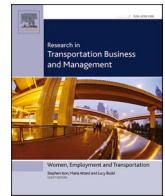


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## Citizen-science approach for an environmental analysis: The case study of university cyclists in Bologna<sup>☆</sup>

Alessandro Nalin, Margherita Pazzini<sup>\*</sup>, Roberto Battistini, Andrea Simone, Valeria Vignali, Claudio Lantieri

Department of Civil, Chemical, Environmental and Material Engineering (DICAM), University of Bologna, Viale del Risorgimento 2, 40136 Bologna, Italy

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### ABSTRACT

Climate change represents a critical vulnerability in urban areas. Shifting from the concept of Urban Resilience (UR) to Urban Sustainability (US) is considered a driver for reducing the impacts of climate change. This transition is feasible by encouraging bottom-up citizen engagement in urban policies and promoting sustainable active mobility, a sector in which cycling plays a significant role. This paper proposes an innovative methodology based on a citizen-science approach (bottom-up level), developed and carried out in Bologna, Italy, to investigate the correlation between the number of bike rides and users' awareness of environmental pollutants. About 50 bicycles specifically designed with environmental sensors to collect environmental data (PM10 and PM2.5) were distributed to university staff. A statistical analysis exploring possible relationships was carried out, and the main outcome was the identification of a multiple regression analysis (MLR) between trips, pollutants, and other variables related to the built environment. This integrated approach represents a novel contribution to the field, combining environmental monitoring and active mobility to support citizen-informed urban sustainability strategies.

### 1. Introduction

Climate change and the increasing concentration of greenhouse gases continue to pose major challenges for urban environments, affecting both environmental quality and public health (Battistini et al., 2023) (Global Monitoring Laboratory, U. D. of C., 2021).

In this context, the concepts of Urban Resilience (UR) and Urban Sustainability (US) have gained prominence as frameworks guiding the transformation of cities toward more adaptive and low-impact mobility systems (Zhang & Li, 2018). As a result, UR and US became pivotal in current urban planning debates, suggesting the promotion and the practice of new paradigms able to tackle social and ecological challenges in the transformation of urban areas (Wilkinson, 2012). Among the various strategies supporting this transition, cycling plays a central role, offering a zero-emission alternative for short urban trips and contributing to reductions in air pollution, noise, congestion, and space consumption. (Bernardo & Bhat, 2014; Corticelli et al., 2022; Maizlish et al., 2013). The COVID-19 pandemic further accelerated this shift, prompting cities to implement emergency cycling infrastructures and policies

(Bereitschaft & Scheller, 2020). Achieving these sustainability goals, however, requires not only infrastructural interventions but also a deeper understanding of how users perceive environmental conditions and how such perceptions influence their mobility choices. Recent technological advancements have enabled the widespread use of crowdsourced and georeferenced data, collected by both expert and non-expert users, to monitor environmental conditions in real time (See et al., 2016; Singh, Dahiya, Kumar, & Nanda, 2021). Within the broader domain of Volunteered Geographic Information (VGI), these data include both objective measurements (e.g., pollution levels) and subjective perceptions of urban environments (Goodchild, 2007; Hahmann et al., 2018; Mirri et al., 2014).

While several studies have examined cyclists' exposure to pollutants and the spatial variability of air quality along urban route (Kaur, Nieuwenhuijsen, & Colville, 2007; Luo, Boriboonsomsin, & Barth, 2020) limited attention has been devoted to understanding whether and how environmental awareness, in terms of what cyclists perceive and how they behave in response to exposure to pollution, may influence cyclists' route choices. Existing research shows that cyclists often prioritise the

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<sup>\*</sup> Corresponding author.

E-mail address: [margherita.pazzini2@unibo.it](mailto:margherita.pazzini2@unibo.it) (M. Pazzini).

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shortest or fastest routes, even when these lack dedicated cycling facilities.

The present study addresses this gap through an exploratory empirical investigation, aimed at assessing whether cyclists' environmental awareness, obtained through a citizen-science-based monitoring activity, relates to their route choices in an urban context. Specifically, this study aims to:

- Integrate data on air pollution exposure collected through crowdsourcing with data obtained from direct environmental monitoring of some of the main pollutants in urban areas, including noise and particulate matter, which were found to have different long-term effects on people's health (Marquart, 2022a; Raaschou-Nielsen et al., 2013)
- Compare cyclists' exposure based on different cycling route options within an urban context,
- Evaluate the relationships between the exposure to pollutants, the number of trips, and the physical or functional characteristics of the roads (e.g., topology of the road network, presence of a bike lane),
- Develop and test a mobile environmental sensing system through the deployment of bicycles equipped with instruments capable of detecting particulate matter and other environmental parameters.

To achieve these targets, this paper proposes a novel methodology based on a citizen-science approach, which was developed and carried out in Bologna, Italy. A sample of the University personnel participated in the study as active users responsible for collecting the data and cycling across the city. This was achieved through a comprehensive examination that involved several consecutive and interconnected steps.

The rest of the paper is structured as follows: Section 2 provides the theoretical background, while Section 3 describes the methodology and the related data. Results are presented and discussed in Section 4, while Section 5 delineates the conclusions and some possible future research streams.

## 2. Literature review

The seminal model that underlies the present research is the CADM Comprehensive Action Detection Model (Klöckner & Blöbaum, 2010) that establishes a connection between the ecological behaviour and the influence of awareness (of need/of consequence) and objective/subjective restraints. In those terms, having access to pollutant information and urban distribution represents a condition that may be located in the group of Awareness, which can interfere with personal restraints.

Awareness of air quality and its impact on the behavioral domain covers several fields, from traditional modal choice to urban choice of routing. Recent research illustrates the relationship between air quality and modal choice (Tajik et al., 2025), while in other previous work, air pollution represents a latent variable taken into account as part of the traditional travel cost factor and consequently able to impact on route choice (Yu-qin, Jun-qiang, Zhong-Yu, Gui-e, & Yi, 2013). Under another perspective, a previous study has been based on the investigation into the potential to define an urban route able to address cyclists toward the lowest air-polluted parts of the city, demonstrating how routes with a lower level of pollutants should be selected in comparison with the shortest path in a Danish city (Hertel et al., 2008). In such terms, also more recent research (Vij & Walker, 2016), examines the role of personal exposure to PM<sub>10</sub> in optimizing route choice selections, using a land use regression model applied to Dublin city. Similarly, a hybrid choice model has been developed (Dabirinejad, Habibian, & Khorsandi, 2024) in order to evaluate both the effects of air pollution perception and actual air pollution on commuters' mode choice and the effects of socio-economic status on the latent variables related to air pollution perception.

Even in the field of awareness, a different 2024 study related to Carbon Footprint awareness, (Deveci, Delen, & Ding, 2024) explores the

advantage of prioritizing digital carbon footprint awareness in optimized urban mobility using fuzzy Aczel Alsina-based decision making.

Research conducted in 2024 (Salimbene, Baeza-Romero, Pilla, & Çök, 2024) Within the European project PA-MAP (Participatory Approach to Monitoring Air Quality in Urban Environments), the project examines citizens' perceptions of air pollution in Turin (Italy) and Dublin (Ireland), to measure the effect of that awareness in the domain of the changes of habits, encompassing several fields, one of which is sustainable mobility.

Currently in the literature, a lack of direct measurement between air quality awareness and the effect of bicycles passages through more polluted lanes. This field is part of the present research in order to define an early initial study on direct measurement of the awareness impact on cyclists' exposure, personal perception and consequence on bicycle flow.

While not the core focus of the present study, the literature on mobile sensing is relevant as it provides the methodological foundation for the data-collection approach adopted here.

