This is the preprint of the contribution published as:

Becker, A.M., Masson, T., **Helbig, C.**, **Mohamdeen, A.**, **Schlink, U.** (2023):
Wearable sensors increase perceived environmental health threat in cyclists and pedestrians:
A randomized field study
J. Transp. Health **32** , art. 101660

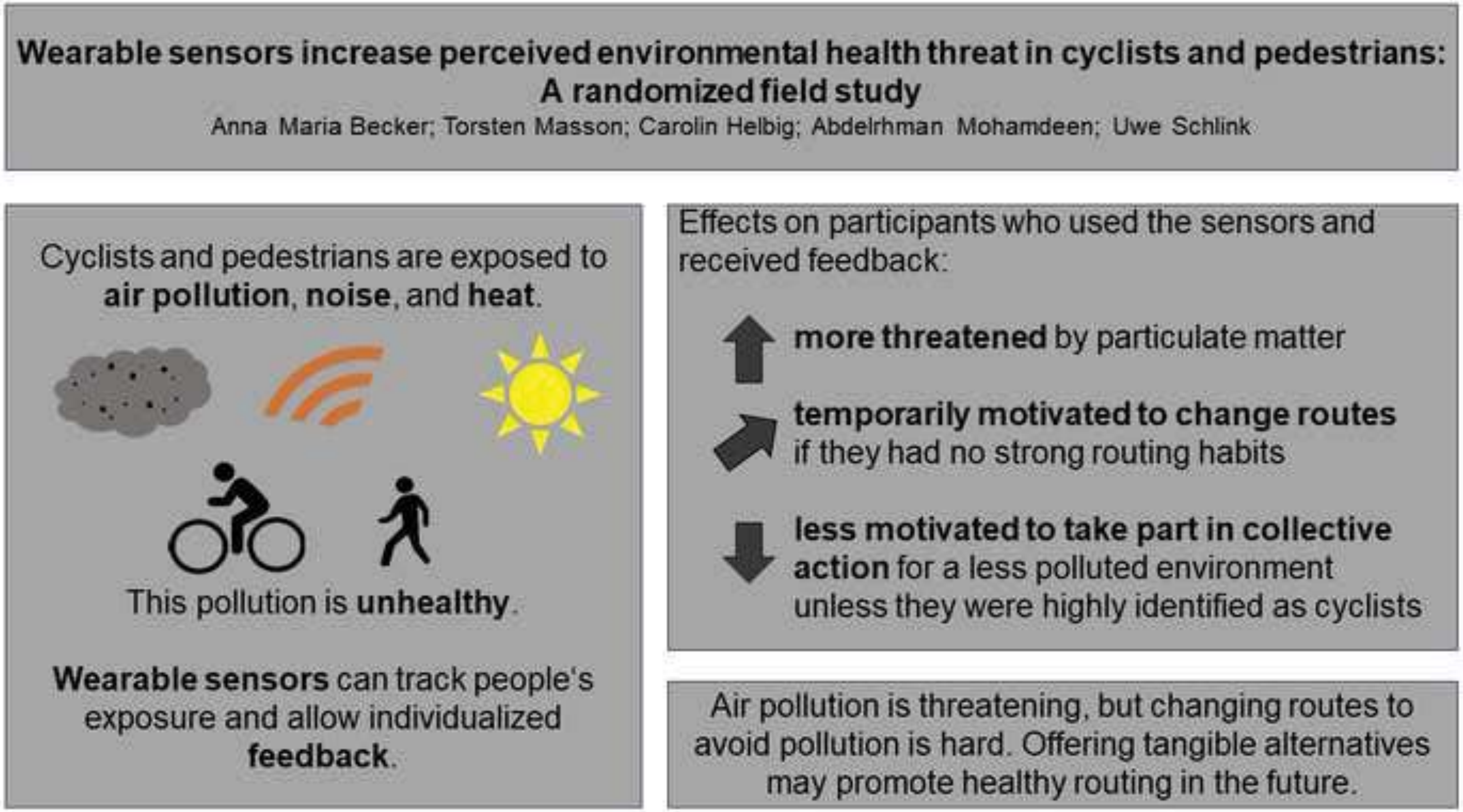
The publisher's version is available at:

https://doi.org/10.1016/j.jth.2023.101660

Highlights: Wearable sensors increase perceived environmental health threat in cyclists and pedestrians: A randomized field study

- Portable sensors were used to measure air pollution (PM), noise and heat in city traffic
- Feedback on environmental stressors increases threat perceptions for cyclists and pedestrians
- The wearables changed protection behaviour intentions for participants with low routing habits

Graphical Abstract



Wearable sensors increase perceived environmental health threat in cyclists and pedestrians: A randomized field study

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Abstract

Introduction. Environmental stressors such as particulate matter, noise, and heat can cause severe health issues. Cyclists and pedestrians in urban areas are exposed to environmental stressors on their everyday routes through the city. While these stressors have been monitored by measurement stations in the past, the use of wearable sensors is becoming more popular. Wearable sensors allow measurements with high spaciotemporal resolution and can be used to track individuals' exposure while they are moving. **Methods**. In a field experiment (final *N* = 109), we applied Protection Motivation Theory (Rogers, 1975) to test the effects of wearable sensors and receiving feedback on exposure levels of particulate matter, noise, and heat in the city of Leipzig in Germany. Participants in the intervention group used the sensors on their everyday routes through the city for three days while the control group did not use the sensors. **Results**. Wearing the sensors and receiving feedback about exposure levels significantly increased participants perception of particulate matter as a health threat. While there were no direct effects of the intervention on intentions to choose less polluted routes, participants with low routing habits were motivated to protect themselves from environmental stressors after using the sensor. Participants motivation to take part in collective action for a less polluted city decreased, unless they were highly identified with the group of cyclists. **Conclusions**. The experiment shows that wearable sensors and feedback on environmental stressors can lead to stronger threat perceptions. However, to motivate healthier route choices, this technology should offer alternative routing suggestions to elevate the user's capacity to cope with the health threat.

