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Transit pollution exposure monitoring using low-cost wearable sensors

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ABSTRACT

Transit activities are a significant contributor to a person's daily exposure to pollutants. Currently obtaining accurate information about the personal exposure of a commuter is challenging as existing solutions either have a coarse monitoring resolution that omits subtle variations in pollutant concentrations or are laborious and costly to use. We contribute by systematically analysing the feasibility of using wearable low-cost pollution sensors for capturing the total exposure of commuters. Through extensive experiments carried out in the Helsinki metropolitan region, we demonstrate that low-cost sensors can capture the overall exposure with sufficient accuracy, while at the same time providing insights into variations within transport modalities. We also demonstrate that wearable sensors can capture subtle variations caused by differing routes, passenger density, location within a carriage, and other factors. For example, we demonstrate that location within the vehicle carriage can result in up to 25% increase in daily pollution exposure – a significant difference that existing solutions are unable to capture. Finally, we highlight the practical benefits of low-cost sensors as a pollution monitoring solution by introducing applications that are enabled by low-cost wearable sensors.

1. Introduction

Transit activities are a significant contributor to an individual's daily exposure to pollutants. While the average time for transport

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(a) (b)

Fig. 1. Wearable sensor prototype used in our work (a) and a portable sensor used as a baseline (b).

activities tends to be only between 1 –1.5 hours per day (Jenelius, 2018; Devillaine et al., 2012), most of the travel is undertaken during rush hours when ambient pollution levels are at their highest, significantly increasing personal exposure (Guo et al., 2018). In modern mega-cities, which are the most susceptible to high pollution levels (Kulmala et al., 2021), travel times often are even longer, e.g., in 2015 the average travel time in Beijing and Shanghai was 35% higher than elsewhere in China[1]. As vehicles tend to be crowded and follow congested routes, pollution exposure can be up to 50 times higher than during other regular everyday activity (Hudda et al., 2011; Bigazzi and Figliozzi, 2012). Even when the pollution during transport itself is low, people typically need to wait for transport to arrive which similarly increases their exposure. Indeed, transit and roadside areas have been shown to be prominent sources of exposure to particulate matter and other air pollutants (Lee et al., 2006).

Minimizing the adverse effects of pollutants to commuters and providing information on how to improve the quality of transport services requires having accurate information about the exposure of commuters during transit activities. Currently exposure is monitored using techniques such as coordinated measurement campaigns and travel surveys (McNabola et al., 2008; de Nazelle et al., 2012; Ham et al., 2017) or specialized measurement systems deployed or operated in vehicles (Aarnio et al., 2005; Kim et al., 2008; Van Ryswyk et al., 2017). These solutions are insufficient as they can be highly labour-intensive, unable to capture subtle variations in pollutant concentrations caused by changes in the monitoring contexts. Indeed, these solutions mostly capture pollutant information in aggregate form without being able to capture of factors such as different transportation routes, the commuter's location within the vehicle, weather, vehicle types, time-of-day, or number of passengers inside the vehicle. Another limitation of these solutions is that they fail to capture exposure to pollutants between transit activities or in other modalities that are not covered by the transport provider. For example, pollutant concentrations at roadside passenger pick up points can exceed the exposure inside the vehicles (Lee et al., 2006) and alternative means of transport, such as taxis, cars, or even rickshaws also contribute to the person's daily exposure.

Wearable low-cost pollution monitoring devices have recently emerged as a potential solution to scale up pollution monitoring and improve the resolution at which information can be captured (Concas et al., 2021). By having commuters carry sensors instead of relying on dedicated and fixed sensor deployments, a broader range of transportation factors can be captured, while at the same time being able to capture information about the exposure of the individual carrying the sensor. The price and technical quality of low-cost sensors has reached a point where they can be made available to commuters – or at least some subset of them. For example, the sensor designs used in this article, and shown in Fig. 1(b), cost around $200 per unit and can be carried by individuals. This contrasts with scientific measurement instruments which tend to cost upward of $10000 and be larger in-size (Lagerspetz et al., 2019). While there have been several efforts to build wearable monitoring systems, these generally focus on monitoring the overall air quality of a city rather than capturing the pollutant exposure of an individual (Lin et al., 2018; Cheng et al., 2019; Chen et al., 2019; Motlagh et al., 2020; Stevenson et al., 2017; Piedrahita et al., 2014; Zappi et al., 2012). Adapting these solutions to monitor personal exposure, however, is far from straightforward as the accuracy of wearable low-cost devices tends to be poor – especially when compared to professional measurement instruments (Borrego et al., 2016). To this end, there is a need to understand whether low-cost sensors can indeed capture pollutant exposure during transit activity and, if so, what other benefits they can offer.

In this article, we contribute by systematically analysing the suitability of using low-cost wearable sensors for capturing the personal pollutant exposure of commuters during transit activities. We present a prototype hardware design that integrates state-of-the-art low-cost sensors, and systematically assess its potential in capturing the personal exposure of the individual carrying it and the additional benefits it can offer over current solutions. We conduct extensive experiments in the Helsinki metropolitan area that cover a broad range of transport modalities, including bus, tram, train, metro and ferry. Our results demonstrate that low-cost sensors have evolved to a stage where they can capture variations in pollutants across different transportation modalities, different geographic

[1] https://www.statista.com/statistics/942507/china-average-travel-time-for-work-by-city/

areas, and even locations within a vehicle, becoming a potential mechanism for monitoring air quality inside transport vehicles. For example, we show that low-cost sensors can capture variations in pollutants caused by differing densities of people inside the vehicle, and we show that up to 25% differences in pollutant concentrations can be observed in different locations within the same carriage. As part of our experiments, we compare personal exposure monitoring to the use of measurement campaigns, demonstrating that wearable low-cost sensors capture differences that are in line with those reported in previous studies (Aarnio et al., 2005; Kukkonen et al., 2016; Asmi et al., 2009). Finally, to highlight the practical benefits of low-cost sensors, we also briefly introduce examples of applications that would benefit from the use of low-cost exposure monitoring sensors, including a seat mapping solution that helps to identify optimal seating locations for the most vulnerable people and a citizen science solution that uses information captured by individuals to identify localized defects, such as clogged ventilation, inside vehicles and informs the public transport provider. Taken together, our results show that wearable low-cost sensors not only can monitor personal exposure during transit activity with sufficient accuracy, but also provide additional insights into subtle variations in pollutant concentrations across different modalities, times-of-day, locations within the same carriage and other factors. Ours is the first work to demonstrate that the exposure of individual commuters during public transportation can indeed be monitored accurately using low-cost wearable sensors. Indeed, existing works to consider low-cost sensors during transit activities have mostly used sensors mounted on vehicles to collect urban air quality information without monitoring the personal exposure of the commuters inside the vehicles.

Summary of Contributions:

- **Transportation Exposure Monitoring using Low-Cost Sensors.** We conduct extensive measurements in an urban transport network to demonstrate the feasibility of using low-cost sensors to monitor personal exposure to pollutants during transit activities. We demonstrate that the sensors can accurately capture differences across a broad range of transport modalities, and capture subtle details about variations in exposure caused by differences in transit routes, passenger density, location within the transit carriage, and other factors.
- **Practicability of low-cost sensors.** We present a miniaturized and improved low-maintenance sensor unit design with a convenient attachment clip (See Generation 2 sensor in Fig. 1(a)), suitable for carrying on a daily commute. We also analyze the practicality of carrying a pollution monitoring device and compare the accuracy of our sensor unit to reference measurements as well as across similar sensing units.
- **Novel Insights and Applications.** Through controlled experiments considering different placements inside vehicles, times of day and urban densities, we derive new insights about the personal exposure to pollutants inside public transportation vehicles. For example, we demonstrate that exposure within a single vehicle can increase by 25% depending on time-of-day, location inside the vehicle, amount of passengers, and characteristics of the route. We also highlight the practical impact of our results by presenting a set of applications that benefit from low-cost sensors.