Further, at the basis of the novelty of the present research remains also the innovative data harvesting methodology, that engage scattered light sensors, portable installed aboard bicycles. Traditionally, air pollution was monitored by measuring concentrations of various pollutants, basically carbon monoxide (CO), ozone (O<sub>3</sub>), nitrogen dioxide (NO<sub>2</sub>), sulphur dioxide (SO<sub>2</sub>), and particulate matter (PM) at specific locations, using accurate and expensive instruments (Kumar et al., 2014). Monitoring sites in the EU are determined based on the Air Quality Directive 2008/50/EC, which clearly defines the minimum number of fixed monitoring stations for population and area covered. These sites are generally distributed in cities and provide concentrations of different pollutants with various degrees of temporal resolution (e.g., on an hourly or daily basis), and the output data is usually used as groundtruth.

Along with official references, there is a wide range of case studies on data collection through mobile sensors, and most of them are bicycle-based sensors, thus leading to the emergence of a new paradigm for monitoring air pollution (Kumar et al., 2014; Morawska et al., 2018), which can also be used both as input and to validate exposure models (Steinle, Reis, & Sabel, 2013). The goal of these survey campaigns is to collect high spatial and temporal resolution data on air pollution (Van den Bossche et al., 2015) by using a network of low-cost sensors to monitor real-time concentrations of different air pollutants. Finally, recent studies highlighted the importance of citizen science in the transport sector, not only as a framework related to data collection, but also as a participatory process capable of shifting user behaviors and addressing transport policies. However, there is a lack in the literature on citizen science methodologies applied to cycling phenomena at the urban scale (Storme et al., 2022). While a few citizen science projects engaged cyclists in data collection and focused on perceived road safety and accident risks (González-Ibáñez, Bonacic, & Fernández, 2015) (Nelson, Denouden, Jestico, Laberee, & Winters, 2015), the effects of air quality on cyclists' perceptions, behaviors, and route choices are largely unexplored, representing a significant gap in the literature. Environmental awareness has been considered as a conceptual framework in which individuals operate, particularly considering the study of (Sottile, Meloni, & Cherchi, 2015) on the relationship between awareness, attitude, and behaviour in mode choice and on the effect of awareness after implementation of soft measures in the field of travel behaviour and sustainable transport.

From this perspective, the present study incorporates crowdsourced data and environmental considerations to investigate how awareness of pollution influences cyclists' route choices in an urban context, analysing the relationships between sustainable mobility, environmental awareness, and user behaviour change. The concept of environmental awareness is defined as the participants' perception and understanding of air pollution, enabled through direct exposure, feedback, and a visual interface support. The novelty of the present study lies in the evaluation of the impact of environmental awareness on cyclists' route choices. This

is a factor not yet analyzed in literature, which has mostly focused on objective variables such as shortest or fastest routing and amenities. Thus, the present study also provides rational approaches to environmental sensitivity and personal environmental concerns.

### 3. Materials and methods

The research involved a sample of volunteers recruited from the administrative staff of the University of Bologna. Each user participated in both active and passive activities, as detailed in the following Sections. The cyclist sample was defined to reflect typical home-to-work commuting. A targeted call was issued among academic and administrative staff to recruit volunteers for the project. Since participation was limited to the availability of sensors, i.e., 50 sensors, the selection criteria were based on the self-reported frequency of bicycle use over a five-day workweek, i.e., the more days participants commuted by bike, the higher their score and likelihood of inclusion in the sample. Environmental data were collected through an optical sensor kit developed in collaboration with FabLab Barcelona in 2020 (Woods et al., 2018).

As previously argued, the main aspect of this research was to investigate whether and how the awareness of pollutant concentration may be considered as a possible driving factor in route choice. The methodology adopted took into account the following steps: design and development of the sensor kit and the related containment bag (Section 3.1); selection of the experimental sample and preliminary testing (Section 3.2), data processing and analysis (Section 3.3). Fig. 1 briefly outlines the proposed methodology. The analysis of data has been carried out mostly in a GIS environment, while the investigation on the cyclists' choices has been implemented with a multiple regression analysis (MLR). It is worth noting that the combination of analyses performed with the complementary use of GIS and statistical approaches can reveal notable results, as widely demonstrated since the early work of Briggs et al., 1997). MLR is based on the following Eq. (1) (Nalin et al., 2024):

$$y_i = \beta_0 + \sum_{j=1}^p x_{ij}\beta_j + \varepsilon_i \quad (1)$$

Where  $y_i$  is the dependent variable,  $\beta_0$  is the constant,  $\beta_j$  is the coefficient associated with each regressor  $x_{ij}$ , and  $\varepsilon_i$  is the random error term. MLR was chosen as a suitable statistical technique in unveiling relations between the users' behaviors, i.e., the number of trips, and several candidate variables, including the pollutants.

Terms adopted in the following sections include: User, i.e., the volunteer cyclist who took part in the experiment; Record, i.e., the GPS data acquired by the sensors during the survey; Trip, i.e., any displacement between an origin O and a destination D; University area,

i.e., a portion of Bologna where most of academic buildings and facilities (e.g., administrative offices, classrooms, libraries, university museums) are located.

#### 3.1. Sensor kit and settlebag design and development

Sensors from an updated version of Smart Citizen Kit (SCK) were considered through scientific collaboration between the Department of Civil, Environmental, and Material Engineering (DICAM) of the University of Bologna, Italy, and Fablab Barcelona, a spin-off innovation center of the Public University of Barcelona, Spain. SCK is a set of devices for monitoring a wide range of environmental variables already used in several research efforts (Brattich et al., 2020; Mahajan & Kumar, 2020). SCK is at the heart of what is internationally known as the Smart Citizen System, an adaptive hardware framework capable of configuring environmental functions in the citizen science and scientific research domain, as advocated elsewhere (Mahajan & Kumar, 2020) SCK are assemblies of small, low-cost commercial sensors that measure temperature, relative humidity, noise, light, NO<sub>2</sub>, and CO concentrations.

#### 3.2. Experimental design and data collection

The sample of cyclists was selected from academic and administrative staff through a call. As the main selection criterion, the average number of days per week each participant declared to use a bicycle for home-work commuting was considered. This criterion was intended to engage proactive users and was not intended to influence the number of rides, as the activities were not programmed in advance. In this regard, it is important to note that, in contrast to previous comparable studies (Gelb & Apparicio, 2022; Samad & Vogt, 2021; Thai, McKendry, & Brauer, 2008a), this research was based on individual attitudes and preferences, thereby avoiding the imposition of pre-scheduled trips or predetermined routes, neither of which were the primary or the alternative ones. To encourage participation, each cyclist was also provided with a bicycle designed and branded by the University of Bologna. In order to prevent damages, malfunctions or any illegal use of the sensor, as well as erroneous interpretations of the data during the subsequent analyses, participants were required to sign a declaration on the proper use of the sensor (e.g. storage, recharging, routine maintenance), and to agree not to transfer it to third parties during the experimental phase.

According to project guidelines, participants were asked to install the sensor under the saddle and use it every time they cycled. Before each trip, they were required to access a web application displaying pollutant concentrations as a point cloud overlaid on the road network, using data previously collected by riders themselves. In addition to the collection of environmental and mobility data, the research team recurrently monitored the use of the web application. This ensured adherence to the project guidelines, particularly with regard to the frequency of data upload. The system also included a feedback mechanism that allowed participants to visualize their exposure data through a Web portal, fostering awareness and potentially inducing changes in future route choices. As for the Web portal, it was based on a client-server architecture and built to show cyclists the level of pollutants on each lane travelled by all cyclists. The server was built using the Node.js language and using express.js, a Node.js module. JS-based framework that helps manage the server itself and routing. A relational database was created with MySQL to store data from the sensors. Once runs were finished, sensors had to be recharged and the recorded data (formatted as .csv files) uploaded to the Web portal, which automatically processed the incoming data and tracked the records, thematizing them against relevant thresholds. Each row of the .csv sheets was a record. The information was both spatial (e.g., GPS coordinates, formatted in the WGS84 reference system) and temporal (e.g., day; dd/mm/yyyy format and time; hh:mm:ss format), with the following environmental variables: PM1, PM2.5, PM10, and Noise. It is important to note that no restrictions or requirements were imposed on the use of bicycles during the survey.

