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Development of Software Tool for Optimization and Evaluation of Cycling Routes by Characterizing Cyclist Exposure to Air Pollution

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***Abstract*—In modern cities, poor air quality has contributed to replacing motorized cars with active modes of transportation such as cycling. However, when designing and building bike infrastructure, officials neglect to consider air quality concerns connected to cyclists, and most cycling lanes are developed next to heavy-traffic roadways. This poses additional health risks to cyclists, due to their increased ventilation rate. To preserve a sustainable quality of life for a city's residents, it's critical to understand how to detect and quantify PM exposure, especially in potentially hazardous locations. This study offers a software tool based on experimental data to optimize and evaluate cycling routes by calculating the overall amount of particulate matter intake in terms of the physiological response of cyclists.**

I. Introduction

AIR POLLUTION is a significant public health problem that has long been a source of anxiety for citizens. An air pollutant is described as any substance that can affect humans, animals, plants, or materials. In the case of humans, an air pollutant may cause or lead to an increase in mortality or serious illness, as well as pose a current or potential health risk [1]. Measurements of air emissions are critical for epidemiology and air quality control, but the scope of ground-based air pollution observations has limitations [2]. Somatic symptoms of asthma in adults and children have been linked to moderate increases in vehicular exhaust such as fine particulate matter (PM2.5), nitrogen dioxide (NO2), ozone, carbon monoxide, and traffic-related air pollution (TRAP) [3].

The presence of PM (Particulate Matter) is one of the key causes of increased morbidity and mortality in modern cities. It is a suspended combination of solid and liquid particles that vary in quantity, size, shape, surface area, chemical composition, solubility, and origin. Total suspended particles (TSPs) have a trimodal size distribution in the ambient air, including coarse particles (PM10), fine particles (PM2.5), and ultrafine particles (PM1) [4]. PM size-selective sampling refers to the collection of particles that are below, above, or within a defined aerodynamic range of sizes, which is commonly chosen to be relevant to inhalation and deposition, causes, or toxicity [5].

Poor air quality in large cities has contributed to the substitution of motorized vehicles with an active means of transportation, such as cycling [6]. This method has been extensively adopted by multiple communities due to reduced congestion [7] and the numerous health benefits of physical exercise. Cycling infrastructure near roadways, on the other hand, has been identified as a harmful scenario for cyclists owing to air pollution exposure [8]. Although this has piqued the scientific community's interest [9], there have been few studies conducted in European cities where many individuals are continually exposed to PM from anthropogenic sources, such as automobile traffic.

Estimates of air pollution exposure for research projects are frequently based on measurements obtained by stationary regulatory monitors, such as those operated by the European Environmental Agency (EEA). While these monitors are highly precise and well-suited to assuring compliance with federal air quality requirements, their utility for recording individual-level pollution exposure is limited for many reasons: 1) Firstly because monitor locations rarely coincide with exposure locations (e.g., home, work, or school), an individual's exposure to air pollution can only be measured indirectly through spatial interpolation techniques such as inverse distance weighted interpolation and kriging, or statistical methods such as land-use regression modeling. [10] 2) Secondly, regulatory monitors offer limited temporal resolution (e.g., hourly averages in the case of particulate matter monitors), which may lead them to miss transient spikes in pollution levels; 3) Thirdly, indirect methods of exposure assessment typically estimate exposure for a single location per individual, such as their location of residence, place of work [11], or school [12], which does not capture exposures that occur while people are at different locations or during regular activities like commuting and errands.

The majority of dedicated bicycle lanes in cities are close to heavy-traffic roadways, this can lead to a substantial health risk to cyclists due to their high pollutant intake via higher ventilation rates [13], [14] and high levels of physical activity [8], [15]. Researchers have concentrated on assessing actual exposure levels of cyclists on pre-selected routes using personal samplers [16] or inferring personal exposure from measurements of street-level pollution using mobile labs or fixed-site ambient air monitoring stations [17]. Many studies have also sought to connect particular physiological responses with cyclists' exposure to air pollution and discovered evidence that short-term exposure can result in harmful health effects [18]. One research even found that cyclists absorbed a greater proportion of fine PM2.5 particles and black carbon than drivers of motorized forms of transportation [19].