2. Personal Exposure Monitoring System

The focus of our research is on investigating the potential and benefits of using wearable low-cost sensors for monitoring pollution exposure during transit activity. To explore these aspects, we have designed a wearable sensing unit that combines (i) low-cost air quality sensors; and (ii) a smartphone application that analyses and processes the measurements. The overall system design is shown in Fig. 1(a). The overall design is comparable to those used in earlier wearable sensing units (Concas et al., 2021), but upgraded to take advantage of the latest technological advances. Indeed, the price and quality of low-cost pollution monitoring sensors is rapidly improving and thus it is important to accommodate latest technological advances while evaluating the true potential of current sensor technology. Another limitations with existing solutions is that they are largely research prototypes and thus cannot be easily replicated or manufactured at appropriate scale. Our design attempts to bridge these issues, offering a state-of-the-art design, while being sufficiently easy to manufacture at scale[2]. The combination of a wearable sensor and a mobile system allows better energy-efficiency by distributing tasks among the devices and offers an opportunity to inform individuals of their personal exposure and to deliver applications that support mitigating air pollution exposure. Minimizing processing on the sensor also helps to improve the quality of measurements as processing generates heat which in turn affects the accuracy of low-cost sensors (Concas et al., 2021). While the sensor components are based on off-the-shelf components, the overall design, including casing, sensor placement, and software operating it are novel.

2.1. Wearable Sensor Design

Fig. 1(a) shows the design of our wearable sensor. We focus exclusively on particulate matter, i.e., tiny particles of liquid or solid compounds that are suspended in gases, and specifically on $PM_{2.5}$ which is the most common pollutant for transportation activities[3]. $PM_{2.5}$ results from exhaust emissions, tyre wear, brakes, and street dust and is propagated by people as they enter and exit vehicles (Onat and Stakeeva, 2013). While not being the only important pollutant, $PM_{2.5}$ is the most common during transit activity. Other pollutants, such as carbon oxides (Chan, 2003), are limited to vehicles with combustion engines and depend heavily on ambient pollution. Our experiments are conducted in a location with low ambient pollution levels and a transportation network with low

[2] The sensing units are available through loopshore.com.

[3] 2.5 refers to the diameter of the particles in μm

carbon footprint, which further motivates our focus on $PM_{2.5}$.

We monitor $PM_{2.5}$ using a light-scattering particle sensor (LSP), which is a popular low-cost and low-energy solution for monitoring particle concentrations (Chowdhury et al., 2018; Cheng et al., 2014; Gao et al., 2016; Liu et al., 2017; Liu et al., 2018). LSP sensors comprise of an air inlet, a source (which can be based on infrared or laser) and a detector. When air enters the inlet, particles passing through the light beam scatter light, which is captured by the photodiode. Typically the sensors have separate lenses for focusing the light and capturing the scattered light, and the configuration of these lenses determines the resolution at which different particle sizes can be detected. The primary capacity is determined by the wavelenght of light where the interaction between the particles and light depends on the ratio between the particle size and wavelength of light. From the resulting light measurements the sensor estimates the total number of particles in the air. Note that LSP sensors are only capable of estimating overall particle counts, and cannot characterize the source of these particles. Thus, also benign sources, such as mist particles, are included in the values. The specific sensor we consider is a Sensirion SPS30 with a red laser arranged in 90 degree scattering angle to observe the sample airflow generated by a fan. The sensor has a detectable size range of 0.3 to 10 μm and is capable of measuring PM_1, $PM_{2.5}$, PM_4, and PM_{10}. The SPS30 sensor has been calibrated by the manufacturer prior to deployment. The minimum sampling interval is 1 s on the continuous measurement mode with operating temperature range between -10°C to $+60^{\circ}$C (Sensirion, 2018).

2.2. Mobile System

The sensors interact with a mobile system that has been integrated into a smartphone application (Android and iOS) that is responsible for recording sensor measurements locally and transmitting them to a backend server for analytics. Both prototypes sample $PM_{2.5}$ every 30 s which was chosen according to technical capabilities of the corresponding PM sensors. The first prototype connects to the smartphone via Bluetooth, whereas the second uses a smartphone as a WiFi hotspot for transmitting measurements to a remote platform. The use of a WiFi hotspot is motivated by user experience considerations as it reduces the needed interactions for pairing the sensor with the mobile phone. Location information is gathered through the sensor hub of the mobile device, using the last acquired location. This allows us to reduce energy footprint of the overall solution by taking advantage of energy optimized localization on the smartphones instead of connecting the sensor with a GPS. The iOS version is currently in private beta, while our application is publicly available on Google Play for Android devices[4].

2.3. Personal Exposure and Deposited Dosage

The mobile system offers the user real-time information about his/her exposure to pollutants, and an estimate of the total daily accumulation. Besides helping the uses to get timely information about personal exposure, having an interface to the collected data helps motivating people to actively carry the sensor with them. The total accumulation is referred to as *deposited dose* (DD), which depends on characteristics of the individual (e.g., gender, age, and breathing rate) and the intensity of his/her activity (Hussein et al., 2015; U.S. Environmental Protection Agency (EPA), 2011). Deposited dose is directly related to health (Peters et al., 2004), and commuters can receive many times more pollution than urban background levels would indicate (Zuurbier et al., 2010). To provide an estimate of the total personal exposure, our system calculates average values based on the pollutant concentrations in the air and the total time the user is exposed. The average exposure (EXP) per kilometre (km) is defined as (Ham et al., 2017):

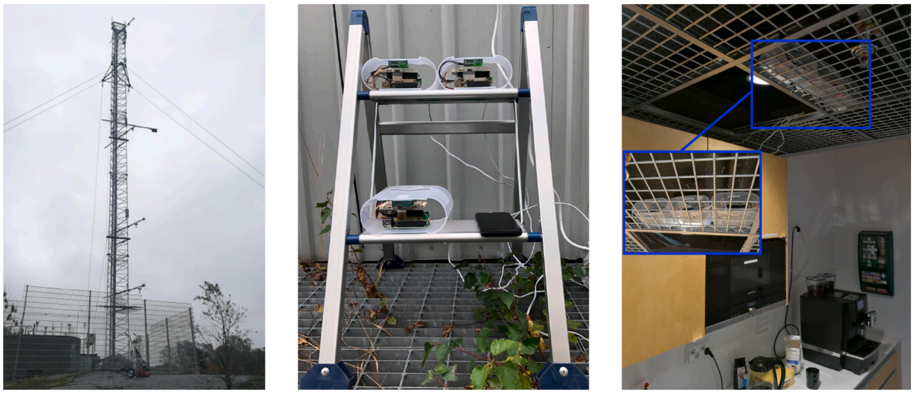
$$EXP\left(\frac{\mu g}{km}\right) = \frac{CON\left(\frac{\mu g}{m^3}\right) \times T(min)}{D(km)} \times IHR\left(\frac{m^3}{min}\right)$$

where CON is the pollutant concentration, as given by the sensor, T is the duration of the activity (in minutes), D is the distance of the commute (in km) and IHR is the inhalation rate of the individual (in m^3 / min). The distance D and the time T are estimated from location measurements, whereas for the inhalation rate IHR we use an estimate of 0.66 m^3/h which corresponds to the recommended average long term exposure rate for people between 30 −51 as given by the EPA handbook (U.S. Environmental Protection Agency (EPA), 2011). The deposited dose is then simply given by the exposure multiplied by the travel distance. In the smartphone application we show both average exposure and the total deposited dose to users.