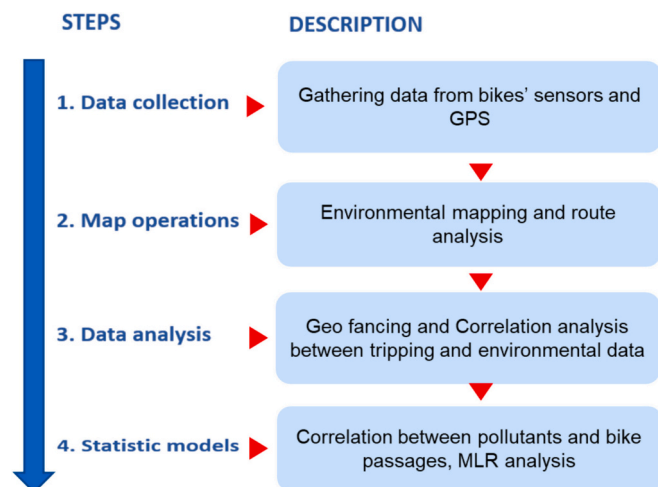


Fig. 1. Methodology to evaluate cyclists' exposure to pollution concentration.

This included no restrictions on the times of day when bicycles could be used, nor any requirement to use pre-assigned routes. As a consequence, cyclists were allowed to ride their bicycles as desired and according to their needs. Regarding the temporal analysis, the entire survey was conducted from May 2022 to July 2022. Due to the late spring end of classes and the specific sample of users (i.e., university staff selected through a call), only a subset of days (May 16, 2022, to June 30, 2022; weekdays only) was monitored. The timeframe was large enough to include the end of the regular academic period and the exam session, when administrative and teaching activities are usually still ongoing. During the first week of data collection, a comparative study was conducted in which cyclists were asked to ride along the same route at the same time on the same day. This was done to test the sensors for correct operation.

### 3.3. Sensors

#### 3.3.1. Conceptual dimension

Low-cost sensors used for particulate matter (PM) monitoring are usually based on the light scattering method. The reason for using this method in low-cost PM-related sensors is related to the fact that sensors based on this principle are cheap to produce, have low power requirements, and fast response times (Wang, Akar, & Guldman, 2015). In this method, a light source illuminates the particles and then measures the light scattered by the particles. For particles with diameters greater than  $\sim 0.3 \mu\text{m}$ , the amount of scattered light is related to their mass/number concentration; however, particles with diameters smaller than  $\sim 0.3 \mu\text{m}$  cannot be detected by this method (Koehler & Peters, 2015; Thomas & Gebhart, 1994). Detectable particles ( $> 0.3 \mu\text{m}$  in diameter) can be dimensionally segregated through a specific algorithm (Northcross et al., 2013) or by using filters (Jones et al., 2016). As suggested elsewhere (Rai et al., 2017) to implement a large-scale sensor network and use all the data generated in a meaningful way, standard guidelines need to be formulated to evaluate its short and long-term performance. The main issues are related to calibration, stability, field measurements, gas interference, and the influence of temperature and relative humidity.

In general, sensors can be installed on bicycles to collect data on pollutants and environmental variables, or data related to temperature in urban contexts (Pena Acosta, Vahdatikhaki, Santos, & Dorée, 2022). These studies have contributed to mapping cyclists' exposure to air pollutants at a finer spatial resolution. However, as noted in prior research, sensors mounted on mobile vehicles, such as bicycles, cannot track temporal variability in the same way as fixed stations, even if they provide better spatial coverage in terms of resolution and granularity. Bicycle-based analyses emerged because of the proximity of mobile sources of pollution to bicyclists (Kaur et al., 2007), and air quality is a source of concern and discomfort for cyclists, especially in urban areas (Badland & Duncan, 2009). Some factors influencing cyclists' exposure have been identified, and they include, e.g., time of day, effects of local climate, congestion (Hatzopoulou et al., 2013), and cycling infrastructure, i.e., route choice, where separation from car traffic has a strong impact (Dons et al., 2019; Dons, Int Panis, Van Poppel, Theunis, & Wets, 2012; Hertel, Hvidberg, Ketzel, Storm, & Stausgaard, 2008). A peculiar air pollution measurement campaign in Minneapolis, United States, based on Particle Numbers (PN), Black Carbon (BC), and PM 2.5 concentrations measured along three routes ( $\sim 100 \text{ km}$ , about 62.14 mi overall) during the morning and afternoon peak hours, was geared to explore the level of bicycling exposure (Hankey & Marshall, 2015). The research, defined over 34 days between August 14 and October 16, 2012, showed that the share of bicycle exposure that could be attributed to near-traffic emissions was about 50% for PN and BC, and 25% for PM2.5. In a study conducted in Stuttgart, Germany, a data collection methodology based on mobile measurement with a bicycle has been explored (Samad & Vogt, 2021). Several sensors were selected and installed on the bicycle to take mobile measurements along a specific

route in February 2018. The pollutants measured included particulate matter (PM), ultrafine particles (UFP), black carbon (BC), nitrogen oxides (NO, NO<sub>2</sub>, and NO<sub>x</sub>), and ozone (O<sub>3</sub>). The results showed high spatial variability and the influence of factors such as local traffic and weather conditions on pollutant concentrations. The research also showed that mobile sensing offers a highly adaptive and flexible method (Samad & Vogt, 2021). Another study of 32 volunteers in Dublin, Ireland, analyzed the pollution exposure of cyclists compared to different modes of transportation (public transport, cars, walking), finding that although cyclists' exposure concentrations were not always the highest, their inhalation doses of pollutants were the highest (Nyhan, McNabola, & Misstear, 2014). Similar research on three European cities (Helsinki, Finland; Rotterdam, the Netherlands; and Thessaloniki, Greece) measured the level of particulate matter (PM) and noise exposure on different modes of transportation (bicycle, bus, and car), finding that, in the Thessaloniki case study, PM was generally higher while using bicycle and public transportation than while driving cars with closed windows. The results showed that active and public transport commuters were often at higher risk of air pollution and noise exposure than private car users (Okokon et al., 2017). In contrast, another study conducted in 2001 showed that cyclists sometimes have lower exposure concentrations than motorized modes, especially when they use facilities separated from traffic (Adams, Nieuwenhuijsen, Colvile, McMullen, & Khandelwal, 2001). In a recent application (Qiu, Wang, Liu, & Luo, 2022), the real-time exposure of cyclists to particulate matter (PM) and black carbon (BC) was assessed. The experimentation was carried out in Xi'an, the largest city in Northwest China, and the total route length was 6.3 km. The exposure level was defined through a dosimetry model. A statistical analysis was conducted by the authors themselves through a linear regression model to explore the impact of different factors, such as exposure time and distribution of pollutants along the route. Exposure to PM<sub>2.5</sub> and BC was associated with specific urban locations, such as hot spots, intersections, and parking lots.

#### 3.3.2. Sensors equipment description and testing

To evaluate their performance in the field, the sensors were tested under real-world conditions in the city of Bologna, Italy, during winter and summer as part of several extensive experimental campaigns (Cameli et al., 2025). Sensors have been tested under different meteorological conditions, allowing us to formulate some guidelines for their implementation. Some solutions were studied to integrate SCK sensors into bicycles. A significant part of the preliminary steps of the research focused on studying and allocating the integration of sensors on board bicycles, defining sensor data communication systems, finding compact and micronized dimensions for the entire sensor package, and studying the shape and technical characteristics of the containment bag, which contains the sensor package. The system leverages the ability to be integrated with a central data logger, non-hardware components such as a storage unit, and a sensor analysis tool. The central data logger is supported by an ARM M0+ 32-bit 48Mhz SAMD21 model with Citizen Smart firmware embedded in the 32-bit processor with 32 KB RAM and 256 KB FLASH memory. The on-board sensors have adequate memory space to record data for several consecutive days. Moreover, the platform is a front-end and back-end solution for receiving, storing, and interacting with public data, with a focus on crowd-sensing applications. The sensor analysis framework was written in Python, a programming language that allows to work and ensures effective system integration. The sensor package consists of the following components: sensor kit with GPS and antenna, as reported in Table 1, charger and USB cable, and custom case.