Keywords: wearable sensor, air pollution, noise, heat, urban, behavior change

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1. Introduction

Environmental stressors are a major problem in urban areas. Despite a drop in particular matter concentrations in Germany over the past years, the limits recommended by the World Health Organization are still exceeded regularly (Kessiger et al., 2022; World Health Organization, 2021). Emissions from fuel-burning cars contribute to high levels of particulate matter and NO_2 (Kessiger et al., 2022). Within the European Union, exposure to particulate matter has caused 238000 premature deaths in 2020 alone (European Environment Agency, 2022). Poor air quality can lead to lung cancer and various chronic diseases such as obstructive pulmonary disease, heart disease, and stroke (World Health Organization, 2018). Another pressing problem in urban areas is noise pollution (Hänninen et al., 2014). Noise pollution has been found to affect health in multiple ways: it causes not only annoyance, but can also lead to sleep disturbance, cognitive impairment in children, tinnitus, cardiovascular diseases, and mental health problems (Petric, 2022; World Health Organization, 2011). Traffic is one of the major causes of noise related annoyance and sleep-disturbance (World Health Organization, 2011). Increasingly, heat in urban areas is another problem, that affects health and wellbeing particularly for vulnerable groups such as older people (Heaviside et al., 2017). The problem of excessive heat exposure is predicted to further increase due to climate change, while many cities are ill-equipped to handle heatwaves (Heaviside et al., 2017). We conducted a study to make these environmental stressors visible to cyclists and pedestrians by providing them with wearable sensors and feedback about their exposure to particulate matter, noise, and heat on their everyday routes through the city. We investigated the effects of carrying wearable sensors and receiving feedback on threat perceptions and participants' motivation to change their everyday routes to avoid high pollution levels.

1.1. Environmental stressors and Protection Behaviour

As climate change is expected to worsen urban environmental conditions, residents need to adapt (Egerer et al., 2021; Lin et al., 2021) and avoid places and times of high pollution. Environmental monitoring and feedback about exposure levels can equip people with useful information for precautionary behaviour. Small-scale wearable sensors are becoming more common in scientific monitoring and in everyday use (Helbig et al., 2021). These mobile sensors have great advantages in comparison to stationary measurements, as they can capture not only pollution levels in one area but allow insights in the cumulated exposure of individuals as they move through different areas. This high spatial and temporal resolution allows individualized feedback and may thereby motivate protective behaviour.

Protecting oneself from particulate matter may include changing one's routes in city traffic. In the city of Leipzig, where this research was conducted, street traffic is a major cause of airborne particulate matter, e.g., through whirling up particles, abrasion, and engine combustion (Stadt Leipzig, 2019). Exposure to car fumes is particularly dangerous for cyclists, as they are inhaling larger quantities of air than car drivers (Panis et al., 2010). Hence, avoiding main roads and choosing side-streets with less car traffic or travel times outside of rush hour can be a way of avoiding air pollution (Ragettli et al., 2013). Similarly, choosing routes that lead through parks rather than main roads may reduce heat and noise exposure in comparison to the main roads (Magaritis et al., 2018; Tashakor et al., 2021).

In the light of the massive health impact of particulate matter, noise, and heat, adapting travel behaviour is an important precautionary health behaviour. Throughout this paper we define healthy mobility behaviour in terms of avoiding polluted routes by changing route trajectories or travel times to avoid rush hour traffic. However, we acknowledge that there are other important health aspects to mobility, for example choosing active travel (i.e., cycling or walking) has health benefits in terms of physical activity which outweigh the negative effects of exposure to environmental stressors or risk of injury as a cyclist or pedestrian (Mueller et al., 2015). Further aspects that impact health for active mobility are road safety or the effects of greenspaces or cycling or walking in a socially and aesthetically pleasing environment on wellbeing (Glazener et al., 2021; Marquart et al., 2022). However, we focus on avoiding environmental stressors (particulate matter, noise, and heat) as a personal health behaviour.

Health behaviour is generally defined as a preventative behaviour shown by persons to protect themselves from future illness (Kasl & Cobb, 1966). One prominent theory to explain protective behaviours is Protection Motivation Theory (PMT; Rogers, 1975). It differentiates between threat appraisal and coping appraisal that motivate protective action. Threat appraisal in PMT is made up of the perceived probability of the negative health outcome (e.g., exposure to air pollution is likely to have an impact on my health) and the severity of these potential health effects (e.g., air pollution can have severe effects such as lung cancer). Later versions include fear as an emotional component of threat appraisal (Maddux & Rogers, 1983). Coping appraisals must allow a person to see adaptive behaviour as effective (response efficacy) and feasible (self-efficacy), while behavioural costs of this adaptation (e.g., longer routes to work when avoiding pollution) inhibit personal protection intentions (Maddux & Rogers, 1983). Meta-analytic evidence supports the feasibility of the PMT for explaining health behaviours (Milne et al., 2000).