Despite the discussed findings, municipal authorities in Sofia and other Bulgarian cities fail to take air quality concerns into account when developing and building bike infrastructure. Most of the dedicated cycling lanes in the cities are built on heavy traffic roadways. As a result, more scientific information is needed to describe the air pollution exposure on cyclists and optimize bike routes. This study reviews the development and the evaluation of a tool that proposes optimized cycling routes by calculating the intake dosage of ambient PM. We also emphasized the effects of transportation on air quality and that bike paths should be prioritized on small streets instead of building cycling infrastructure near high-traffic roadways.

After the introduction the rest of the paper is designed as follows. In section 2 we give a brief overview of the methodology used in this study. There is discussed how the software is built, how study routes are selected, who are the participants of this study and how mobile and fixed sensors are used. In addition, it is shown how the inhalation rate and the intake dosage are calculated. In Section 3 we introduce the computational results, analysis, and discussion. Finally, Section 4 presents the conclusions and recommendations for future research.

II. Methodology and instruments

Cities are notorious for their high levels of air pollution and sickness. Transportation, household heating, and industry are considered to be the main sources of air pollution in urban areas. Sofia is situated in a valley, where the two main sources of air pollution are household heating and transportation. The city is one of the most polluted ones in the European Union with high concentrations of particulate matter, especially during the winter season due to household heating during low temperatures and low ventilation as a result of temperature inversions.

Sofia is the capital of Bulgaria with nearly 1.5 million inhabitants. The city has a relatively small bicycle infrastructure with nearly 60 km of cycling paths. This paper describes the development of a software tool that optimizes biking routes by evaluating cyclist air pollution exposure.

A. Study design

An increase in morbidity in Sofia after days of high air pollution was investigated in recent research [20], [21]. On fig. 1 is illustrated the exposure-health effect model on which this study is based. Air pollution concentrations lead to different doses of inhaled polluted air. The doze leads to different health effects. Generally speaking, the higher the dose - the bigger the risk for health effects.

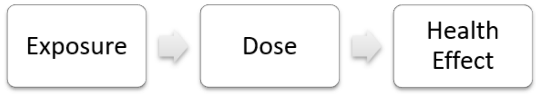

Fig. 1. Exposure - Health effect development

This study discusses the creation of a software tool that aims to select an optimized cycling route that provides the least PM inhalation dose for a cyclist trying to go from point A to point B.

Inhalation Dose (ID) depends on pollutant concentrations, the time, and the Ventilation Rate (VR) [min]. We calculate the inhalation dose by incorporating into the model the PM exposure for each cyclist with biomarkers such as heart rate, and time needed to take each route. The next subsection will provide more depth into the formulas used in the calculation model.

B. Method for calculating ventilation rate and inhalation dose

To calculate cyclist's VR (in L/min), we utilize [22]'s model equation that is based on the Heart Rate (HR) [min] (Eq. (1)).

$$VR = 0.00070724 \times HR^{2.17008537} \tag{1}$$

To determine the amounts of particular matter that are impacting cyclists, we use Eq. (2) [22] to compute the PM inhalation dose for each stretch:

$$PM_{inh} = PM_{conc} \times VR \times time \tag{2}$$

where PM_{inh} (μg) is the mass of pollutants entering cyclists' respiratory tracts over the course of the journey (round trip); PM_{conc} (μg/m^3) is the median pollutant exposure.

The following formulas (Eq. (1) and Eq. (2)) lead to the following hypothesis: if we want to build a tool that reduces the inhaled dose of PM it should select a track that is:
(1) Fast and short. The lesser the time, the lesser PM_{inh}
(2) Requires less effort. HR is increased during ascending and high speed. Looking for routes with denivelation.
(3) Go through less PM concentrations. Heavy-traffic roads should be skipped. Small streets and parks are preferred.