GPS sensors were carefully chosen with regard to accuracy and transmission capability, even in covered areas such as underground parking lots. Specifically, the model chosen is Sparkfun NEO-M8U GPS Breakout, a high-quality GPS board capable of receiving signals from GPS, GLONASS, Galileo, and BeiDou constellations with a horizontal accuracy of about 2.5 m, which is sufficient since GPS coordinates are

**Table 1**  
Sensor types.

Measurement	Units	Sensor
Air temperature	°C	Sensirion SHT-31
Relative Humidity	%RH	Sensirion SHT-31
Noise level	dBA	Invensense ICS-434342
Ambient light	lx	Rohm BH1721FVC
Barometric pressure	kPa	NXP MPL3115A26
Equivalent Carbon Dioxide	ppm	AMS CCS811
Volatile Organic Compounds	ppb	AMS CCS811
Particulate Matter (PMx)	µg/m <sup>3</sup>	Plantower PMS 5003

recorded every 60 s (at a speed of 15 km/h, this means one measurement point every 250 m). As additional information, the number of in-view satellites is provided for each record, thus enabling analysts to discard biased data, e.g., coordinates recorded with <4 in-view satellites (Chen, Shen, & Childress, 2018). In terms of time resolution, sensors recorded data with an average interval of 5 s. With regards to the case, it was specifically selected for the following reasons: widely available from any established bicycle equipment manufacturer, it is lightweight and waterproof, with an appropriate size, materials, and flexible external mounting to reduce vibration and transmissibility. The sensors are protected internally by a polypropylene folder, and vents produced by a 3D printer are installed to allow proper air circulation inside. Fig. 2 illustrates the saddle bag concept installed on bicycles as developed in collaboration with FabLab Barcelona. The waterproof bag is designed to protect the SCK system from external agents such as dirt. The measurement method in the bag ensures sufficient air flow, limited gas flow through the sensors, and minimal gas soaking time to ensure sensitivity.

The sensor kits have been developed in partnership with FabLab Barcelona, which has directly conducted several Indoor particulate tests and Outdoor tests. The indoor particulate tests were conducted indoors using a Marlin Smoke Machine in order to assess the difference between each enclosure. They have been divided into four major tests, specifically. The first is Free air comparison, which permitted an initial comparison between both sensors in open air in order to assess the difference between each sensor measuring in open air with smoke injection up to 4000µg/m<sup>3</sup>. The second test is Enclosure comparison, whose purpose was to determine which measurement principle, between directly exposing the sensors to the air flow caused by the bicycle's movement and exposing them inside a "chamber" in which air flow is contained. The third test is the Chamber vs. Reference test, which shows how the enclosure effectively slows down the air flow charged with particles and still correlates properly with the free air sensor in the injection phase, although not in the dispersion phase. This indicates that the accumulation and evacuation process of the particles within the chamber is not fully controlled in this enclosure. Finally, the fourth test is Direct exposure vs. Reference test, which shows an inferior sensitivity, already seen in the enclosure comparison, of the direct exposure option versus the actual concentration. The measurements also show less reactivity in some instances, smoothing out some peaks in particle

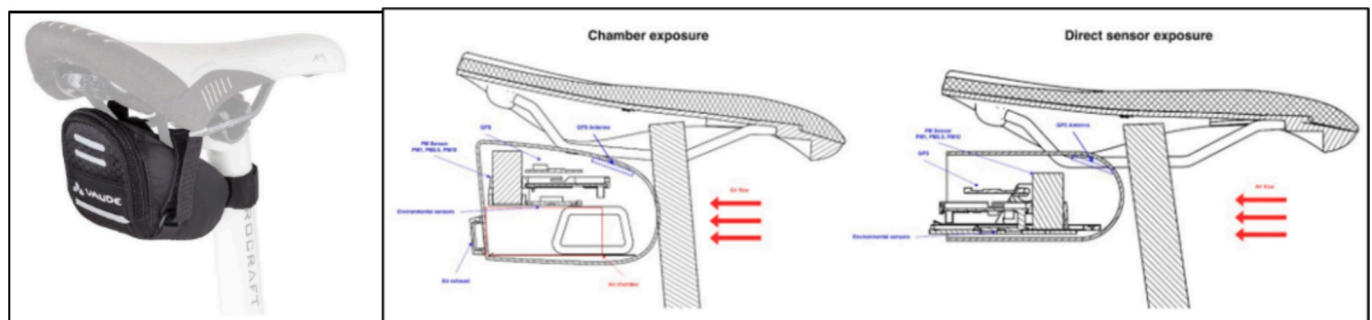
concentrations. The temperature trace shows an offset of 3degC at the end of the test, similar to that of the other enclosure, with a humidity difference of 4–5%rh. The Outdoor tests are aimed at comparing outdoor measurements with sensor trips. These measurements use the same sensor as the ones mounted on the bicycle. A script is used to post-process the data based on location and derive a comparison between both measurements. The tests demonstrate the appropriate accuracy of the sensor kit for the research purpose, and they are illustrated in detail in USER Guideline of the sensor kit.

An example of analysis in an indoor setting to evaluate the difference between each case and free air sampling is shown in Fig. 2. Another important test was based on the evaluation of the most appropriate position on the bicycle. Specifically, the front installation was compared with the rear position. This test showed that PM2.5 measurements are not affected by the installation position. Regarding temperatures, it was inferred from the test that there is a difference of about 2 °C between front and rear installation. Considering the purpose of the research and the little attention paid to temperature, both positions were considered adequate. After the test analysis, the production of 50 sensor kits was carried out to provide experimental materials.

### 3.4. Data processing

#### 3.4.1. Preparation of the dataset

As previously demonstrated (Brauer, Mäkinen, & Oksanen, 2021; Chen et al., 2018) GPS data needs a comprehensive and thorough review. In fact, the signal can be exposed to several types of errors and biases, including misfunctions of receivers or in-view satellites, or adverse atmospheric conditions. Moreover, in dense urban environments, the signal can be affected by the presence of high buildings, which can cause signal loss, thus reducing accuracy and precision (Dekoninck, Botteldooren, & Int Panis, 2013; Merry & Bettinger, 2019). Consequently, troubleshooting can be challenging to address comprehensively (Menghini, Carrasco, Schüssler, & Axhausen, 2010; Van den Bossche et al., 2015) especially in the case of surveys employing low-cost sensors. Yet, it constitutes a fundamental preliminary stage in GPS-based analyses. Therefore, a thorough evaluation of records was performed to make the original dataset as robust as possible to minimize the effects of distortions that potentially affect the records, especially in terms of the accuracy of coordinates. The main purposes of this processing phase were the selection of usable data (i.e., records with ≥4 in-view satellites) and their subsequent correction by analysing temporal (e.g., time interval between subsequent records) and spatial (e.g., coordinate errors, irregular sensor records) information. It was performed in Microsoft Excel, Microsoft Power BI, and QGIS (version 3.22). With regards to the latter, GIS has been proven to be a suitable tool for analysis and detection of pollutant hotspots (Puyana-Romero, Cueto, & Gey, 2020). In analyses based on GPS surveys, a time resolution of 60 s could be considered an appropriate value, so all data with a time interval between subsequent records ≥5 s, i.e., as mentioned above, the average time resolution, and ≤ 60s, were kept. This time span tends to minimize



**Fig. 2.** (a) Settlebag concept. (b) Test #1 Free air sampling PM2.5.

fluctuations in the records, which might occur within a short time scale (Van den Bossche et al., 2015). As further temporal characterization of the records, a filtering procedure was conducted to select only records related to weekday peak hours (i.e., from 07:30 am to 10:30 am, and from 4:30 pm to 8:30 pm, Mondays-Fridays only). This filter was imposed by the authors to focus on the exposure of users during the main commuter time windows and is consistent with the research question introduced in Section 1 and the research design, pivoted on university personnel.