Adaptation costs for changing one’s everyday routes can be high. They may include longer travel times, surfaces that are harder to cycle on and even less obvious hurdles such as less lighting that can be perceived as unsafe (Tan & Smith, 2021). Another important factor in travel behaviour are habits (Bamberg & Schmidt, 2003). Routing choices are likely to be habitual for example when people ride their bike to work or another destination they move to regularly. Habits are characterized by behaviour that is shown repeatedly, formed for goal-directed behaviour, and triggered by specific cues (e.g., deciding to go to the office;

Verplanken & Orbell, 2003). A habitual behaviour has become automatic which means that the behaviour is largely unintentional and often lacks awareness and control (Bargh, 1994; Verplanken & Orbell, 2003). The repetition and automaticity of habits make these behaviours particularly resistant to change (Aarts & Dijksterhuis, 2000; Matthies et al., 2006). Travel behaviour, is likely to be strongly habitualized as most people travel to similar destinations daily (e.g., to work), but also because this is not a task that takes a lot of mental preparation and is easy to automatize.

Travel-related behaviours, such as choice of travel mode can also be an expression of identity (Gössling, 2023; Murtagh et al., 2012). Every person is part of different groups and categories, with which they can identify to a varying degree (e.g., the group of cyclists). Group memberships and their emotional significance make up a person's social identity (Social Identity Theory; Tajfel & Turner, 1979). Ingroup identification can also drive collective action in favor of one's ingroup (van Zomeren et al., 2008). Social identification with specific groups of transport users (e.g., cyclists) is an important factor in predicting collective action for transport policies. Previous research has shown that higher identification with the group of cyclists or the group of pedestrians was associated with collective action intentions and policy support for a redistribution of street space in favor of active transport users, while identification with the group of car drivers (but not simply car use) was associated with protest against such measures redistributing street space (Allert & Reese, 2023).

1.2. Providing information about environmental stressors

Previous studies have shown that participants' perceptions of e.g., air pollution are not always in line with the pollution levels measured by sensors (Cori et al., 2020; Marquart et al., 2022; Ueberham et al., 2019). This highlights the necessity to make the pollution levels visible for people to understand their exposure. To enable this understanding, it is important to provide information that is easily understood and relatable and comes from trusted sources (Riley et a., 2021). The information should also be tailored to individual receivers and tap into emotions rather than only communicating numbers (Riley et al., 2021). Ideally, feedback on environmental stressors should include actionable behavior suggestions – while this can be individual adaptation, the communication can also encourage collective action to improve pollution levels (e.g., through policy measures; Riley et al., 2021).

Receiving information on air pollution levels as well as the availability of greenspaces marked in a map influenced walking route choices to avoid busy roads in a lab setting (Königsdorfer, 2018). While travel time and heavy traffic volume were found to be the most important aspects of route choices for cyclists, their preferences when choosing between different route options on a map showed that air pollution levels were also taken into account and cyclists were more concerned about air pollution if they were provided with information about its negative health impacts (Anowar et al., 2017). This study found that if a less polluted alternative route was available, participants were willing to choose this route even if it added a few minutes of extra travel time (Anowar et al., 2017). While these studies gave information on pollution levels in a hypothetical setting by providing information in maps, we will focus on providing information about measured levels of pollution. For example, citizens may be informed about high levels of air pollution by regional alerts (e.g., via television or radio) to reduce strenuous outdoor activities as well as behaviors contributing to air pollution (Riley et al., 2021 for a review). Similarly, the public may be warned from heat waves on a regional level (Mehiriz et al., 2018; Rabassa et al., 2021).

Another form of information provision can result from wearable sensors, allowing individualized feedback on a person's exposure. Studies on noise exposure using small scale sensors provided feedback on noise levels at work (Trawick et al., 2019), in school (Di Blasio et al., 2019; Tabuenca et al., 2021), or outdoors (Becker et al., 2013; Marquart et al., 2022).

Only few studies used wearable sensors to provide participants with information on their exposure to extreme outdoor temperatures (Nelson et al., 2020; Thompson et al., 2018). Importantly, most studies providing noise or temperature feedback from wearable sensors were not conducted in a transportation context. An exception to this the study by Marquart et al. (2022) combining noise measurements and en-route interviews. This demonstrates that there is a research gap for providing feedback from wearable noise and temperature sensors and studying the effects of providing such information.