3. Sensor validation

Low-cost air quality sensors, and especially particulate matter sensors, are vulnerable to inaccuracies resulting from drift, temperature, humidity and other factors (Concas et al., 2021; Zaidan et al., 2020). We next demonstrate that the wearable sensor prototype, shown in Fig. 1(a)), is well-suited for pollution monitoring within transit activities. We accomplish this by comparing three different devices of the same sensor type and showing they have high internal consistency and accuracy. To ensure the sensor operates accurately both inside transport vehicles and outdoor transit, we conduct the experiments in both indoor and outdoor environments; see Figs. 2(b) and (c) for illustrations of the two test setups. The indoor and outdoor locations also have significantly different pollution characteristics, which helps to ensure the results of the validation are in line with regulatory criteria on evaluation Agency (2018).

[4] https://play.google.com/store/apps/details?id=com.loopshore.hope_app



(a) (b) (c)

Fig. 2. (a): Smear III reference station, (b): Consistency experiment of portable sensors outdoors at the base of Smear III, (c): Consistency experiment indoors.

Table 1
Results of sensor consistency experiments for three different devices. The different devices are referred to as D1, D2, and D3.

	Indoor			Outdoor	
	R	**MAE**		**R**	**MAE**
D1 - D2	0.986	0.937	**D1 - D2**	0.992	0.638
D1 - D3	0.989	0.823	**D1 - D3**	0.991	1.399
D2 - D3	0.986	0.940	**D2 - D3**	0.991	1.646

3.1. Experimental Setup and Metrics

Outdoor functionality was tested by deploying the three devices in proximity of the campus of University of Helsinki, at the bottom of a SMEAR III scientific measurement station (Kulmala, 2018); see Fig. 2(b). Measurements were collected for one week sampling the devices once per minute (9013 data points). To protect the devices from rain and wind, we wrapped the sensors inside a weatherproof casing. While encasing the devices, we made sure the air-intake of the PM sensors remained unobstructed and outside of the casing to maintain the characteristics of the measurements compared to our main experiments. Indoor functionality was tested by deploying the devices close to the ceiling inside a break room for staff at the University of Helsinki; see Fig. 2(c). Measurements were collected from the three devices for one week. In the indoor experiment the devices were sampled twice per minute (17745 data points). The devices were placed side by side to ensure they capture similar air concentrations. As evaluation metrics we consider Pearson correlation coefficient (R), which measures similarity in the sensor responses, and Mean Absolute Error (MAE), which measures the offset between the sensor units. These metrics were chosen as they give complementary views of performance and as they are the most widely used measures in air quality research (Concas et al., 2021).

3.2. Sensor Consistency

We evaluate consistency by comparing measurements between the three devices to ensure the values they report are close to each other. The results of the consistency experiment for both outdoor and indoor measurements are shown in Table 1. Overall the results show that the devices have high internal consistency, both in indoor and outdoor environments. The high correlation values indicate that the devices have close to identical response to $PM_{2.5}$ concentration in the two different environments. The variability between the devices is well within acceptable levels (MAE $< 1.65\ \mu g/m^3$) as harmful $PM_{2.5}$ levels are usually measured in tens to hundreds of $\mu g/m^3$, e.g., the regulatory standards set by the EU consider concentrations higher than 25 $\mu g/m^3$ to be harmful (Council of European Union, 2008).

3.3. Sensor Accuracy

We next evaluate sensor accuracy by comparing the measurements from the outdoor experiment to those given by the SMEAR III scientific reference station which measures $PM_{2.5}$ concentration using a Thermo Scientific TEOM 1405-D Ambient Particulate Monitor. The results of the experiments are shown in Table 2. With a mean correlation of $R = 0.73$, the low-cost sensors show good correspondence with the scientific instrument. Also the mean absolute error (averaged MAE $= 5.59\ \mu g/m^3$) is well within acceptable limits, again compared to what is considered as harmful (Council of European Union, 2008). Possible reasons to cause differences with the reference station include differences in height between the measurement instruments (the TEOM monitor is located at approximately

Table 2
Accuracy of the three wearable sensor devices (D1, D2, and D3) compared to a professional-grade reference station (Ref) using Pearson correlation (R) and mean absolute error (MAE).

	R	MAE
D1 - Ref	0.731	5.252
D2 - Ref	0.727	5.006
D3 - Ref	0.728	6.507

Table 3
Summary of field data collection experiments.

Experiment	First	Second	Third
Sensors Considered	Portable baseline sensor (Fig. 1(b))	Wearable sensor (Fig. 1(a))	Wearable sensor (Fig. 1(a)) × 3
Experiment	Baseline	Uncontrolled	Controlled
Route	Bus, Metro, Tram, Train, and Roadside	Bus, Metro, Tram, Train, Ferry and Roadside	Bus, Metro, Tram and Roadside
Duration	6 days	7 days	3 days
Daytime	Random	Random	11:30–13:30
Num. of Datapoints	794	682	196 (each sensor)
Num. of Travellers	Unknown	Unknown	Known
Location	Random	Random	Specified

three meter height from the ground level, whereas the wearable sensors are located at around one meter height at the bottom of the reference station), difficult weather conditions with high levels of humidity and wind speed, and generally low ambient pollution levels during the experiment (mean $PM_{2.5}$ of 3.77 $\mu g/m^3$).

4. System Evaluation: Measurements

The results of the validation studies demonstrate that the accuracy of our wearable sensor is sufficient for capturing meaningful information about particulate pollutants. The internal consistency of the sensor, measured across three different devices, is high, which ensures differences in measurements across devices can be meaningfully compared. We next describe the experimental setups and measurements that we use for evaluating overall system performance. The collected data is summarized in Table 3 and comprises of an uncontrolled baseline campaign, an uncontrolled field experiment, and a controlled experiment where the mode of transport and device placement were controlled. All data collection was conducted within the public transportation network of Helsinki, Finland. The pollution levels of $PM_{2.5}$ in Finland are among the lowest in the world (Lehtomäki et al., 2020), which means that the total concentrations across our studies are small. Nevertheless, even low-level pollution can have a significant effect on mortality (Kampa and Castanas, 2008), suggesting that solutions that can mitigate pollutant exposure in any form are beneficial to society and human well-being. To fully understand the effect of transit activity, we consider measurements that were collected prior to the start of the COVID-19 pandemic as these reflect overall pollution exposure levels when no restrictions are in place.

4.1. Baseline Campaign

We consider as baseline an earlier data collection campaign that was carried out using a single baseline wearable sensor, shown in Fig. 1(b). The sensing unit measures $PM_{2.5}$ using a Sensirion SPS30 sensor utility. The sensing unit is equipped with a GPS, WiFi module and mobile phone connectivity for data logging and visualization. These portable devices have been used for real-time and spatial $PM_{2.5}$ monitoring and its performance has been evaluated and reported in earlier work (Motlagh et al., 2020).

In baseline campaign, the data collection comprised of 44 days of continuous measurements inside different vehicles and outdoors and was carried out intermittently during late spring - summer (May - July). Of this period, we chose 6 days with most various transport means were selected to be included in this research for comparison. For each of the days, we had records of corresponding activities and location, such as transport (metro, bus, train and tram) and outdoor environments. In this campaign, the device was carried by a male traveller and random seats were selected inside transportation systems to perform measurements.

4.2. Uncontrolled Field Experiment

We use our wearable sensor, shown in Fig. 1(a), to conduct a field experiment that focused on collecting measurements from different transportation modalities throughout the Helsinki public transportation network and that was designed to offer a comparison against the baseline campaign. During this experiment, participants kept diary of their transportation modes, but otherwise the selection of transportation modalities or the placement of sensors within the vehicles were not controlled. The main focus of these experiments is to assess whether our low-cost sensor design can correctly identify differences across transportation modalities, and to assess the ease of using the wearable sensor.