These formulas (Eq. (1) and Eq. (2)) are also used in the validation of the tool, which will be later discussed. In the next section we examine the path finding algorithms.

C. Path finding algorithms

Path finding algorithms are built on top of graph search algorithms and examine connections between nodes by starting at one node and moving via relationships until they reach their target. These algorithms determine the cheapest route in terms of weight or hops. Weights may be everything that can be measured, including capacity, cost, time, and distance.

As discussed in the previous section, for the purposes of this software, it is required to not enough to compute the shortest path in linear time [23], [24]. In addition, it should present options that are longer than the shortest way but have different desired characteristics, such as less vehicle traffic and small denivelation. The k-Shortest Paths problem is a straightforward method for calculating alternative routes [25].

In this study, we use an alternative routing, and in particular the k-Shortest Paths with Limited Overlap (k-SPwLO), previously introduced in [26]. The k-SPwLO query seeks paths that are (a) sufficiently distinct from each other and (b) as short as possible. Although the method performs better than a baseline solution that lists pathways in order of increasing length, OnePass is not useful even for medium-sized road networks [27]. For this purpose, we use MultiPass, a more accurate method that, by adding second pruning criteria, expands and enhances OnePass. MultiPass travels the network k-1 times but only evaluates and extends the most promising pathways, in contrast to OnePass, which traverses the road network once and expands only those paths that satisfy the similarity criterion. Pruning is done on any path that cannot lead to a solution.

Let P specifically be a collection of routes on a road network G that connect nodes s and t. A path p' (s→t) is referred to as an "alternative" in P when p' is enough dissimilar to every path p ∈ P. Formally, the overlap ratio between p' and p determines how similar they are:

$$Sim(p', p) = \frac{\sum_{(n_x,n_y)\in p'\cap p} w_{xy}}{l(p)}, \tag{3}$$

where $p' \cap p$ indicates the group of edges that both are shared by p' and p. Given the similarity threshold θ route p' is alternative to set P if $Sim(p', p) \leq \theta$.

Given a source node s and a target node t, a k-SPwLO query provides a collection of k routes from s to t, ordered in increasing length order, such that:
(1) the shortest route p'(s→t) is always included,
(2) all k routes are pairwise dissimilar with regard to the similarity threshold θ, and
(3) all k routes are as short as possible.

This paper uses a new approach to the k-SPwLO. Most of the applications use alternative paths, leaving the final route choice to the user. While in this software we add weights in order to choose the shortest alternative route with the least traffic and smallest denivelation. The following subsection is revealing insights into the software's development.

D. Development of the software tool

The software is developed on a cloud infrastructure and for its development is used free software Python, Django, and GraphQL (for the database). It is connected to gis data providers such as Google maps, Strava, and the route is rendered on Openstreet map.

Firstly, using the pathfinding algorithm described in the previous section, the software is programmed to search for a route that: (1) is the shortest; (2) has the smallest denivelation; and (3) skips heavy-traffic roadways when possible. The calculation model is based on previously mentioned formulas (Eq. (1) and Eq. (2)), which were used for developing the weights for the search algorithm.

After the calculation is done, the software renders the optimized path. To evaluate the model and further improve its search algorithms we designed a tool that combines air quality data from fixed sensors and gis data from the Strava app.

The software uses an aggregation tool that extracts air quality data both from standard instruments and low-cost sensor networks such as Luftdaten, Smog, Openaqi, and many others. It receives, records, cleans, and calibrates the air quality data from fixed low-cost sensors.