Other studies used wearable sensors to give feedback about participants' exposure to air pollution during their everyday routes (Bales et al., 2019; Haddad & de Nazelle, 2018; Heydon & Chakraborty, 2020; Marquart et al., 2022; Oltra et al., 2017; Tan & Smith, 2021; Varaden et al., 2018). En-route interviews while using wearable sensors with cyclists and pedestrians have shown that greenspaces and water along the daily commuting route, as well as lively neighbourhoods with many social activities (e.g., cafes, playgrounds) and aesthetic architecture can greatly improve the commute by bike while perceived pollution levels, and danger in terms of high car traffic or low lighting reduced wellbeing while cycling (Marquart et al., 2022). Studies using small scale sensors and providing feedback on air pollution levels in the realm of transportation showed mixed results in their effectiveness of changing individuals' behavior (Becker et al., 2021). Some studies found small-scale adaptations such as planning to take less polluted routes while cycling or walking (Marquart et al., 2022; Tan & Smith, 2021) or avoiding pollution by making small changes such as keeping windows closed when driving on streets with a lot of traffic (Bales et al., 2019). However, in many cases, wearable sensors did not lead participants to change their routes (Haddad & de Nazelle, 2018; Heydon & Chakraborty, 2020). Many participants in these studies reported constraints to behavioural adaptation. As choosing alternative, less polluted routes was often found do to be too costly (Haddad & de Nazelle, 2018; Heydon & Chakraborty, 2020; Oltra et al., 2017; Tan

& Smith, 2021). Furthermore, participants also reported that they were already doing their best to avoid polluted routes (Haddad & de Nazelle, 2018; Marquart et al., 2022).

Nonetheless, many found their participation in these studies interesting and insightful (Heydon & Chakraborty, 2020; Tan & Smith, 2021; Marquart et al., 2022; Oltra et al., 2017; Varaden et al., 2018). Some studies found that using air pollution measurement devices led participants to talk about pollution with friends and family (Bales et al., 2019; Tan & Smith, 2021; Varaden et al., 2018). Participants who could explore their surroundings with a sensor found that it helped them learn about the different situations in which they were most exposed to air pollution (Bales et al., 2019). However, it is important to note that only a small proportion of studies was explicitly focused on using the sensors during commutes to work (Marquardt et al., 2022), on the way to school (Varaden et al., 2018), or on everyday routes (Haddad & de Nazelle, 2018). Some studies had participants use the sensor during all activities including travel, but also in their homes (Bales et al., 2019; Heydon & Chakraborty, 2020; Oltra et al., 2017; Tan & Smith, 2021). This shows the need to conduct studies that are focused specifically on active mobility and route choices.

Generally, studies using wearable sensors are relatively rare, as the widespread availability and use of wearable sensors is a rather new development (Helbig et al., 2021). Most studies have a very limited sample size (Tan & Smith, 2021) or are focused on the usability of the sensors (Haddad & de Nazelle, 2018). One major limitation of these studies is that most do not implement experimental designs to test the effects of the sensors on human behaviour. To study the causal effects of using the sensors and receiving feedback, it is necessary to run a randomized controlled trial, comparing participants who use the sensors to a control group. As the dissemination of wearable sensors is increasing, it is important to study their effects on people’s threat perceptions and their potential to motivate healthy routing choices.

1.3. The Current Study

Feedback on personal exposure to environmental stressors (e.g., by using wearable sensors) has recently gained attention as a tool for health risk communication (Becker et al., 2021; Helbig et al., 2021). Providing information on personal exposure levels is expected to affect people's risk perception and may also foster their protection behavior, i.e., behavior aimed at reducing personal exposure to environmental health risks. However, studies investigating the effects of exposure feedback from wearable sensors have often applied non-experimental evaluation designs, thus limiting their power for casual inference. The current study investigated how feedback on personal exposure to three environmental stressors (particulate matter, noise, and heat) could influence people's health risk awareness and their intentions for healthy mobility behavior by utilizing a four-wave experimental research design. Participants were randomly assigned to one of two groups, an intervention group (received a measurement kit to record their exposure levels for three days as well as feedback on their personal exposure) or a control group (received neither a measurement kit nor feedback) and filled out a total of four questionnaires throughout the study period (3 - 4 months). Building on psychological action models, we tested the effects of the feedback treatment on respondents' threat appraisals and protection motivation.

Specifically, we assumed that participants in the intervention group would report stronger increases in perceived environmental health risks related to particulate matter (Hypothesis 1a), heat (Hypothesis 1b) and noise (Hypothesis 1c) than respondents in the control group. We further explored whether participation in the intervention (but not in the control group) would foster respondents' action intentions to reduce personal exposure levels, for example by changing their everyday routes. Additionally, we explored possible intervention effects on more collective forms of behaviour. Previous research has focused on individual strategies to limit exposure to environmental health stressors, such as switching to less polluted routes when commuting to work (Tan & Smith, 2020; Haddad & de Nazelle, 2018). However, effectively addressing environmental health risks such as exposure to particulate matter might not only require changes in individual behaviour but also collective efforts to protect or restore common goods such as clean air. Thus, we investigated within-participant changes in their action intentions to collectively fight against environmental health risks.

For exploratory analysis, we included a number of additional predictors of the target behaviour in our questionnaire, such as items on participants' routing behaviour habits and coping appraisal (i.e., efficacy beliefs) to protect themselves against personal exposure to environmental health risks, or their identification with mobility-related social groups (e.g., self-identification as a cyclist).

2. Methods

2.1. Participants and Procedure

Results of an a priori power analysis using G*Power indicated a required sample size of N = 128 to detect an intervention effect of moderate effect size (d = 0.5, 80% power, α = .05) on health risk perception (Faul et al., 2009). Participation was advertised in local news and over social media and participants received a small gift (tote bag, regional tour guide, and chocolate).

The study took place in Leipzig, a city in Germany with approximately 600.000 inhabitants (Statistisches Landesamt Sachsen, 2023). Many of the large roads in Leipzig are accompanied by bicycle lanes, while side streets usually have no specified bike lanes. Besides the street infrastructure, there are multiple park areas which allow cycling. A green corridor along a river runs through the city from north to south leading into a forest area.

