%]	-3 [-15.0%]	-5 [-25.0%]	+4 [+22.2%]	+4 [+18.2%]	+8 [+34.8%]
No. of groups with size = 2	+21 [+161.5%]	-4 [-66.7%]	+5 [+500.0%]	+3 [+300.0%]	+1 [+100.0%]	+13 [+325.0%]
No. of groups with size = 3	-6 [-60.0%]	+1 [+-%]	0 [-%]	-2 [-100.0%]	0 [0.0%]	-4 [-80.0%]
No. of groups with size > 3	0 [0.0%]	0 [-%]	0 [-%]	0 [-%]	0 [-%]	0 [0.0%]
People walking on roadbed	+1 [+25.0%]	0 [-%]	+2 [+-%]	0 [0.0%]	-1 [-100.0%]	+1 [+100.0%]

Table A.3: Number of observed Pedestrians over time before and after speed humps installation in Hartland

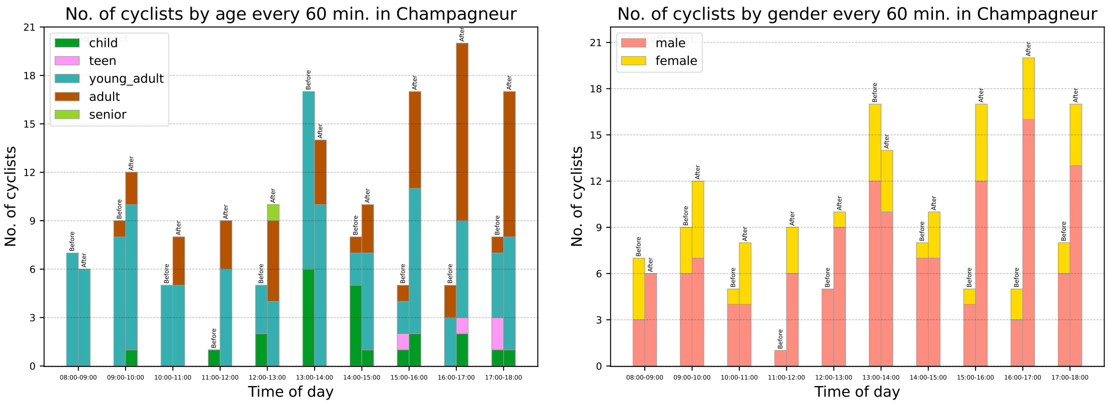

Fig. A.23: Age and gender of observed cyclists over time before and after speed humps installation

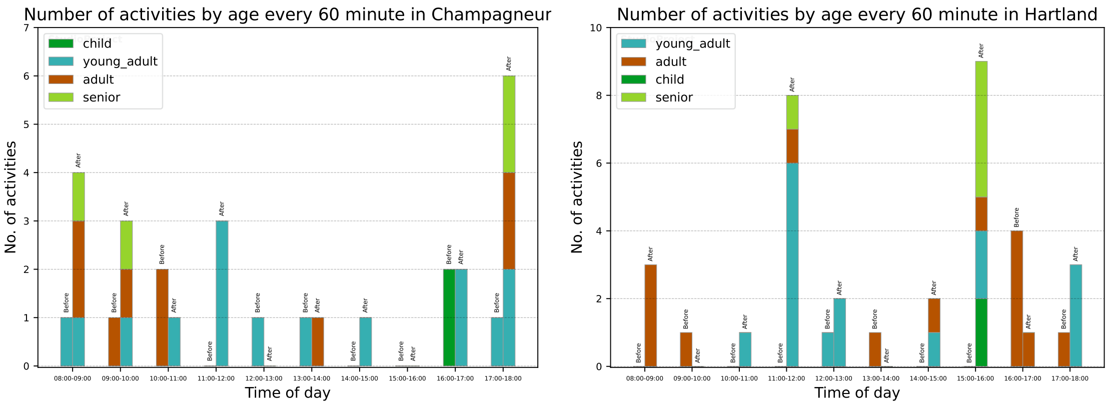

Fig. A.24: Age of observed people doing activities over time before and after speed humps installation

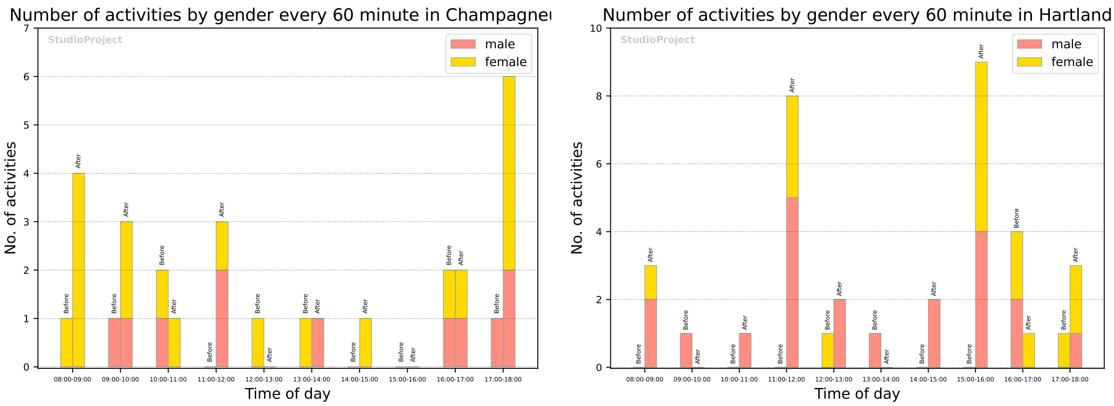

Fig. A.25: Gender of observed people doing activities over time before and after speed humps installation

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