About spatial analysis, it was performed mainly in QGIS. Loading records in the GIS environment allowed outliers and unacceptable records to be recognized. Several geoprocessing tools were applied to identify records with incorrect coordinates (e.g., Lat = 0; Long = 0), a recurring operation in the case of GPS surveys (Ghanayim & Bekhor, 2018), and records outside the study area (i.e., outside the boundaries of the Bologna Municipality), while a density analysis was computed to identify unexplained hotspots. Regarding the latter, some areas of the city appeared unreasonably overcrowded during daytime or nighttime hours. The combined analysis of space (i.e., coordinates) and time (i.e., day and time) revealed that sporadic and erroneous use of sensors (e.g., failure to turn off the sensor after running) caused a high concentration of records within university areas during working hours, or nighttime stationary point clouds next to urban blocks (presumably the place of residence of users). Therefore, these records have been discarded, as they reasonably were not part of a trip. In addition, and similar to the methodology already applied in (Battistini, Nalin, Simone, Lantieri, & Vignali, 2022). Records that should not be considered as part of the ride (e.g., moving bicycles during parking manoeuvres, positioning for “green” at traffic lights, waiting for “free space” at street intersections) were captured by a buffer analysis. For this purpose, a subset of OpenStreetMap entities (traffic lights, street intersections, bicycle racks) was downloaded and processed within a 20-m-wide buffer, and the records included were appropriately characterized. Table 2 shows the size of the database post-processing. Despite the reduction in the number of records, the described operations created a consistent and dense dataset in which a considerable number of the original users were monitored. The heat map shown in Fig. 3 depicts the density of records, where the brightness of colour is proportional to the number of points, i.e., the darker the colour, the higher the concentration of records. First, an apparent result of the map-matching procedure, the distribution of records is uneven, with most records being located near university facilities. In fact, the density of records averaged 11 points per hectare, while within the university area, the value rises to 27 records per hectare. While this outcome may appear to be a relatively evident consequence, given that sensors were provided exclusively to University personnel, it proved to be a significant element. This is due to the fact that it reinforced the rationale behind selecting a specific area of interest, namely the University area in Fig. 3, characterized by a considerable density of records, thereby ensuring that statistical analyses would be as informative and consistent as possible.

**Table 2**  
Post-processing database size.

Database processed elements	
Number of records before database revision	329,034
Number of monitored sensors (i.e., users) before database revision	29
Number of records after database revision, without time window filtering procedures (i.e., weekday morning and evening peak hours, from May 16, 2022, to June 30, 2022)	209,882
Number of records after database revision, with time window filtering procedures	26,872
Number of records within university area after database revision, with time window filtering procedures	6360
Number of monitored sensors after database revision (all procedures applied)	24

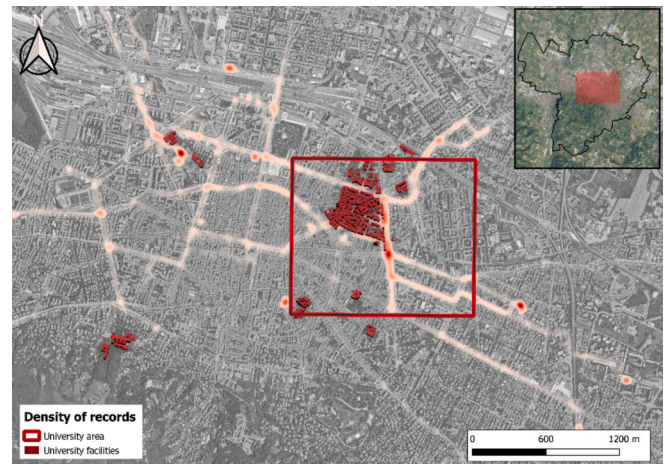


Fig. 3. Density of records.

#### 3.4.2. Preparation of road network and trips

This Section delves into the technical aspects related to the preparation of the road network, the procedures for the creation of the trips, and, consequently, the definition of the unit for the subsequent statistical analysis. The shapefile of the official road network of the Municipality of Bologna was used as a spatial reference. Fig. 4 shows the road network within the study area, whose main parameters are reported in Table 3. About the characteristics of the road network, data on the reserved bicycle network was extracted by filtering the specific attributes of the links describing the types of roads and selecting those where bicycle traffic is permitted. In addition, two indicators, namely closeness centrality (CLOS) and betweenness centrality (BETW) (Porta et al., 2009), were calculated in relation to each road segment, and then included in the statistical analysis (Section 4.2). These indicators have been regarded as suitable proxies for investigating whether the location of the road segments and the topological characteristics of the road network might be considered among the determining factors of the hypothetical route change, in addition to and in combination with the other variables included in the analysis. The inclusion of CLOS and BETW as control variables is substantiated by the necessity for a comprehensive examination of the users' selection of convenient routes, given that commuting tasks of users and the a priori knowledge of different routes may have influenced the number of trips recorded at each road segment. About CLOS, it measures the extent to which an element of a given road network is close to all the others, along the shortest distances available (Porta et al., 2009). In this analysis, the

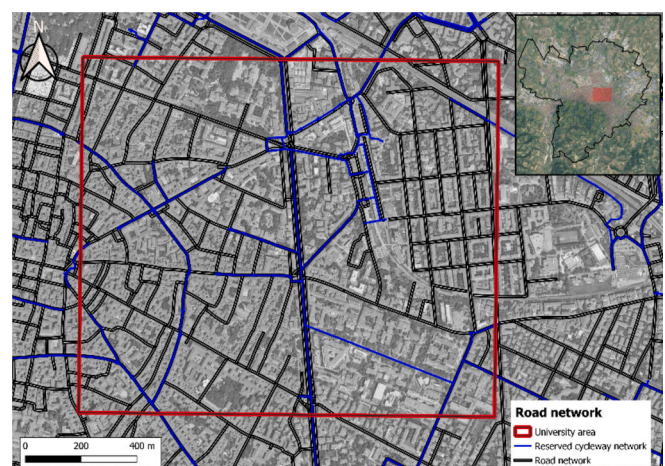


Fig. 4. Road network (focus on the University area).

**Table 3**  
Descriptive statistics for environmental variables.

Road network parameters	Unit	
Number of road links in the Bologna municipality		8096
Road network length in the Bologna municipality	m	853,609
Number of road links in the university area		240
Road network length in the university area	m	46,841
Number of reserved cycleway links in the Bologna Municipality		1052
Reserved cycleway network length in the Bologna Municipality	m	225,151
Number of reserved cycleway links in the University area		69
Reserved cycleway network length in the University area	m	7951

centroids of each road segment in the selected road network were extracted in a GIS environment, and then process node  $i - th$ , with  $i \in N$ . CLOS was calculated following the Eq. (2):

$$CLOS_i = \frac{N - 1}{\sum_{j=1, j \neq i}^N d_{ij}} \quad (2)$$

Where  $N$  is the total number of nodes in the network,  $d_{ij}$  is the shortest distance between nodes  $i$  and  $j$ .