After signing up on the study website, participants were contacted and allocated to a week in the study period (July - September 2020). A total of 333 persons signed up through the website, though approximately one third did not further respond after being contacted.

Participants were randomly assigned to the intervention or control group and were surveyed at four points: pretest (before the sensor measurement phase), posttest (after the sensor measurement phase), after receiving feedback (only intervention group surveyed), follow-up (approximately two to three months after posttest). Informed consent was given at the beginning and end of each questionnaire ensuring compliance with ethical standards. The study procedure was in compliance with laws on privacy rights and approved by the institutional data protection officer.

After filling out the pretest questionnaire, participants in the intervention group received the measurement kit and were asked to use it on their everyday routes for three days. The measurement kit consisted of a particulate matter (PM) sensor (Dylos DC1700) counting particles of different sizes (PNC – particle number concentration of PM 2.5 and PM10) every minute. The kit further comprised a gas sensor, as well as a temperature/humidity sensor (Leo/ateknea sensor). The kit could be carried with a shoulder strap. The kit also included a Motorola smartphone with a microphone for noise measurements, as well as a GPS and time log. The smartphone could be strapped to one arm. A more detailed description of the measurement kit can be found in publications by Ueberham & Schlink (2018) and Ueberham et al. (2019). The participants received verbal and written instructions (see supplemental materials) and could further access a video explaining how to use the sensor on the study website.

After one week, all participants received a second questionnaire (posttest). One week after this, participants from the intervention group received written feedback with general information on particulate matter, noise, and heat including health impacts of these stressors. The feedback consisted of histograms showing the participant's individual exposure to these three stressors during the measuring period. The feedback showed cumulative exposure over the entire measurement period and did not refer to specific routes or days. The feedback graphs were colour-coded and showed the amount of time in minutes, in which the participant measured certain levels of particulate matter, noise, or a certain temperature. The colour coding was labelled with reference points for noise (silent room – pain threshold) and heat (no temperature stress – extreme temperature stress) to make the information more relatable. For particulate matter the feedback was also colour coded. An example feedback report can be found in the supplemental materials. Immediately after viewing the feedback, they filled out a third questionnaire. Two to four months after the first measurement, all participants received the link to a follow-up questionnaire.

2.3. Measures

All of our study variables were assessed at pretest, posttest, after receiving exposure feedback and at follow-up (or at pretest, posttest and follow-up for the control group) with the exception of habit, which was only measured in the pretest questionnaire. We registered the responses to all items on seven-point scales (1 = "not agree at all" to 7 = "strongly agree"). Each scale was calculated as mean score across the items of this scale (see Table 1).

As the main dependent variables, we measured threat perception regarding particulate matter, noise, and heat (in summer) with five items respectively. Items for the threat perception scale measured severity and probability of negative health outcomes as well as fear. Efficacy beliefs (response efficacy and self-efficacy) as a measure of coping appraisal were captured with four items each for particulate matter, noise, and heat (in summer). Next, we measured participants' personal intention to change their routing behavior to avoid pollution with twelve items. We then measured collective action intentions using seven items.

As a moderator, we measured habits for travel to work/school/university, for shopping trips, and in leisure time. For each of these destinations we used nine items from the Self-Report Habit Index (Verplanken & Orbell, 2003). We then took a mean of all 27 items as a scale for general routing habit. Identification with cyclists was measured with a single item (Postmes et al., 2013). Demographic variables were measured at the end of the questionnaire.[1]

Table 1: *Items of the study scales*

Threat perception
each item was answered separately for particulate matter, noise, and heat (in summer)
Particulate matter, noise, and heat on my daily routes have very negative effects for my health.
How much do you feel your health is endangered by particulate matter, noise and heat on your daily routes? (1 – not endangered at all, 7 – very strongly endangered)
How likely is it that particulate matter, noise, and heat on your daily routes will affect your health?
I worry about particulate matter, noise and heat on my daily routes.
The thought of particulate matter, noise and heat on my daily routes scares me.
Efficacy beliefs
each item was answered separately for particulate matter, noise, and heat (in summer)
There are effective ways to reduce one's personal exposure to environmental stressors on daily routes.
Changing the routes' spacial course can help to reduce exposure to environmental stressors.
Changing the temporal start of the routes can help to reduce exposure to environmental stressors.
I can reduce my exposure to environmental stressors in street traffic.
Individual action intentions
To reduce my environmental pollution (PM, noise, heat) in the next 4 weeks, I will…
..avoid roads with high (car) traffic.
...avoid large street intersections.
...choose detours where my exposure to environmental stressors is lower.
...use a map to look for alternative routes for my everyday commutes.
...use side roads with less traffic.
...pay attention to noise pollution when choosing a route.
...pay attention to particulate matter when selecting routes.
...pay attention to heat when choosing the route.
...avoid the rush hours.
...drive/walk detours, even if they take longer.
...make my trips at different times.
...change the spatial course of my paths.
Collective action intentions
I will talk to my friends and family about environmental stressors in traffic.
In the next regional election I will vote for people/parties that advocate for less environmental stressors in road traffic.
I am willing to sign petitions calling for greater protection against environmental stressors in Leipzig's road traffic.
I am willing to join others in a demonstration for a bicycle and pedestrian friendly city.
I am willing to join a group that is committed to a bicycle and pedestrian friendly Leipzig.
I am willing to join a Facebook group to share ideas on the topic of environmental stressors in urban transportation.
I am willing to follow a social media channel (YouTube, Instagram, Twitter) that provides information on the topic of environmental impacts in urban transportation.
Habit (adapted from Verplanken & Orbell, 2003)