Traditionally, concentrations of air emissions have been monitored by air monitoring stations equipped with standard equipment, allowing for highly reliable monitoring results. However, the high costs of equipment and servicing make meeting the demands of high-resolution surveillance and assessing the extent of personal exposure impossible [28], [29]. As the need for more condensed monitoring is gradually increasing, low-cost air quality sensors have been widely used in air monitoring in recent years due to the benefits of low cost, low power usage, quick operation, and rapid response [30]. As a result, environmental monitoring stations are often sparsely dispersed, resulting in observations with inadequate geographical resolution. Low-cost air quality monitors have recently been developed as an option that can increase monitoring granularity. However, using low-cost air quality monitors comes with a number of drawbacks: They are impacted by cross-sensitivities between different ambient contaminants, as well as external variables such as traffic, weather fluctuations, and human activity, and their accuracy declines with time.

To mitigate the above-mentioned drawbacks of fixed low-cost sensors we calibrate the data from them. We examine both the data from environmental monitoring stations and the Luftdaten network of low-cost sensors. To calibrate the data from low-cost sensors and increase its reliability we use the [31]'s two-step calibration method that utilizes artificial neural networks and anomaly detection.

After the selection, the two study routes are evaluated through mobile and fixed sensors.

E. Study routes

The two study routes start from the national stadium Vasil Levski and end up at Pette kiosheta, two spots in the center of Sofia with active cycling flow.

The two study routes are in the center of Sofia and are picked so they can meet the following criteria:

(1) should have the same start and end points;

(2) one of the routes to be on the dedicated bike lane, while the other is the proposed from the software (short; low denivelation; follows small streets);

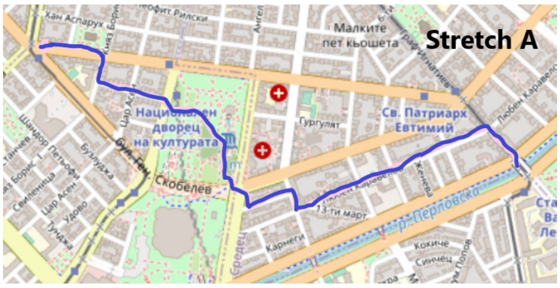

Fig. 2. Stretch A - suggested by our software as it searches the least inhalation dose

Fig. 3. Stretch B - suggested by the majority of navigation softwares as it is on a dedicated bike lane

(3) the routes should be actively used by cyclists;

(4) both routes pass nearby fixed sensors from the Luftdaten network;

Stretch A (fig.2) is the optimized cycling route that is suggested by the software tool and software point that goes on the shortest path through small central streets and parks, while Stretch B (fig.3) uses the developed cycling infrastructure (that mainly includes cycling near heavy-traffic roadways), it is longer in distance and is suggested by the navigation software due to the dedicated bike lanes.

The tool also evaluates the routes using mobile and fixed sensors for gathering air quality data. In the next section is described the implication of mobile sensors.

F. Measuring PM exposure with wearable mobile devices

Low-cost wearable pollution sensors are inexpensive environmental monitoring devices that people can carry or wear while going about their daily activities. Because they detect pollution levels directly and in real time, they may allow health providers and researchers to monitor individual-level exposures and empower citizens to manage their personal exposure to pollutants beyond what regulatory monitors can do [32].

For this study, PM1, PM2.5, temperature, and relative humidity are measured by AirBeam2. To quantify particle matter, AirBeam2 employs a light scattering approach. Light from a laser scatters off particles in the airstream as air is pulled through a sensor chamber. A detector registers the light scatter and converts it into a value that estimates the number of particles in the air. When recording a mobile session, these measures are sent to the AirCasting Android app via Bluetooth once per second.

The tests are conducted by 10 study participants. The mobile equipment was connected to the front of each bicycle, allowing the sampling lines to catch pollutants without being obstructed; it was also braced at the bottom to reduce vibration. Round trips were made on working days in the morning during High Traffic (HT) hours (8:00–9:30 h) and Low Traffic (LT) hours (10:30–12:00 h) and during the Non-Working Days (NWD): weekends and holidays.