About BETW, it is based on the hypothesis that a node becomes more central when it is crossed by a greater number of the shortest paths connecting all pairs of nodes in a network (Porta et al., 2009). From this perspective, BETW can be defined as a metric pertaining to the property of an element of a road network to be part of multiple interactions, intended as trips between any given pair of origin and destination. Similarly to the computation of CLOS, the centroids of each road segment in the selected road network were extracted and then processed as node  $i - th$ . BETW was calculated following Eq. (3):

$$BETW_i = \frac{1}{(N - 1)(N - 2)} \sum_{j=1, k=1, j \neq k \neq i}^N \frac{n_{jk}(i)}{n_{jk}} \quad (3)$$

Where  $n_{jk}$  is the number of shortest paths between nodes  $j$  and  $k$ , and  $n_{jk}(i)$  is the number of these shortest paths containing the node  $i$ .

In addition, information on green infrastructure extracted from the Open Data portal of the Municipality of Bologna, namely the canopy coverage, was included. In detail, a percentage of canopy coverage was calculated as GIS geoprocessing output, namely an overlay between the green infrastructure vector layer and the road segment vector layer. This variable was calculated and then used in the subsequent statistical analysis (see Section 4.2) to assess whether the green infrastructure and the related environmental and recreational benefits (e.g., cooling, shading) may be considered a factor in the route choice.

Once the preparation of the road network was completed, trips were created by applying appropriate spatial algorithms to the processed database of records. First, map-matching was performed in a GIS environment by snapping records to the nearest road segment (distance threshold: 20 m). Map-matching was used also to link coordinates and the set of information recorded during the ride. It includes all the information related to the users' movements, including the sensor ID and the timestamp of the ride, as well as information on the pollutants. After the map matching procedure, trips were created in a GIS environment as an ordered sequence of consecutive records. The identity of the trips could always be identified through the attributes of the records, namely the sensor ID and timestamp. Conversely, users' identities could not be distinguished due to privacy restrictions, and therefore an anonymous identifier was assigned to the sensors.

In contrast to the predominant approach adopted in earlier studies and as previously mentioned, trip scheduling, routing and frequency of travel were not defined a-priori; hence, a subset of road segments where only road segments where  $n_{trips} \geq 3$  made was selected. The exclusion of road segments with a limited number of trips is aligned with the research, as it is purposeful to establish a consistent basis for the subsequent statistical analysis. This procedure created a set of 213 trips,

whose main parameters and characteristics are summarized in Table 4, while an overview is presented in Fig. 5. It is worth noting that the creation of trips revealed two particular and illustrative subsets, namely those that originated, concluded, or transited through the University area (letter (B) in Table 3) and those passing through the city centre area (letter (C) in Table 3). In view of the previous observations, it can be deduced that a trip should be regarded as an ordered sequence of records that have been registered along different road segments. Consequently, it can be posited that each trip may have been included in the number of those recorded at each road segment. This would denote that the unit for the subsequent statistical analysis should be set as the cumulative number of trips registered at each road segment, rather than the absolute number of trips (letter (D) in Table 3).

## 4. Results and discussion

### 4.1. Spatial distribution of pollutants

The procedures described in the previous sections allowed to plot the distribution of pollutants across Bologna, and hence to visually analyze the exposure of cyclists. The following figures show the measured exposure to the monitored pollutants with a focus on the University area. Fig. 6 refers to PM1, Fig. 7 to PM2.5, Fig. 8 to PM10, and Fig. 9 to noise. It is worth noting that PM2.5, PM10 and Noise have been thematized based on the different regulatory thresholds established by Italian laws (Gazzetta Ufficiale della Repubblica Italiana, 2010), while PM1 exposure limits are not strictly defined.

### 4.2. Statistical analysis

#### 4.2.1. Preliminary results

To pursue the research targets, MLR introduced in Section 3 was performed. The dependent variable was defined as the number of trips made by the cyclists recorded along each road segment (NOT), as described in Section 3.3.2. Regarding the independent variables, the following set was selected: particulate matters (PM2.5 and PM10; unit:  $\mu\text{g}/\text{m}^3$ ) for each road segment; noise (NOI; unit: dBA); presence of dedicated bicycle infrastructure for each road segment (DBI) as dummy variable derived from the processing steps described in Section 3.3.2 (i. e., 1 = bikes are allowed; 0 = bikes are not allowed); proximity to relevant green infrastructure (PGI) as described in Section 3.3.2; closeness centrality and betweenness centrality (CLOS, BETW), following the considerations argued in Section 3.3.2. PM1 was not included, due to the abovementioned limited availability of regulatory and local policies concerning this pollutant. The inclusion of DBI, PGI, CLOS and BETW in addition to PM2.5, PM10 and NOI is intended to explore the role of the built environment in the route choice when awareness of exposure to pollutants is taken into account.

As a preliminary step, a correlation analysis has been calculated (Pearson's  $\rho$ ) to detect possible issues related to, e.g., multicollinearity, which may lead to unreliable estimates in the MLR. Some relevant

**Table 4**  
Overview of trips and their characteristics.

Overview of trips and their characteristics	
Total number of trips after database revision (A)	213 (100%)
Number of trips with origin, destination and/or in transit through the University area (B)	186 (87%)
Number of trips passing through the city centre, after database revision (C)	69 (32%)
Number of road segments with $\geq 3$ trips, as detailed in Section 3.3.2 (D)	110
Cumulative number of analyzed events, as the sum of the number of trips (A) counted per each road segments where $n_{trips} \geq 3$ (D), as described in Section 3.3.2	76,230

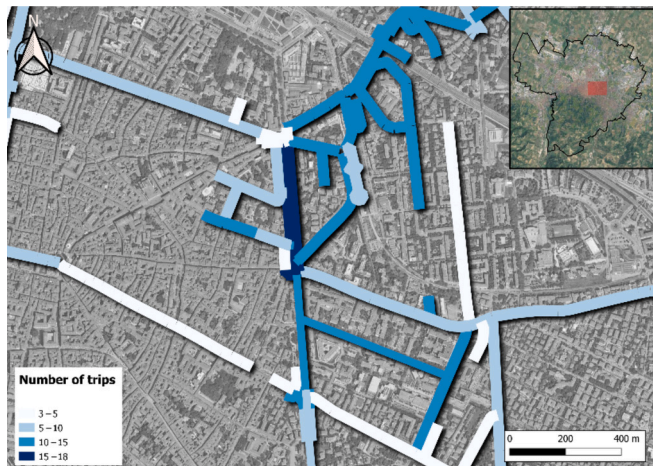


Fig. 5. Number of trips per road segment (focus on the University area).

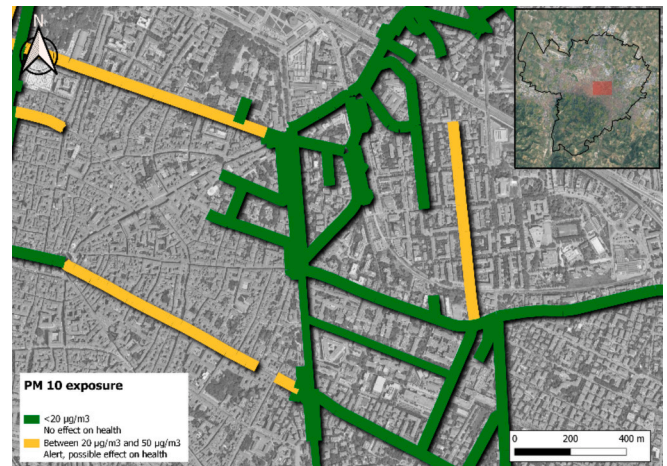


Fig. 8. Exposure to PM10 (focus on the University area).



Fig. 6. Exposure to PM1 (focus on the University area).