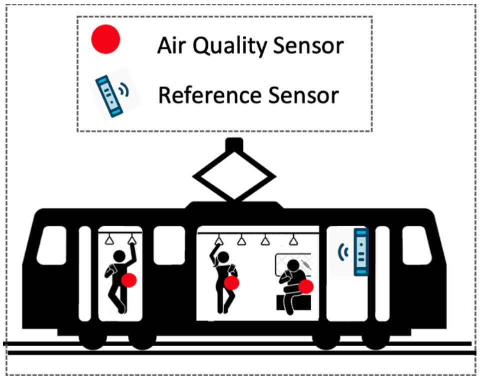


Fig. 3. Comparison of wearable sensors to a fixedly deployed sensor.

The experiment was carried out during spring (April-May) and was separate of the baseline campaign. The measurements took place in different means of transportation that are used on a daily basis by people living in the city of Helsinki. These include buses, trams, trains, metros and ferries. In this campaign, the device was carried by a female traveller and random seats were used inside transportation systems to perform measurements. The outdoor measurements were focused on the areas close to the vehicles' stops and also some measurements were collected by walking around in the city center area of Helsinki.

4.3. Controlled Experiment

We supplemented the measurements by carrying out a controlled evaluation where three devices of our wearable sensor were used to simultaneously collect measurements inside transit vehicles. In the experiment, we controlled for *i*) the transport route (constant distance), *ii*) the time-of-day, and *iii*) the urban characteristics of the route. The measurements were conducted on successive days between 11:30 and 13:30, and the order of modalities was counterbalanced across the days. We also kept a tally of the average number of passengers in the vehicles during each trip. The weather conditions were similar to the outdoor measurements considered in the previous section for evaluating sensor validity.

We considered three transportation modalities: Metro, Bus and Tram. All experiments were conducted in the Helsinki metropolitan area. We repeated two days of controlled measurements inside all of transportation systems on two weekdays in October between 11:30 to 13:30 in a densely built and populated area in Helsinki. We also performed a second round of measurement during another weekday during the same hours. Measurements were collected inside Metro and Bus and the experiments took place in an area with lower urban density. Tram was omitted from the second round of measurements due to lack of a tram route passing through the same area – or another area with similar urban characteristics. In the experiments, we used three low-cost devices of the same type which were carried by three travellers (2 male, 1 female). One of the travellers (Device 1) carried the device at the front of the vehicle, another was approximately in the middle (Device 2) and the final at the rear-end of the vehicle (Device 3).

4.4. Baselines and Ecological Validity

The results in Section 3 established the validity and accuracy of our wearable sensor prototype and in our subsequent analysis we focus instead on comparing the insights that can be derived with low-cost sensors compared to other monitoring solutions. Firstly, we contrast low-cost sensors against measurement campaigns by comparing differences in transport modalities to those shown in the reference campaign and previous studies. We focus on comparing *relative* differences in modalities instead of absolute ones due to the fact that many factors influence pollutant concentrations, making a direct comparison infeasible. Specifically, our measurements have been collected during a different time period than the previous studies, resulting in differing weather patterns, transport fleet characteristics, commuting patterns and other factors.

Secondly, we contrast low-cost sensors to dedicated measurement instruments by using the controlled evaluation to emulate a fixed deployment. We take a single device as a reference device, similarly to the information that a dedicated measurement device placed in the carriage would obtain. The general idea is illustrated in Fig. 3. We thus establish the baseline by using a single sensor for all passengers, rather than using a separate measurement device – and we repeat this process using each of the devices once as the baseline. As we previously showed in Table 1 the measurements of the devices are highly consistent both outdoors and indoors, and hence variations in measurements are unlikely to be caused by manufacturing differences or measurement errors in the devices. Using a reference instrument as a baseline would require placing the low-cost sensors side-by-side with reference instruments in transit carriages – with multiple sensors needed per carriage to cover variations at different locations inside it. Even then proximity to passengers, ventilation, and other subtle factors could impact the measurements. Additionally, the practical challenges in installing, maintaining and operating the devices inside transit carriages would necessarily limit the scale of the evaluation. As the goal of our work is to validate the use of low-cost wearable sensors for monitoring personal exposure during transit activities, not on developing a novel monitoring solution – even if our prototype is an upgrade on existing hardware solutions in terms of sensor quality and usability –

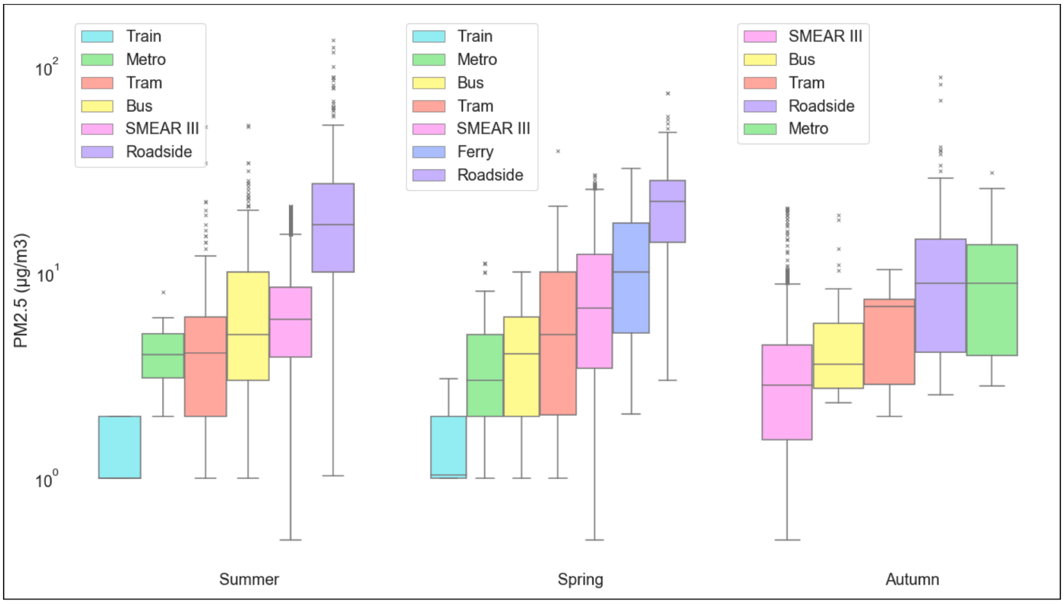


Fig. 4. The $PM_{2.5}$ level in different transportation systems during our experiments.

using a single device to emulate a fixedly deployed sensor results in the least biased evaluation and best serves the overall goals of our work. The results in Section 3 showed good correspondence with reference instruments, which further motivates the use of a single low-cost sensor for emulating a fixed deployment.

5. System Evaluation: Results

We next present results from our main evaluation which focuses on validating the use of low-cost sensors as a solution for capturing pollutant exposure during transit activity and demonstrating that additional benefits that low-cost wearable sensors can provide. We also report on small-scale usability experiment focusing on assessing the practicality of using low-cost sensors as part of everyday activities.

5.1. *Performance Across Different Transportation Modalities*

We first demonstrate that low-cost sensors offer a cost-effective and accurate solution for monitoring pollutant concentrations during transit activity. We compare concentration differences across transportation modalities and between different studies; see Table 7 in Section 8 for a summary of the studies. The average $PM_{2.5}$ concentrations in the three experiments (nearly four months of measurements) are summarized in Fig. 4. The median concentrations of the modalities range from 1 $\mu g/m^3$ to 5.25 $\mu g/m^3$ in the baseline campaign, 1.35 $\mu g/m^3$ to 4.25 $\mu g/m^3$ in the uncontrolled field experiment, and 3.67 $\mu g/m^3$ to 8.90 $\mu g/m^3$ in the controlled experiment. These values are well within the level of good air quality, e.g., according to the Environmental Protection Agency (EPA) the limit for good air quality is 10 $\mu g/m^3$ (European Environment Agency, 2019). For the controlled study where multiple devices were used simultaneously the plots show the average measurement values across the three different locations. As part of the plots we have included the ambient pollution level as given by a high precision urban air measurement station located at a stationary deployment site.