G. Participants

We recruited 10 people (ages 27–41) by word of mouth and contact with a local cycling network (8 males and 2 females). Prior to study enrolment, subjects completed a preliminary screening survey. Exclusion criteria included respiratory (including asthma), cardiovascular, or other chronic illnesses, as well as smoking (current or recent). We only enrolled those who were already frequent riders in Sofia.

These factors were utilized to reduce the risk of harm from unfamiliarity with streets in Sofia or inexperience with riding, as well as adverse acute health effects. Further, the participants were asked to restraint from alcohol and caffeine for 48 hours before the tests. The 10 participants performed round trips on the two stretches during the HT, LT, and NWD.A certified pulmonologist (one of the coauthors) taught the project participants how to identify their Heart Rate (HR) [HB]/min using a pulse oximeter. In addition, the HR was tracked during cycling by a smart wrist.

III. Results

A. PM1 and PM2.5 concentrations from Mobile measurements

Table 1 shows the minimum, maximum, and median of PM1 and PM2.5 concentrations for the two examined stretches on working days during HT. The concentrations for ultrafine particles with a diameter below 1 micron (PM1) were measured in a range between 8 and 24 μg /m3 (mean 11 μg /m3) for Stretch A and between 8 and 41 μg /m3 (mean 14 μg /m3) for Stretch B. The concentrations for fine particles under 2.5 microns (PM2.5) are between 12 and 29 μg /m3 (mean 15 μg /m3) for Stretch A and between 12 and 45 μg /m3 (mean 19 μg /m3) for Stretch B.

Table 2 are presented the PM1 and PM2.5 concentrations for Stretch A and B on working days during LT. Measurements from Stretch A show lower concentration levels both for PM1 and PM2.5. The concentrations for ultrafine particles with diameter below 1 micron (PM1) was measured between 6 and 19 μg /m3 (mean 10 μg /m3) for Stretch A and between 5 and 34 μg /m3 (mean 12 μg /m3) for Stretch B. The concentrations for fine particles under 2.5 microns (PM2.5) are between 10 and 24 μg /m3 (mean 13 μg /m3) for Stretch A and between 9 and 38 μg /m3 (mean 15 μg /m3) for Stretch B.

Table 3 illustrates the minimum, maximum, and median of PM1 and PM2.5 concentrations for the two examined stretches during weekends and holidays. Measurements for Stretch A

TABLE I
PM1 AND PM2.5 CONCENTRATIONS FROM MOBILE MEASUREMENTS ON WORKING DAYS DURING HT

Routes	**PM1**			**PM2.5**		
	min	max	mean	min	max	mean
Stretch A	8	24	11	12	29	15
Stretch B	8	41	14	12	45	19

TABLE II
PM1 AND PM2.5 CONCENTRATIONS FROM MOBILE MEASUREMENTS ON WORKING DAYS DURING LT

Routes	**PM1**			**PM2.5**		
	min	max	mean	min	max	mean
Stretch A	6	19	10	10	24	13
Stretch B	5	34	12	9	38	15

TABLE III
PM1 AND PM2.5 CONCENTRATIONS FROM MOBILE MEASUREMENTS DURING WEEKENDS AND HOLIDAYS

Routes	**PM1**			**PM2.5**		
	min	max	mean	min	max	mean
Stretch A	3	7	4	4	11	7
Stretch B	3	8	4	5	11	7

show nearly the same lower concentration levels for PM1 and PM2.5. The concentrations for PM1 are between 3 and 7 μg /m3 (mean 4 μg /m3) for Stretch A and between 3 and 8 μg /m3 (mean 4 μg /m3) for Stretch B. The concentrations for PM2.5 are between 4 and 11 μg /m3 (mean 7 μg /m3) for Stretch A and between 5 and 11 μg /m3 (mean 7 μg /m3) for Stretch B.

Despite the fact that the dedicated cycling route is rather open, the high volume of cars, buses, and trucks in this corridor is the primary cause of elevated pollution concentrations. As a result, PM2.5 concentrations were similar during weekends, but with nearly 20% higher concentrations between the two routes during working days.