[1] Additionally, the questionnaires included measures of participants' preferred mode of transport for different routes, how often the go for walks, their preference for specific aspects of their routes (e.g. speed, low traffic), participants' stage of behavior adaptation to environmental stressors, costs of behavior change and non-stressor-specific coping appraisal to change travel times and routes, participants' willingness to pay for an app that provides alternative route suggestions, non-protective coping responses, social norms, identification with the city, pedestrians, and car-drivers, derogation of the group of car-drivers, perceived responsibility of legislators, moral outrage, general health concerns, perceived control, and preference for technology. Lastly, we measured variables regarding the COVID-19 pandemic. The results regarding these outcomes will not be discussed here because they are not central to our interpretation.

each item was answered separately for travel to work/school/university, shopping trips, and leisure time
I often drive/walk the same spatial route to...
I often travel the distance to … at the same time of day.
I drive/walk the distance to…frequently.
I drive/walk the distance to…automatically.
I drive/walk the distance to…without thinking.
Getting to … belongs to my (daily, weekly, monthly) routine.
The route to … is typical for me.
I have been driving/walking the distance to…for a long time.
I drive/walk the distance to…without having to consciously remember.
Identification with cyclists (adapted from Postmes et al., 2013)
I identify with the group of cyclists.

3. Results

3.1. Data Preparation

Table 2 shows the number of participants who filled out the questionnaire at each measurement point. We excluded cases without a second informed consent at the end of the questionnaire, as well as doublets where a person with the same identifier filled out the same questionnaire more than once.

Table 2

Number of participants for each measurement point

	Pretest	**Posttest**	**Feedback**	**Follow-up**
Intervention group	93	85	78	61
Control group	89	82	-	60
Total N	182	167	78	121

The datasets were merged based on an identifier-code, generated by each participant at the start of each questionnaire. The identifier was made up of three letters and a digit. Questionnaires were also matched when only one digit or letter was inconsistent. In these cases, we made sure, that age and gender in the merged questionnaires were the same and they were filled out within the same week of participation. Seventy-five respondents did not provide data at posttest and/or after receiving feedback on exposure and/or at follow-up, resulting in a final sample of 109 participants ($N_{intervention}$ = 56, $N_{control}$ = 53; 59.89% of the pretest sample). The level of dropout did not differ significantly between the intervention group (37.3%) and the control group (40.4%; $\chi^2(1) = 0.008$, $p = .927$). Furthermore, results of multiple t-tests showed no significant differences at pretest for all but two of our central study variables between participants who completed all questionnaires and drop-outs (health risk perceptions, personal action intentions, efficacy beliefs, routing behavior habits), except for collective action intentions ($M_{drop\text{-}outs} = 5.15$, $M_{complete} = 4.68$, $t(180) = -3.03$, $p = .003$) and self-identification as cyclist ($M_{drop\text{-}outs} = 6.59$ $M_{complete} = 6.14$, $t(180) = -2.52$, $p = .013$).

We conducted between-group comparisons to identify potential differences in our central study variables at pretest between the intervention and the control group. Results revealed no significant between-group differences for health risk perceptions, efficacy beliefs regarding PM and noise, personal action intentions, collective action intentions, routing behavior habits (all ps > .125), indicating no substantial baseline differences for most of our central study variables. Results showed that participants in the intervention group reported higher efficacy beliefs regarding heat ($M = 4.31$, $SD = 1.06$) than the control group ($M = 3.83$, $SD = 0.98$; $t(107) = 2.36$, $p = .020$).

3.2. Descriptive statistics

Sixty-one participants identified as female and 48 identified as male. Ages ranged from 19 to 67 years ($M = 36.33$, $SD = 9.68$). Most participants (72.5 %) had a university degree, 76.1% were employed part time or full-time, 5.5 % were self-employed, 14.7 % were students, and 3.7% were unemployed or retired. Median household income (measured with income brackets) was 3,000-3,999€. 6.4 % of the sample had moved to a new house or apartment within the last six months and 54.1% reported not driving a car, while 11.9% do not own a car, but drive regularly e.g., using a carsharing service and 33.9% own a car. Regarding health condition, 6.4 % reported having a respiratory health condition such as asthma and 29.4% reported having allergies. Overall, participants rated their health as good ($Mdn = 6.00$ on a seven-point scale ranging from 1-very bad to 7-very good). Finally, participants rated their initial knowledge about PM, heat and noise pollution as limited to medium (for particulate matter: *Mdn* = 3.00; heat: *Mdn* = 3.00; noise: *Mdn* = 3.00).

Detailed information on the central study variables, means, standard deviation, scale reliabilities (Cronbach's alpha coefficients), and inter-scale correlations for all study variables are presented in Table 3. Information on the usability of the sensor kit (e.g., rated ease of use and frequency of use) as well as the participants' evaluation of the feedback report are given in appendix A.