We first compare the uncontrolled measurements against the baseline campaign since the characteristics of the measurements are similar across these studies and as the ambient pollution levels were similar. The measurements of the uncontrolled study contain more variation than those of the reference campaign, which is in line with the higher variation in ambient pollution levels during this period. The pollution levels for all modalities are generally well below the ambient pollution level, which is in line with the state of the transport fleet in Helsinki. Indeed, pollution levels inside vehicles are strongly dependent on the age of the vehicles and the existence of air conditioning and filtering systems (Zuurbier et al., 2010; Zhang and Zhu, 2010). Finland's public transportation system is modern and hence the indoor air is heavily filtered. For trams and buses, some older vehicles remain in operation, which partially explains the higher variation in measurements. However, as we show in Section 5.2, the main factor to affect variation is the number of passengers inside the vehicle. The sole exception is the ferry where pollution levels exceed levels of ambient pollution. This is largely due to mass concentration being overestimated due to so-called hygroscopic growth whereby the size of particles increases as a result of water absorption or evaporation (Gao et al., 2016).

During the controlled measurement setup, the pollution levels were generally higher than the ambient levels, which is mainly due to using congested routes and due to collecting the measurements during rush hours. Indeed, studies have shown pollutant exposure to

Table 4
Results of the third experiment and each particle sensor's standard deviation's difference (in %) to combined sensor measurements.

MEASUREMENT EXPERIMENT RESULTS						STDV DIFFERENCE (IN %)			
Days	**Environment**	**Mean**	**STDV**	**No. of Travellers**	**Duration (min)**	**Sensor 1 (front)**	**Sensor 2 (middle)**	**Sensor 3 (back)**	**Sensor Difference**
Day 1	Bus	4.28	3.67	24	20	−0.15	−0.08	0.26	0.07–0.41
	Metro	14.75	6.89	81	12	0.08	−0.1	0.09	0.01–0.19
	Tram	2.76	0.49	39	21	0.02	−0.1	−0.02	0.04–0.12
Day 2	Bus	8.21	3.7	33	14	0.01	0.25	−0.21	0.22–0.46
	Metro	12.69	5.57	69	13	−0.07	0.1	0.07	0.03–0.17
	Tram	7.67	0.89	35	23	0.1	−0.25	0.16	0.06–0.41
Day 3	Bus	3.57	1.04	45	26	−0.18	−0.25	0.22	0.08–0.45
	Metro	3.23	0.4	44	16	0.43	−0.23	−0.47	0.03–0.58
Average	Bus	5.35	2.80	34	20	−0.1	−0.03	0.08	0.12–0.44
	Metro	10.23	4.29	64	14	0.12	−0.07	−0.02	0.02–0.31
	Tram	5.21	0.69	37	22	0.06	−0.18	0.07	0.05–0.26

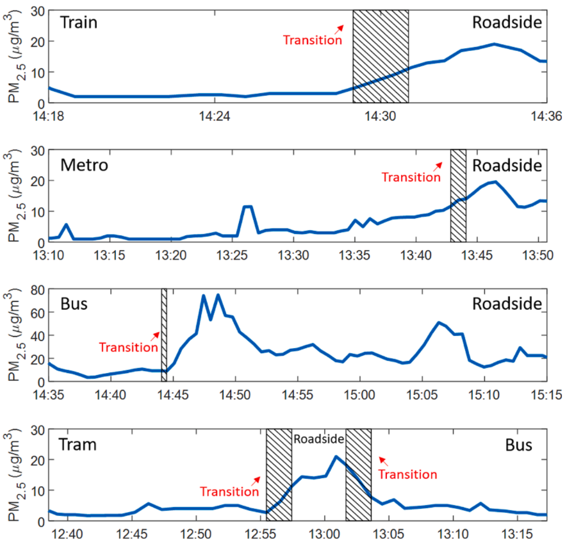


Fig. 5. Sample time series plots from bus, metro and train with transitions to roadside for the third experiment.

be significantly higher during rush hours (Apparicio et al., 2018). In terms of differences across modalities, metro consistently has the highest number of travellers, and the stations are indoors (underground) with lower air circulation than what the other modalities experience. These differences are responsible for its high levels of exposure (see Table 4). Finally, in line with previous studies, roadside pollution levels are highest among all the conditions. Road traffic and characteristics of transit stops are known to result in a high concentration of pollutants at roadside areas (Goel et al., 2015). Fig. 5 further highlights the differences by showing measurements around points where transitions from vehicle to roadside occur. In all instances we can see a significant spike in pollutant exposure, even if the accumulated effect of all periods spent outside vehicles can be small. *Current solutions based on ambient pollution monitoring or dedicated sensors located in transportation vehicles fail to capture these periods of significant exposure and hence would result in significant underestimates of the total daily pollution exposure.*

To summarize, our results show that low-cost sensors can correctly identify differences in pollutant exposure during different transportation modalities. The relative differences across modalities are well in line with the reference campaign and findings reported in previous studies on transit pollution exposure. The comparison also highlights how a wide range of factors affect the overall pollution exposure of an individual. These variations in exposure cannot be reliably captured with fixedly-deployed sensor systems or an ambient pollution monitoring solution, further motivating the need for wearable sensors that can capture the personal exposure of commuters.

5.2. Intra-Transportation Variation

We next assess how pollution levels vary within the same transportation vehicle by comparing measurements from devices in

Table 5
Average deposited dosage with different means of transport for the second measurement experiment.

Transport System	Duration (min)	Distance (km)	DD (μg)	DD_d (μg/km)
Bus	40	14.6	7.30	0.49
Train	30	25.6	1.70	0.06
Metro	42	26.1	3.18	0.12
Tram	60	16.8	10.74	0.63
Ferry	60	10.4	15.66	1.50
Roadside	40	2.3	40.12	17.43

different locations within the same carriage, as collected in the controlled experiment. As described in Section 4.4, we consider the measurements of a single device as a baseline that emulates fixed deployments.

The measurements for the three devices in different placements are summarized in Table 4. From the results we observe that differences across transportation modalities generally are larger than those within the same carriage. The differences inside the same carriage, while smaller, are significant and on average there is a variation of 9% to 38% in the magnitude of standard deviation that depends on the deployment location inside the vehicle. The smallest difference is only 1% whereas the largest differences are significantly higher (58%). For metro, the highest concentration is at the back of the vehicle with a median value of 10.92 $\mu g/m^3$ compared to 8.08 $\mu g/m^3$ and 8.61 $\mu g/m^3$, for the middle and front of the vehicle, respectively. Bus and tram have more confined spaces and a more even distribution of passengers, which results in lower variation in particle matter concentrations. We stress that these differences are intended to highlight variations within the same confined space rather than serve as guidelines about air quality differences at different locations inside the vehicle. Indeed, the findings are specific to the context where the measurements were taken and dependent on the route, the age of the vehicle, the density and distribution of passengers inside the vehicle, among other factors. Nevertheless, the results highlight how there are significant differences within the same carriage which need to be captured to estimate the total exposure and effects of air pollutants on commuters.

We also assessed the effect the number of passengers inside the carriage has on pollution concentrations. The (Pearson) correlation between pollution concentration ($PM_{2.5}$) and passenger count is equal to $R = 0.52$, corresponding to a large and statistically significant effect. The effect was highest for metro, where the passenger count was highest and contained most variation. This is to be expected as differences in baseline pollution, i.e., the current daily pollution level and the density of the area where the transit activity takes place have a larger effect on the concentrations than the number of passengers when the number of passengers is approximately constant.