B. Ventilation rate

To measure the Ventilation Rate (VR), we took measurements of the Heart Rate (HR), oxygen saturation (SpO2), and Respiratory Rate (RR) of each project participant. Each parameter's mean has a modest level of variability and the final results for the VR are presented in Table 4. There were no differences observed in these three factors on whether the route was taken on a working day or a non-working day, as they are not affected directly by traffic or different levels of short-term air pollution exposure. The speed and denivelation data are shown in the table were taken from the developed software tool thanks to the Strava API integration.

Despite the same start and end points different distances and Stretch A was shorter 3.8 km compared to 4.4 km of Stretch B and was faster 15:52 min compared to 18:04 of Stretch B. The values were rather constant during working and non-working days. The dedicated cycling route had longer straight corridors with fewer intersections and crossroads that lead to higher maximum and average speeds. Also, Stretch B has a higher denivelation - 15m compared to 3m in Stretch A. All these data findings lead to an increased the VR of the cyclists on Stretch B - 11.06 L/min, compared to 10.14 L/min for Stretch A.

Table 5 are shown the results of the cyclists' inhalation doze for PM1 and PM2.5. They are calculated based on the mean value of PM exposure during the round trip, measured by mobile sensors, together with the time needed to take it and the VR for each cyclist.

Stretch B shows an increased inhalation as it takes a longer time to complete the round trip, takes more effort, and the cyclist is exposed to higher PM concentrations due to vehicle exhausts. Even during the weekends when PM concentrations were similar on the two routes - Stretch B showed higher inhalation dozes due to the prolonged time and higher ventilation rate (higher denivelation, higher average speed).

The measurements for SpO2 and RR did not show any particular short-term health effects. This was expected as participants in the study, due to safety reasons, were non-smokers, without chronic illnesses, and regular cyclists. This does not mean that people with chronic illnesses and sensitivity to air pollution might not receive some symptoms or irritations as some studies observe [2], [3].

C. Rendering cycling routes and incorporating data from fixed sensors

To demonstrate the technology for our fixed sensors that we developed, in this study we are using Luftdaten fixed low-cost sensors. It is a citizen science project in which the air stations are adopted and maintained by citizens and situated on their balconies. Sofia has a dense mesh of over 300 low-cost air

TABLE IV
FIELD MEASUREMENTS

	Stretch A	Stretch B
VR (L/min)	10.14	11.06
HR (beats/min)	82.30	85.66
Denivelation gained (m)	3	15
Avg. Speed (km/h)	14.3	14.7

TABLE V
PM1 AND PM2.5 INHALATION DOZE DURING THE ROUNDS

Period	Pollutant	Stretch A (optimized)	Stretch B (cycling lanes)
High Traffic	$PM1_{inh}$	29.74	46.45 (↑56%)
	$PM2.5_{inh}$	40.56	63.04 (↑55%)
Low Traffic	$PM1_{inh}$	27.04	39.82 (↑47%)
	$PM2.5_{inh}$	35.15	49.77 (↑42%)
Non-Working Days	$PM1_{inh}$	10.82	13.27 (↑23%)
	$PM2.5_{inh}$	18.93	23.23 (↑23%)

Fig. 4. Cycling route exposure from fixed sensors

quality stations from the Luftdaten network providing spatial and temporal resolution for PM2.5 and PM10 concentrations.

On fig.4 can be seen the concentrations for stretch B during LT where measurements from fixed sensors in a vicinity of 200m or closer to the route are applied on the stretch. The rendered route shows exactly where the participants in the survey have passed thanks to the gis integration of Strava and Openstreetmap APIs. The black colored line means that there is no fixed sensor in this part of the route that is closer than 200m, while the green and yellow colored lines represent the concentrations measured by the fixed sensors nearby. For concentration values of PM2.5 between 0 and 12 - green color is used, while yellow color stands for values of PM2.5 between 12 and 35. These color categories are inspired by the EPA's air quality index and are the same for visualizing the Aircasting routes measured with the wearable sensors.