Table 3

Means, standard deviation, reliability, and inter-scale correlations of study variables

Time	No.	Variables	M	SD	α	2.	3.	4.	5.	6.	7.	8.	9.	10.
Pretest	1.	PM health threat	4.32	1.43	.88	.49**	.37**	.12	.40**	.10	-.02	-.10	.17	.05
	2.	Noise health threat	3.66	1.40	.87		.53**	.17	.22*	.04	-.11	-.01	.11	-.03
	3.	Heat health threat	3.46	1.38	.89			.18	.13	.17	.02	.10	-.02	.05
	4.	Individual intentions	3.36	1.17	.90				.23*	.28**	.21*	.20*	-.11	.10
	5.	Collective action intentions	4.68	1.05	.73					.21*	.16	.06	.17	.20*
	6.	PM efficacy beliefs	4.33	1.08	.58						.64**	.42**	.14	.13
	7.	Noise efficacy beliefs	4.78	0.91	.46							.43**	.06	.14
	8.	Heat efficacy beliefs	4.09	1.05	.60								-.12	.10
	9.	Identification cyclists	6.14	1.31	*s*									-.12
	10.	Routing habits	5.08	0.79	.90									
Posttest	1.	PM health threat	4.39	1.36	.90	.55**	.34**	.29**	.56**	.29**	.05	-.02	.14	
	2.	Noise health threat	3.90	1.32	.88		.56**	.33**	.33**	.15	.02	-.03	.06	
	3.	Heat health threat	3.54	1.39	.91			.34**	.18*	.07	.05	.10	-.06	
	4.	Individual intentions	3.57	1.19	.92				.29**	.37**	.38**	.34**	-.02	
	5.	Collective action intentions	4.56	1.20	.82					.22*	.09	.07	.32**	
	6.	PM efficacy beliefs	4.38	1.04	.71						.68**	.40**	.25*	
	7.	Noise efficacy beliefs	4.86	0.91	.61							.65**	.14	
	8.	Heat efficacy beliefs	4.23	1.07	.70								.09	
	9.	Identification cyclists	6.17	1.33	*s*									
Feedback[a]	1.	PM health threat	4.61	1.33	.89	61**	.44**	.15	.55**	.39**	-.04	-.20	.17	
	2.	Noise health threat	3.94	1.20	.88		.65**	.15	.25	.14	-.09	-.15	-.04	
	3.	Heat health threat	3.31	1.25	.91			.25	.20	.13	-.14	-.16	-.17	
	4.	Individual intentions	3.59	1.26	.93				.13	.36**	.40**	.36**	-.14	
	5.	Collective action intentions	4.52	1.31	.84					.26	-.01	-.03	.31*	
	6.	PM efficacy beliefs	4.51	1.03	.76						.69**	.35*	.03	
	7.	Noise efficacy beliefs	4.92	0.84	.66							.73**	-.02	
	8.	Heat efficacy beliefs	4.17	0.90	.59								-.21	
	9.	Identification cyclists	6.18	1.36	*s*									
Follow-up	1.	PM health threat	4.46	1.33	.88	.58**	.40**	.28*	.49**	.17	.06	.06	.14	
	2.	Noise health threat	4.01	1.27	.88		.50**	.25**	.41**	-.01	-.07	-.12	.08	
	3.	Heat health threat	3.52	1.38	.91			.22*	.23*	.12	.04	.13	-.01	
	4.	Individual intentions	3.46	1.19	.92				.26**	.31**	.20*	.12	.11	
	5.	Collective action intentions	4.39	1.16	.78					.21*	.06	-.09	.27**	
	6.	PM efficacy beliefs	4.44	1.07	.73						.62**	.20**	.27**	
	7.	Noise efficacy beliefs	4.81	0.94	.64							.68**	.11	
	8.	Heat efficacy beliefs	4.22	1.08	.69								.05	

9. Identification cyclists	6.20	1.29	*s*

Note: * $p < .05$, ** $p < .01$; [a] only intervention group surveyed ($N = 56$), *s* = single item, PM = particulate matter

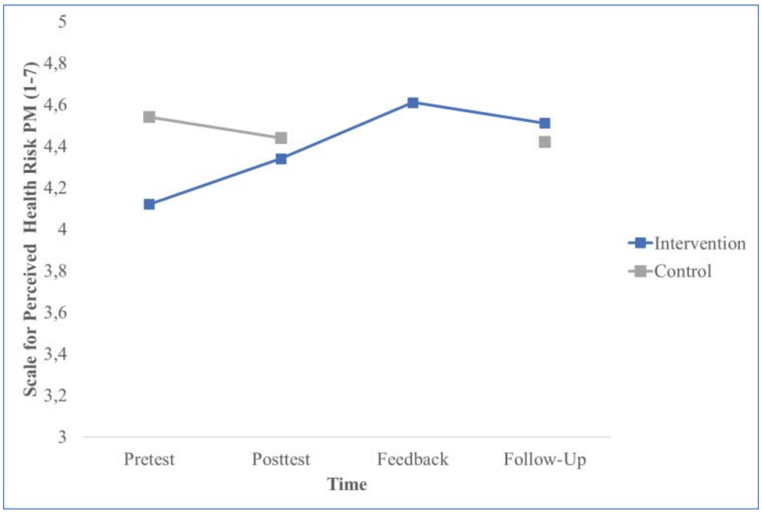
3.3. Mixed-Model Analysis

Linear mixed-effect models with random intercepts were estimated to assess within-participant changes from pretest to follow-up for our outcome measures, as well as differences between the intervention group and the control group. Analyses were conducted applying restricted maximum likelihood estimation (REML) using the GAMLj package (Gallucci, 2019) in jamovi (The jamovi project, 2022). Separate mixed models were estimated for each of the outcome measures including time (pretest, posttest, after receiving exposure feedback, follow-up), group (intervention, control), as well their interaction term. When adding an additional moderator variable to the analysis, we included time, group, the moderator variable as well as all of their two-way and three-way interaction terms in the mixed model. All continuous predictors are mean-centered prior to the calculation of the interaction terms. Simple slopes were tested at ±1 SD of the mean value. Changes in our central outcome measures across the four measurement points are presented in Table 4.