Taken together, the results show that the exposure to particle concentrations can contain significant variations within the vehicle, including the location of the passenger inside the carriage and the total number of passengers in the carriage. Personal exposure monitoring solution is essential for capturing these subtle variations and for ensuring the true pollution exposure of the passenger can be captured. To put our results in a context, the variation between front and back seats differs by 25% during a $10 - 15$ minute subway ride. Assuming similar differences for the entire daily commute, simply using aggregate values – as would be given by a dedicated sensor that is placed inside the carriage – for the entire vehicle would result in a 100% error in the estimates, highlighting the need for taking subtle variations in transportation behaviour into account while estimating personal exposure. Conversely, our results show that reliably estimating the air quality inside the transport carriage is only possible when multiple sensor devices are located at different sections of the same carriage. Indeed, in our measurements, some devices were exposed to significantly lower particle concentrations, and therefore relying solely on them would lead us to believe air quality to be better than that experienced by the average traveller. Similarly, only using the highest values leads to bias, suggesting that multiple sensor devices must be placed to cover the entire vehicle and to properly assess the overall air quality.

5.3. Deposited Dosage

Choice of seating location inside a transit carriage may seem like a trivial choice, but it can actually have significant long-term health impact, particularly if the duration of the daily commutes is long (Wei and Tang, 2018). We next analyze the total deposited dosage and variations in it across different transportation modalities and within the same modality, demonstrating that personal exposure monitoring solutions can significantly improve the estimation of health effects and provide insights on how to reduce personal exposure.

Table 5 illustrates the deposited dosage (see Section 2.3) of pollutants during transit activities in the second experiment. The pollution concentrations are small inside the vehicles, with particularly train and metro having very low dosage. The results generally reflect the characteristics of the vehicles with the modalities relying on electric power and with the most spacious cabins having the lowest dosage. The highest overall pollution is obtained for roadside areas where the total dosage is 2.5 – 23.6 times higher than during transit activities. This result is largely expected due to the highly modern transportation fleet employed in Helsinki and the season during which the measurements were collected. Indeed, the measurement period (April-May) corresponds to a period where there is re-suspension of road dust and also abrasion of road surface due to use of studded tires. Nevertheless, the results show how dedicated sensors mounted in vehicles, as used in prior studies (Kaivonen and Ngai, 2020; Adams et al., 2001; Gómez-Perales et al., 2007; Kaur et al., 2005; Aarnio et al., 2005; Knibbs and de Dear, 2010; McNabola et al., 2008; Onat and Stakeeva, 2013; de Nazelle et al., 2012), significantly underestimate the total pollution accumulation and that personal pollution monitoring solutions are necessary for mitigating long term accumulation and exposure to pollutants.

Table 6
Travelling deposited dosage while using three sensors in the third experiment.

Transport System	**Duration** (*min*)	**Front (Device 1)**		**Middle (Device 2)**		Back (**Device 3**)	
		$PM_{2.5}$ $\mu g/m^3$	**DD** (μg)	$PM_{2.5}$ $\mu g/m^3$	**DD** (μg)	$PM_{2.5}$ $\mu g/m^3$	**DD** (μg)
Bus	60	3.43	2.66	3.74	2.47	4.09	2.70
Metro	41	8.61	3.88	8.08	3.64	10.92	4.92
Tram	44	6.24	3.02	6.99	3.38	6.80	3.29
Roadside	82	8.81	7.94	9.01	8.13	9.27	8.36

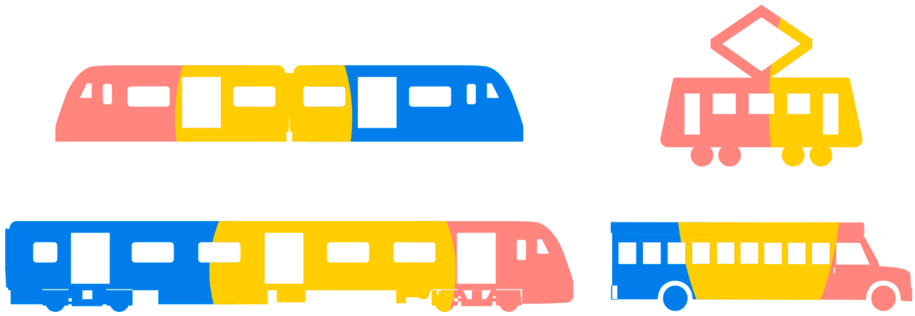


Fig. 6. Public transport vehicle carriages colored by expected pollution levels.

We next consider the variation of deposited dosage within the same carriage. Table 6 presents the median $PM_{2.5}$ for measurements at front, middle, and back of the carriage in the third experiment. The table also contains the estimated deposited dosage for each location (front, middle, back). It can be seen that there is a little variation in DD between different locations. For example, the DD in bus ranges between 1.75 μg and 2.09 μg, and the DD in metro ranges between 2.82 μg and 3.81 μg. For short and infrequent travel, these variations are not significant, but can have a significant impact when commuting is regular. For example, consider a traveller who regularly uses the bus and prefers to sit at the back. For a male passenger traveling with the bus for 60 min a day for five days a week, the deposited dosage in one year will be approximately 420 μg, 453.6 μg, 501.6 μg, depending on the seat location. This means an increase of 20% in accumulated pollution. By using personal exposure monitoring, these types of subtle variations in exposure can be better captured and commuters can be provided suggestions on how to reduce their exposure, e.g., by recommending locations where to sit during different times. Using a single dedicated sensor, as is commonly done in transit monitoring, fails to capture these variations and is unable to estimate long-term health effects.

5.4. *User Feedback on Sensor Usability*

As the final step of our evaluation, we consider the usability of our wearable sensor. The sensor prototype has been distributed to volunteers who are carrying it as part of their everyday activity and we have collected usability feedback from 7 volunteers that have used our wearable sensor for a three month period. The volunteers carried the portable sensors by attaching the sensor to their belongings (backpack or clothes) while conducting their daily activities; we refer to (Rebeiro-Hargrave et al., 2020) for details of the deployment.

Overall, the volunteers found it easy to attach the sensor device (1/7 reported difficulty) and the device also stayed attached without issues (1/7 reported the device having detached during the study). Recharging the device between measurements was not seen as laborious (5/7 reported No). When asked whether carrying the device and measuring air quality with it was laborious, volunteers gave a neutral response (1 Yes, 3 Slightly, 3 No). These results suggest that a separate wearable sensor can be successful, as long as the information it offers to users is sufficiently meaningful and using the device is made easy to the users.

6. Application Use Cases for Personal Exposure Monitoring

Personal exposure monitoring not only enables capturing more detailed information about the user's exposure to pollutants, but also offers possibilities for novel applications and services. We next highlight the practical benefits of low-cost sensors by briefly describing some applications that benefit from our approach and that cannot be implemented using current solutions.

Green Seat Journey Planner: Clean air routing, the integration of air quality information into journey planners, is often mentioned as one of the key use cases that large-scale air quality monitoring enables. Previous research has explored the idea of integrating air quality information with journey planners (Mahajan et al., 2019; Rebeiro-Hargrave et al., 2020), but these works have relied on aggregate information rather than on accurate real-time information of the pollutants. Besides improving the accuracy of air quality information, low-cost sensors also offer support in selecting the best location inside the vehicle. Indeed, by crowdsourcing and comparing pollution values across several users, our system can be used to identify distribution of pollutants inside the vehicle at different times and in different weather conditions. In our current work, we are implementing a prototype system based on this idea together with industrial partners. An early conceptual prototype of the idea is shown in Fig. 6.

Safe Spots for Sensitive Groups: Air quality within different vehicles in the public transport system depends on the quality of the transport fleet. In our experiments, the concentrations were largely smaller inside the vehicles than outside them, but many other studies have shown the opposite (Zhang and Zhu, 2010). An extension of green seat journey planning described above is to identify locations which consistently have lowest pollutant concentrations and to reserve these for vulnerable people that are suffering from breathing problems, such as people with asthma or allergies.

Exposure Estimation on Smartphones: While our approach offers most benefits to users that carry the air quality sensor with them, also users that do not carry the sensor can benefit from the information they capture. Mobile phone accelerometers can detect different transportation modalities with high accuracy (Hemminki et al., 2013) and hence a mobile application can estimate personal exposure without the use of an air quality sensor, simply based on transportation mode, travel time, and distance between departure and arrival.