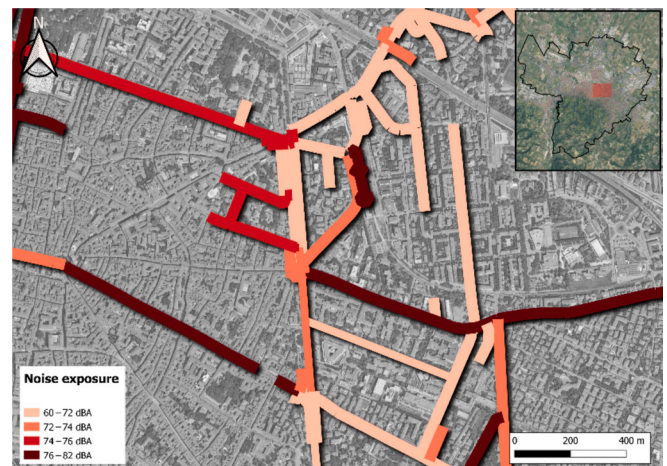


Fig. 9. Noise exposure (focus on the University area).

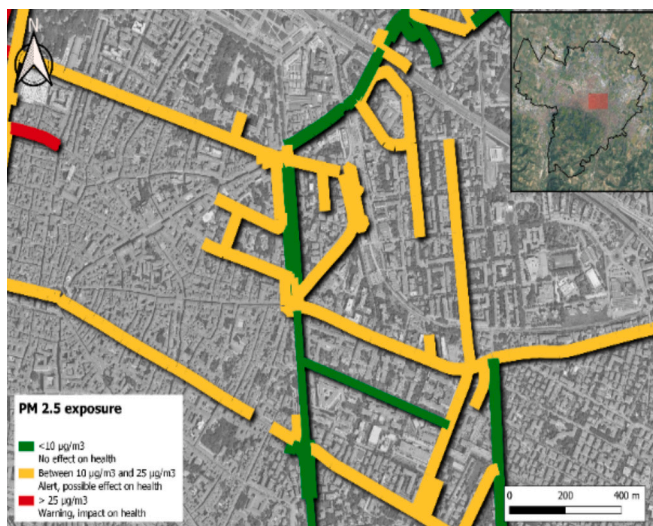


Fig. 7. Exposure to PM2.5 (focus on the University area).

correlations are shown in Table 5. Remarkable results were found between the particulate matter PM2.5 and PM10. The high correlation between the two PMs ( $\rho > 0.9$ ;  $p$ -value  $< 0.001$ ) indicates that, in

relation to the research targets, the inclusion of the two pollutants in a single regression model should be avoided, thereby underscoring the necessity for distinct models. However, this result is worthy of great attention, as the analysis confirmed the uniformity in sensors' performances in detecting pollutants, and finds consistency with similar researches (Cameli et al., 2025). With regards to the correlation between particulate matters (PM2.5 and PM10) and PGI and between NOT and most of the candidate variables, results suggest significant relationships ( $p$ -value  $< 0.05$ ), thus reinforcing the need for further examination with the regression analysis. With this latter regard, authors deliberately included all the candidate variables in the MLR models, to test their actual effect on the dependent variable, namely NOT.

#### 4.2.2. MLR

Following the findings of the correlation analysis, two distinct MLR models have been calculated, including PM2.5 and PM10 separately, while the other variables have been maintained in both models. Results are reported in Tables 6 and 7, respectively. As expected, the values of  $R^2$  are similar, denoting consistency in the explanatory power of the two models. The Variance Inflation Factor (VIF) for all variables resulted  $< 2$ , suggesting no relevant multicollinearity issues. Normality of data was assessed using the Kolmogorov-Smirnov test; results suggest that there is not enough evidence to conclude that the sample distributions in both models differ from a normal distribution, thereby confirming the validity of the proposed method.

About coefficients, some results are worthy of consideration, as they

**Table 5**  
Correlation analysis (excerpt).

		PM2.5	PM10	NOI	PGI	CLOS	BETW
PM10	Pearson's $\rho$	0.981					
	$p$ -value	<0.001					
NOI	Pearson's $\rho$	0.355	0.320				
	$p$ -value	<0.001	<0.001				
PGI	Pearson's $\rho$	-0.209	-0.187				
	$p$ -value	0.028	0.050				
NOT	Pearson's $\rho$	-0.381	-0.399	-0.015	0.301	-0.426	-0.032
	$p$ -value	<0.001	<0.001	0.873	<0.001	<0.001	0.781

**Table 6**  
Results of MLR (PM2.5). Dependent variable: NOT.

Variable	Coefficients (unstd.)	SE	$p$ -value	VIF
Constant	5.852	4.885	0.235	
PM2.5	-0.187	0.058	0.002	1.31
NOI	0.103	0.065	0.121	1.18
PGI	0.621	0.363	0.092	1.17
DBI	0.022	0.988	0.982	1.11
CLOS	-7.231	2.235	0.003	1.15
BETW	1.574	2.566	0.541	1.08
$R^2$ (adj.)	0.279			
F	6.10		<0.001	
Kolmogorov-Smirnov	0.118		0.197	

**Table 7**  
Results of MLR (PM10). Dependent variable: NOT.

Variable	Coefficients (unstd.)	SE	$p$ -value	VIF
Constant	6.315	4.838	0.196	
PM10	-0.182	0.055	0.002	1.33
NOI	0.095	0.064	0.144	1.15
PGI	0.625	0.362	0.088	1.17
DBI	-0.001	0.983	0.985	1.10
CLOS	-6.983	2.368	0.004	1.17
BETW	1.635	2.562	0.525	1.08
$R^2$ (adj.)	0.283			
F	6.19		<0.001	
Kolmogorov-Smirnov	0.129		0.129	

address the initial research questions. That is related, for example, to particulate matter (PM2.5 and PM10). Indeed, they exhibit negative and statistically-significant ( $p$ -value <0.01) coefficients, suggesting that, at increasing levels of pollution, the number of trips tended to decrease. This result is in line with previous research efforts about the effects of awareness of the individual exposure to pollutants (Marquart, 2022b), and it may be indicative of the connotation attributed (Zhao, Li, Li, Liu, & Long, 2018) by users to the pollution in terms of the short- and long-term implications for health (Kousar, Afzal, Ahmed, & Bojnec, 2022).

Further noteworthy results can be derived in relation to CLOS and BETW, which can be considered indicative of the relationships between the number of trips and the characteristics of the road network. CLOS exhibited a negative relation with NOT, thereby suggesting that the more central links may not have been chosen by users in the rerouted, alternative trips. About BETW, it exhibited a non-statistically significant ( $p$ -value >0.05) impact on NOT, confirming the result of the correlation analysis. Consequently, these findings suggest that users may have provided only a partial evaluation of some main characteristics of the road network, namely the inclusion of the road segments in the shortest or the fastest connections between the origin and the destination of trips. In this latter regard, it is reasonable to postulate that the diversion in routing also included indirect, longer routes, aligning with previous research efforts (Hofman, Samson, Joosen, Blust, & Lenaerts, 2018; Thai

et al., 2008a). This result is therefore compatible with the coefficients of DBI, which were not statistically significant ( $p$ -value >0.05). Therefore, authors postulate that the presence of infrastructures devoted to cyclability was not considered a major determining factor of users' behaviors when opting for 'healthier' routes, thus underscoring the role of secondary roads in relation to the exposure to pollutants (Jarjour et al., 2013). This latter consideration may be informed by a combination of several contextual reasons. In fact, the network of cycle lanes in Bologna (see Fig. 4) is characterized by several corridors flanking the main roads and other minor links. While the previous has been designed to connect the main facilities, the latter are located mostly within the city center, including the University area, where the circulation is predominantly ruled by traffic calming and restrictive measures, e.g., pedestrian or car-free zones. Thus, it can be posited that neither the presence of a road where the exclusive circulation of cycles is permitted nor shorter route alternatives are directly related to a 'healthy' environment, as confirmed by the distribution of pollutants (Fig. 6, Fig. 7, Fig. 8, Fig. 9).