Thanks to Sofia's dense mesh of low-cost sensors, 5 fixed sensors are used for stretch A and 6 sensors for stretch B as they pass the selection criteria. By comparing data from mobile sensors, we investigated that (1) Luftdaten's fixed sensors, especially if not located exactly on the route, cannot find ultralocal peaks in PM and failed to identify the zone with the most heavy-traffic and PM concentration; and (2) the sensors also cannot identify temporal exposure such as passing next to a bus, a truck, or a moped, while mobile sensors detect it very successfully. The main reason for these two findings is that Luftdaten's sensors are situated on quiet streets and are not transmitting air quality data every second.

The authors suggest a more dense mesh of air quality sensors on heavy-traffic roads in cities to mitigate the above-mentioned issues. They could be attached or integrated next to traffic lights or street lamps. This will bring accuracy in quantifying PM exposure, especially in potentially hazardous locations.

The created tool can dynamically change values for air pollution and can render the same route in different time frames and respectively different air pollution concentrations. The software can find implementation for selecting pedestrian routes as well, yet it will have more impact on finding bike routes due to cyclists' higher ventilation and often proximity to vehicle exhaust.

IV. CONCLUSION AND FUTURE RESEARCH

This study presented the development of a software tool that optimizes cycling paths based on algorithms that predict the least harmful air pollutants. The algorithm is a new implementation of alternative routing and in particular the k-Shortest Paths with Limited Overlap. It is based on experimental data and equations that calculate the total inhaled dose of pollutants by a cyclist. Together with this, in the study was evaluated through two cycling routes: Stretch A - suggested by the newly developed software; that goes through small streets in Sofia, and Stretch B - suggested by navigation apps; that goes along a designated bicycle lane. Ten cyclists are making round trips on the two routes during 3 periods: (1) high traffic and (2) low traffic on working days and (3) during non-working days. Based on the data gathered in the study are calculated the cyclists' exposure and potential inhalation dose to PM1 and PM2.5 pollution on the two routes.

Exposure concentrations on bicycle lanes happened to be higher than the optimized track's exposure levels, especially on working days. Even in cases when the mean concentrations were nearly equal, the inhalation dose for the cyclist was always greater on the bike lane route as it is longer in time and distance, with higher denivelation, and requires more intensive cycling. By choosing the optimized cycle track, the inhalation dose of PM1 is reduced with 23% on non-working days to 56% (55% for PM2.5) during high traffic on working days. The results show that there is an enhanced risk to the health of cyclists using the studied bicycle paths during working days when traffic-related pollutants.

The outcomes of this study and the developed tool are useful to medical experts, cyclists, and pedestrians. They prove that optimization of mobility and taking data-driven decisions can reduce air pollution exposure. In addition, the research implications can be useful to policymakers and environmental specialists. The results of this study build on previous findings [33] that suggest that redesigning streets for low-speed multimodal traffic without barriers is a more sustainable and pragmatic approach than building cycling infrastructure on high-traffic roadways. In the studied bicycle lanes, cyclist exposure to PM was closely linked to vehicular traffic because the study is not performed during the heating season and there is a significant difference between low-traffic and high-traffic tests. Bicycle lanes with no physical barriers between the bicycle route and the road have higher exposure, a conclusion which is found in another study [34]. Our findings contribute to a better understanding of Sofia's traffic-related pollution issues and emphasize the importance of taking air quality into account when developing and constructing cycle paths in Bulgarian cities.

This study focused on the most problematic urban polluters - fine and ultrafine PM. Further studies will be beneficial in including data for other vehicle-related pollutants such as black carbon and NO2 emissions. In addition, it is useful to analyze the particulate matter from automotive emissions with chemical analysis and further detect the various metals in PM. The integration of more mobile and fixed sensors on high-traffic roadways and using of the software tool from this study will further improve the understanding of transport-related air pollution and reduce exposure.

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