Vehicle Defect Identification: The results of our evaluation demonstrated that pollutant concentrations vary across different locations within a vehicle, but overall these variations are small. A potential application for this result is the identification of defects, such as clogged ventilation, inside vehicles. This can be implemented simply by comparing pollutant values of different users within a vehicle and using an outlier detection technique to determine abnormally high variations in the pollutant concentrations. The main challenge is to ensure the pollutant difference is not due to mixing with outdoor air, e.g., due to having a window open. Indeed, Huang et. al. (Huang et al., 2018) demonstrated that sampling pollutant information when the windows of the vehicle are open can be used to estimate outdoor pollutant concentrations. Thus it is essential to compare any detected abnormalities with an urban baseline to ensure they correspond to true outliers.

7. Discussion

Our work showed that low-cost sensors have evolved to a stage where meaningful differences in pollutant concentrations can be captured, and we demonstrated that our findings are in line with previous studies in the Helsinki region (Aarnio et al., 2005). We considered a combination of controlled and uncontrolled experiments, which helps to improve generality of the findings. Indeed, previous research has shown that fixed-route studies, as used in our third experiment, result in a good approximation of pollutant concentrations (Adams et al., 2001). We next briefly discuss further extensions of our work and cover the main limitations.

Other Stakeholders: The main beneficiary of our work are individual commuters who can better assess their personal exposure to air pollutants. However, personal exposure can also provide essential information for other stakeholders. As discussed in the previous section, personal monitoring solutions can offer public transport providers insights into the conditions of their fleet, identifying problems or other abnormalities in vehicles. Personal exposure monitoring also supports urban planners and policy makers by providing high resolution information of pollutant concentrations within the public transport network. Thus, while the main focus of our work is on individual commuters, the research has broad applicability across the entire transportation ecosystem.

Health Studies: Scientists are another potential beneficiary of our work with public health being one example of fields that can benefit from our work. Exposure to pollutants is widely acknowledged as a major health concern, affecting the occurrence of respiratory diseases, several cancers, and potentially even the spread of airborne diseases. Studying the health effects of pollutants is rather difficult as personal variations in behaviour significantly impact how much pollution people are exposed to. Personal exposure monitoring can potentially enable improvements in health studies by offering more detailed and granular information about the person’s true exposure to pollutants. The results from our validation study showed that low-cost sensors are generally sufficiently accurate to be considered as scientific instruments for such studies and we would expect there to increasingly be studies that utilize low-cost personal exposure monitoring for assessing the health effects of pollutants.

Room for Improvements: As with every work, naturally there are some room for improvements in our work. These mostly relate to the design of the sensor, and practical limitations in the experiments. Our experiments demonstrated that the proposed system captures highly meaningful information about the variation of pollutants inside different public transport vehicles, but naturally there is room for improving low-cost sensors and the presented hardware design, especially in terms of information provided to people using the devices and other stakeholders. For example, currently the deposited dosage calculations only consider the exposure to pollutants and time. Accelerometers and heart rate measurements can be used to estimate intensity of user’s movements, which correlates with breathing rate and could be used to further improve the deposited dosage estimates. While the form factor of the sensor unit is reasonably small, approximately the size of a small tablet device with battery and casing included, its is by no means insignificant. Indeed, the usability and acceptability of the sensor could be significantly improved by reducing the size of the device – or even potentially integrating it with smart devices. In terms of experiments, the routes taken during the three data collection experiments spanned all of the modes of public transport available in Helsinki at the time, but the controlled evaluations were limited to two fixed and orthogonal routes, eastward and north of the city centre, whereas the uncontrolled experiments had limited set of routes. To fully explore different mediating factors, such as land usage, time-of-day, and variations in weather patterns, a broader range of routes would need be explored.

Bootstrapping Applications: While we demonstrated that low-cost sensors enable new types of applications, there is a cold-start (or bootstrap) issue as the applications require a sufficient number of users before they can operate. This problem is present in all data-driven systems, and can be alleviated with the typical response – seed data. Fixed-route data collections along with city-funded and transport authority driven pollution mapping experiments would be enough to have a base pollution map for all vehicle types and routes for a particular city, and bootstrap the system, at which point real-time data from passengers could be used to crowdsense

Table 7
Measurements of mean $PM_{2.5}$ in different modes of transport in the literature.

Campaign	Period	Mode ($PM_{2.5}$ ($\mu g/m^3$))	Sensing System	Note
London, UK (Adams et al., 2001)	1999/07 & 2000/02	Bike (23.5), Bus (38.9), Car (33.7), Metro (157.3)	High Flow Personal Sampler (HFPS)	Significant between-route variation (notably central route and other routes)
Mexico City, Mexico (Gómez-Perales et al., 2007)	2003/01–03	Minibuses (49.0), bus (53.0), Metro (8.0–68.0)	High Flow Personal Sampler (HFPS)	Wind speed was important determinant of exposure
London, UK (Kaur et al., 2005)	2003/04–05	Walking (27.5), Bike (33.5), Bus (34.5), Car (38.0), Taxi (41.5)	High Flow Personal Sampler (HFPS)	Transport mode, route and timing had significant effect on exposure
Helsinki, Finland (Aarnio et al., 2005)	2004/03	Metro (21.0), Roadside (10.0)	GK 2.05 KTL, BGI, Waltham, MA	Electric braking lowers the concentrations High concentrations during the rush hours
Dublin, Ireland (McNabola et al., 2008)	2005/01 & 2006/06	Car (82.73), Walking (63.45), Bus (128.16), Bike (88.14)	High Flow Personal Sampler (HFPS)	Higher $PM_{2.5}$ level in summer than in winter
Barcelona, Spain (de Nazelle et al., 2012)	2009/05–06	Bike (29.0), Bus (25.0), Car (35.0), Walking (21.0)	DustTrak Model 8520, TSI	Longer distances from roads minimizes the exposures

changes in the pollution patterns and keep users informed.

Privacy: Data collection from devices used by the public will result in the dataset containing (relatively) accurate location information of people in real time. This has privacy implications, and will need to be protected and anonymized sufficiently for further use. Naturally if further measurements, such as movement or heart rate information, is included, the potential privacy implications are even more severe. Conversely, our results also show that personal exposure monitoring systems can have privacy implications as our results showed that the sensors can capture variations in pollutants across transport modalities, and even within the same transport carriage. This means that it could be possible to infer the user's movements simply by looking at air quality and time information.

Integration with Smart Devices: We expect smartphones or other wearables to integrate air quality sensors in the future, removing the need to carry dedicated sensors. Some smartphones already integrate basic air quality sensors. For example, the CAT S61 smartphone integrates temperature, humidity and volatile organic compound (VOC) sensors. Small and lightweight air quality sensing products are increasingly affordable and available which is likely to facilitate the move toward smart devices integrating the necessary sensors. For example, Airsniffler and Atmotube are available at prices less than 100 US dollars with just 24 grams and 35 grams weights, respectively. While these measure gaseous pollutants, also sensors measuring particulate matter are becoming cheaper and more lightweight, e.g., the Sensirion SPS30 particulate matter sensor weighs 26 grams. Particulate matter sensors require unobstructed airflow which means they are likely better suited for top-end smartwatches or other wearables. However, before this becoming feasible in practice, also energy-efficiency of the sensors needs to be improved.

8. Related Work

8.1. Measurement campaigns

Measurement campaigns are the most common way to assess pollutant concentrations in different transport modalities. Relevant studies for our work are summarized in Table 7, focusing on studies that have evaluated variations in particulate matter ($PM_{2.5}$). In general, the results of the campaigns have shown significant variations depending on the location of the study, the state of the public transport fleet, and the nature of measurements. The mean $PM_{2.5}$ concentrations have ranged from high concentrations in Dublin, (115.8 $\mu g/m^3$) (McNabola et al., 2008), to moderate concentrations Barcelona (25.9 $\mu g/m^3$) (de Nazelle et al., 2012), to low in Sacramento (7.47 $\mu g/m^3$) (Ham et al., 2017).