About PGI and NOI, coefficients were found in the MLR not significant ( $p$ -value >0.05), suggesting that neither the acoustic pollution nor the presence of green areas in proximity of roads were considered by users in their route choice. These two latter results are worthy of attention, as they are in contrast with previous findings (MacNaughton, Melly, Vallarino, Adamkiewicz, & Spengler, 2014). In particular, results related to PGI may have been affected by the uneven distribution of the green areas, as most of the analyzed roads are not lined by canopy coverage. About NOI, it may be interpreted in relation to the characteristics of the road network and the urban fabric of the study area, where the density of buildings impacts the road width, thereby threatening the so-called 'urban canyon' phenomenon. This result is also consistent with the distribution of values plotted in Fig. 9, where all the roads surveyed reported a high level of exposure to noise. In other words, even with a different route, users could not easily find roads with acceptable levels of acoustic pollution (Mohamed, Paleologos, & Howari, 2021). A similar result has been found in previous research efforts (Gelb & Apparicio, 2022), thus reinforcing the role of the characteristics of urban fabric in determining cyclists' behaviors.

In consideration of the research design, i.e., the absence of pre-scheduled trips or predetermined routes, the data collection relies on individual preferences; the results are considered by the authors as relevant findings. Consequently, results underscore the necessity for greater emphasis to be placed on the divergent routes that users may select as alternative options (Akbarzadeh, Memarmontazerin, Derrible, & Salehi Reihani, 2019; Das & Ram, 2024; Stamos, 2023; Yang & Xu, 2026). Indeed, NOT should be considered in diachronic terms, as the number of trips was accounted for, within the analyzed time window, in relation to each user (see Section 3.3.2), so it is intrinsically related to its own behaviour and needs. As previously outlined, users were required to choose their routes at each trip, contingent on their needs, which may include the location of the desired destinations, their a-priori knowledge of alternative routes, and their purposes, along with the awareness of their potential exposure to pollutants, as available on the Web app. The route choice should then be considered a combination of these factors. Therefore, results suggest that an increased awareness of individual exposure to pollutants may lead to a shift in behaviors, even in the

presence of longer routes.

Based on these results, further discussions can be proposed. Exposure to pollutants could be seen as a major transportation injustice. Indeed, it makes living and traveling in urban areas daunting and distressing. This research considers the relevant transition from UR to US, introducing bottom-up participation methods based on citizen science principles, which can also create benefits for epidemiology studies. In these methodologies, people contribute to data collection and direct experimentation based on their own behaviors, helping to identify innovative aspects, both infrastructural and psychological, that can be leveraged to increase cycling rates in medium-sized European cities. As already analyzed (Dondi, Simone, Lantieri, & Vignali, 2011), the economic benefits have been compounded by the creation of new patterns and social flows produced by a massive university presence. Places and spaces (residential system and production system) are created to redesign the city itself, changing its shape and variables, such as the addition of new bike lanes. Bicycle mobility then becomes one of these variables, capable of redesigning urban space, giving it a new function, consistent with the Healthy Street model, and capable of generating positive change in the environmental dimensions of the city itself. Such dimensions are consequently reminiscent of European urban health and well-being programs. By investigating the level of pollutants along specific road segments, it is possible to gain an initial overview of the urban and infrastructural parameters that influence pollutant distribution. For example, the presence of green barriers (e.g., tree rows) provides effective protection for cycle paths against PM2.5 and PM10 exposure. Similar variables offer local governance a dataset useful to establish specific urban policies. Potential policy recommendations include planting tall trees along cycle paths to act as natural barriers; routing cycle paths through parks or green areas; implementing low-emission or restricted traffic zones, where infrastructure allows a safer and less polluted environment for cyclists.

## 5. Conclusions

Exposure to pollutants can be seen as a major transportation injustice. Indeed, it makes living and traveling in urban settings daunting and distressing. This research considers the relevant transition from UR to US, introducing bottom-up participation methods based on citizen science principles, which can also create benefits for epidemiology. In these methodologies, people contribute to data collection and direct experimentation based on their own behaviors, helping to identify innovative aspects, both infrastructural and psychological, that can be leveraged to increase cycling rates in medium-sized European cities. This research effort refers to Bologna, Italy, which is a medium-sized urban context (about 400,000 inhabitants) with the presence of a widespread university community. This study places the city-university relationship at the heart of the project itself. It is a relationship that frames a heterogeneous type of urban subsystem, with life dynamics closely resembling long-term tourism and a significant carbon footprint. As already analyzed (Dondi et al., 2011) the economic benefits have been compounded by the creation of new patterns and social flows produced by a massive university presence. Places and spaces (residential and production systems) are created to redesign the city, changing its shape and variables such as bike lanes. Bicycle mobility then becomes one of these variables, capable of redesigning urban space, giving it a new function, consistently with the Healthy Street model, and capable of generating positive change in the environmental dimensions of the city itself. Such dimensions are consequently reminiscent of European urban health and well-being programs. The research sought to combine the aforementioned topics and investigated the relationships between the level of exposure to pollutants and mobility behaviors of cyclists. The study adopted a multi-level, proactive approach, whereby users were tasked with the collection of data while riding an instrumented bicycle and the selection of their trip route according to the level of pollution. The statistical analysis carried out found an inverse,

statistically-significant relationship between the number of trips and the pollution levels, while only partial relationships were found between the number of trips and the topological characteristics of the road network. The outcomes align with the preliminary assumptions and the current literature, thereby substantiating the evidence concerning the necessity for tailored solutions for wealthy environments, particularly for cyclists and, in general, for individuals who opt for active transportation for their daily mobility. The present research is focused on the urban context, but it is posited that findings may be applicable also to extra-urban routes and with regard to non-systematic cycling, in areas characterized by, e.g., touristic routes (Carra, Pavesi, & Barabino, 2023).

### 5.1. Limitations

Authors argue that the proposed methodology represents an initial investigation on the relationships between pollution, the built environment and mobility choices, particularly for cyclists. As suggested by the results of MLR, namely the values of  $R^2$ , the current model has a partial explanatory power. Authors acknowledge that the lack of some data is a major limitation of the presented methodology, and further research should be implemented by including additional inputs, such as data related to road traffic or weather. While the former is pivotal in determining the role of other modes in the road network, potentially affecting the safety of cyclists, the latter is necessary to address the impacts on the concentration of pollutants of the weather conditions, such as wind directions or rainfall frequency and intensity (Thai, McKendry, & Brauer, 2008b).

### 5.2. Recommendations, further works and suggestions

It is important to note that further developments should involve both analyses on the infrastructures and transportation models (Ben-Akiva et al., 2002), as well as a wider data collection including several seasons, which would improve the overall consistency of the results. Widening the gaze, authors acknowledge that a pre-post comparative analysis based on individual users, as well as the comparison between the actual and 'best' (e.g. shortest, fastest) routes, would enhance the overall analysis, e.g., allowing the calculation of the degree of route diversion. This can be easily achieved by combining GIS analyses and routing platforms (Kolaxidis et al., 2025), (Ludwig Christina, 2021). Similarly, a more thorough focus on the characteristics of urban fabric, such as the road width or the building height, which can affect the pollutants' spread, or the characteristics of bicycle lanes, would increase the explanatory power of the model.

This research has also an underlying theoretical background rooted in Decision Making (D-M) processes and Behavioral Decision Theory (BDT) (Von Neumann & Morgenstern, 2007), in which general choice behaviour is explained through the interaction between three psychological variables identified by Perception, Cognition, and Attitude. The framework also takes into account the D-M processes as a sequence of mental conditions that permit the development of an initial knowledge (Payne & E. J. J., 1993). Therefore, further developments in this sense may increase the literature on the relationships between transportation and D-M or BDT.

### CRedit authorship contribution statement

**Alessandro Nalin:** Writing – original draft, Methodology, Data curation, Conceptualization. **Margherita Pazzini:** Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Roberto Battistini:** Writing – original draft, Resources, Methodology, Formal analysis. **Andrea Simone:** Writing – review & editing, Supervision. **Valeria Vignali:** Writing – review & editing, Supervision. **Claudio Lantieri:** Writing – review & editing, Visualization, Supervision, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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