The studies have also shown significant variations across different transportation modalities. For example, Adams et al. (Adams et al., 2001) measured $PM_{2.5}$ exposure levels across different transport systems in London, UK. Their measurements showed cyclists to have the lowest exposure levels while the underground rail system had 3.8 times higher exposure than other transport modes. In the study, the mean personal exposure levels were approximately twice as high as the background pollution levels. As another example, Kaur et al. (Kaur et al., 2005) showed personal exposure of $PM_{2.5}$ to be 35.3 ($\mu g/m^3$) on a heavily trafficked route. The personal exposure levels were high during the morning measurements. The study indicates that the background monitoring stations were not representative of the personal exposure of individuals to $PM_{2.5}$ at and around a street canyon intersection, i.e., roadside. Other studies have shown how environmental variables have an important effect on personal exposure. For example, Gomez (Gómez-Perales et al., 2007) showed that wind speed is a significant determinant of exposure during commuting. In Helsinki, Aarnio et al. (Aarnio et al., 2005) highlights that ultra fine particle (diameter less than 0.5 μm) concentrations and size distributions at the underground metro station were very similar to those measured at the urban background monitoring site, where the source of particles of this sizes are the street traffic. The instruments which were used to measure the PMs are not always applicable to be deployed in large scale and for continuous measurement due to the cost and complexity.

In terms of measurement technology, most campaigns have relied on gravimetric samplers which are affordable and accurate, but laborious to use and fail to capture real-time pollutant concentrations. Indeed, gravimetric sampling require conditioning of filters before and after the measurements and manual weighing of the filters to determine the particle concentrations. The main alternative has been to use industrial-grade real-time particle monitors which use air pumps to generate a steady particle flow and can use laser

Table 8
Mobile sensor systems used for monitoring air quality in transport systems.

Reference	Sensor Type	Sensing Capability	Battery lifespan	Environment
Asorey-Cacheda et al. (2018) (Asorey-Cacheda et al., 2018)	Mobile sensor	CO, CO_2, O_3, SO_2, and NO_2	Unknown	Public transportation systems
Devarakonda et al. (2013) (Devarakonda et al., 2013)	Mobile sensors: Mobile Sensing Box & Personal Sensing Device	CO and PM	Extended with battery of vehicle	Public Transportation Infrastructure & Social Community-based Sensing
Zappi et al. (2012) (Zappi et al., 2012)	Wearable sensor	CO, O_3, NO_2, T, RH, and P	5.35 days	Public transport systems Outdoors & (Cycling and Walking)
Dam et al. (2017) (Dam et al., 2017)	Wearable sensor	O_3, PM sensors, T, and RH	160 min	Urban environments
Stevenson et al. (2017) (Stevenson et al., 2017)	Wearable sensor	$PM_{2.5}$, PM_4, PM_{10} and O_3	Unknown	Different places including public transport
Arvind et al. (2016) (Arvind et al., 2016)	Stationary sensor & Mobile wearable sensor	PM_1, $PM_{2.5}$, PM_{10}, NO_2 and O_3	20 days	Public spaces
Hasenfratz et al. (2012) (Hasenfratz et al., 2012)	Mobile sensing system	O_3	50 h	Urban areas

scattering or tapered element oscillating microbalance (TEOM) technology to estimate particle concentrations. These solutions are significantly more expensive than wearable monitoring solutions, and have mostly been used to carry out experiments where a single sensor unit is placed in a fixed position within the carriage. Our work complements these studies by demonstrating the potential of using low-cost wearables for monitoring transit concentrations, and demonstrating the added insights low-cost wearable sensors can provide compared to existing solutions.

To summarize, the results of measurement campaigns highlight how accurate information about personal exposure requires a measurement solution that can capture subtle variations in concentrations caused by changes in the monitoring context. Our work demonstrates that low-cost wearable sensors can capture such variations and that they offer an alternative technology for conducting measurement campaigns. For example, we show that low-cost wearable sensors can capture variations in exposure caused by differences in the transit route, passenger density, and location within the transit carriage.

8.2. Mobile Sensor Systems used for Air Quality Monitoring

Several previous works have developed mobile sensing systems for both indoor and outdoor pollution monitoring. Key systems and studies are summarized in Table 8. There have been some previous works on measuring pollutant concentrations in public transportation vehicles, but these have largely focused on the design of the systems rather on providing actionable and accurate information about pollutants (Arvind et al., 2016; Stevenson et al., 2017; Dam et al., 2017; Dhingra et al., 2019). Most of these works have also focused on gaseous pollutants rather than on particulates (Asorey-Cacheda et al., 2018; Zappi et al., 2012). Gaseous concentrations typically are correlated with vehicular emissions and background pollution levels, whereas particulates are dependent on a wider range of factors, making monitoring them more challenging. The few works to measure particulates ($PM_{2.5}$) have relied on deployments where the sensors are fixed to vehicles (Devarakonda et al., 2013; Hasenfratz et al., 2012; Do et al., 2020; Kaivonen and Ngai, 2020) or expensive portable units that require active effort to collect the measurements Van Ryswyk et al. (2017). As we show in this paper, there are significant variations even within the same carriage and these variations need to be captured to ensure the measurements reflect true exposure to pollutants. Nevertheless, these studies have shown the feasibility of using mobile sensors for measuring pollutant concentrations in vehicles.

In terms of application areas, most works have motivated the design of sensor systems by targeting the construction of high-resolution air quality maps. Examples of these works include (Dam et al., 2017; Stevenson et al., 2017; Arvind et al., 2016). Hasenfratz et al. (Hasenfratz et al., 2012) showed that dense maps can be created with limited set of mobile sensors. These works show the potential of wearable and mobile sensors and suggest that even small-scale deployments can offer significant benefits for air quality monitoring.

Our work builds on this tradition of wearable sensor designs, and introduces a prototype a sensor unit that is easy and convenient to carry around by citizens. While we introduce a novel sensor, we stress that the main contribution of our work is on demonstrating the feasibility of using low-cost wearable sensors for capturing exposure of individuals, and demonstrating the additional benefits they provide over existing solutions. In terms of wearable sensors, we also demonstrate the accuracy and practicability of the sensors – the former through controlled co-location studies and the latter through a small-scale user study.

9. Summary and Conclusion

We contributed by systematically analysing the feasibility of using low-cost wearable sensors for capturing the pollution exposure of commuters. Through empirical experiments within the Helsinki metropolitan region, we demonstrated that low-cost sensors have reached sufficient accuracy to be used for monitoring pollution exposure during transit activities, and that they can provide additional insights into personal exposure by capturing subtle variations in concentrations caused by changes in the monitoring context. Specifically, we demonstrated that differences across transport modalities are consistent with previous studies, and that wearable low-cost sensors can capture subtle differences in pollution concentrations inside a vehicle. We also demonstrated that fixed sensor systems, such as labour-intensive gravimetric samplers used in current state-of-the-art, are insufficient as they do not cover the entire transit chain (e.g., they do not estimate roadside exposure and they are unable to capture exposure during other modalities such as private cars and taxis) and are unable to account for the measurement context (e.g., variations in the number of passengers or the exact seat of the user). Finally, we highlighted several practical benefits in the use of low-cost wearable sensors by introducing different applications that are enabled by the data the wearable low-cost sensors provide. Examples of these applications include green seat routing and assistance for vulnerable people. Our work paves way to using personal monitoring solutions to collect information about pollutant exposure during transit activities, and highlights how different stakeholders, including individuals, policy makers, and public transport providers can benefit from such technologies.

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