Perceptions of environmental health risk. We fitted three mixed models to separately test how our intervention might affect perceptions of PM, noise and heat health risks. For perceived PM health risk, results showed the expected interaction effect of time and group, $F(2, 269) = 4.081$, $p = .018$ (see Figure 1). Simple effects analysis revealed a marginally significant increase in PM health risk perceptions from pretest to posttest and a significant increase from pretest to exposure feedback for participants in the intervention group ($M_{\text{post-pre}} = 0.22$, $t = 1.72$, $p = .086$, $d_{av} = 0.15$; $M_{\text{feedback-pre}} = 0.49$, $t = 3.90$, $p < .001$, $d_{av} = 0.35$; effect size based on Cumming, 2012), but not in the control group, $M_{\text{post-pre}} = -0.10$, $t = -0.75$, $p = .451$, $d_{av} = -0.07$. Importantly, participants in the intervention group retained increased levels of PM health risk perceptions throughout the follow-up period, $M_{\text{follow-pre}} = 0.39$, $t = 3.08$, $p = .002$, $d_{av} = 0.28$, indicating a robust intervention effect. For perceived heat and noise health risks, we found no significant interaction effects of time and group, indicating that our intervention did not affect perceptions of noise and heat health threats (all *ps* > .133). Our results thus support Hypothesis 1a, but not Hypotheses 1b and 1c.

Figure 1

PM health risk perception as a function of time and group

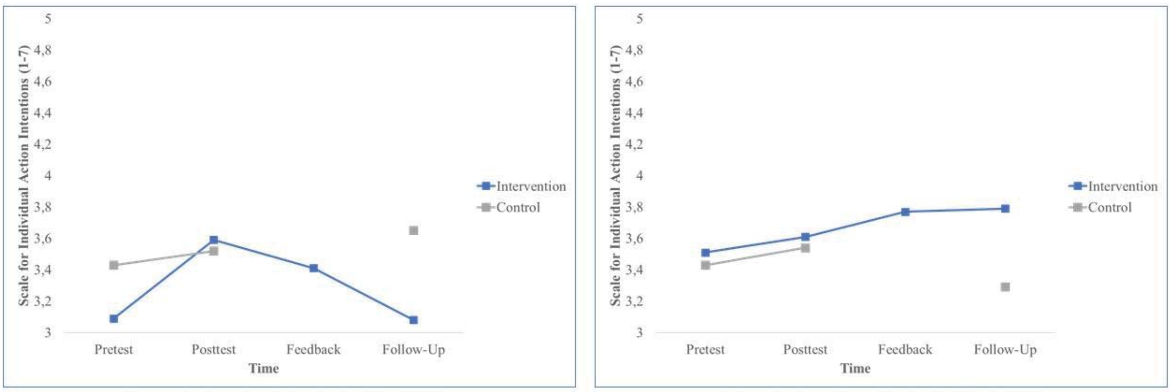


Individual action intentions to reduce personal exposure to environmental health risks. For individual action intentions, results showed no significant main effects of time and group and, more importantly, no significant interaction effect of time and group (all *ps* > .126). In other words, our results did not show that participation in the intervention group increased respondents' action intentions to protect themselves against environmental health risks. Next, we explored people's routing behavior habits as a possible moderator.

We reasoned that our intervention would be more effective for participants with weak (vs. strong) habits, as individuals with strong habits should be more resistant to changing their routing behavior (Klöckner & Blöbaum, 2010; Matthies et al., 2006). Results of mixed model analysis including routing behavior habits as an additional moderator variable showed the expected three-way interaction effect of time, group and habits, $F(2, 264) = 3.67$, $p = .027$ (see Figure 2). Simple effects analysis revealed a significant increase in individual action intentions from pretest to posttest for participants with weak routing behavior habits in the intervention group, $M_{\text{post-pre}} = 0.50$, $t = 2.62$, $p = .009$, but not in the control group, $M_{\text{post-pre}} = 0.10$, $t = 0.48$, $p = .628$. However, this initial increase in the intervention group was not stable throughout the study period as individual action intentions for participants with weak routing behavior habits in the intervention group were almost identical at pretest and follow-up, $M_{\text{follow-pre}} = - 0.01$, $t = - 0.05$, $p = .964$. For participants with strong routing behavior habits, we found no significant changes in individual action intentions throughout the study period, neither for participants in the intervention group nor for participants in the control group (all *ps* > .131). Taken together, our findings suggest that feedback on personal exposure only increased individual action intentions for certain parts of the intervention group. Specifically, we found positive, but short-lived intervention effects for respondents with low (but not high) routing behavior habits.

Figure 2

Individual action intentions as a function of time, group and routing behavior habits

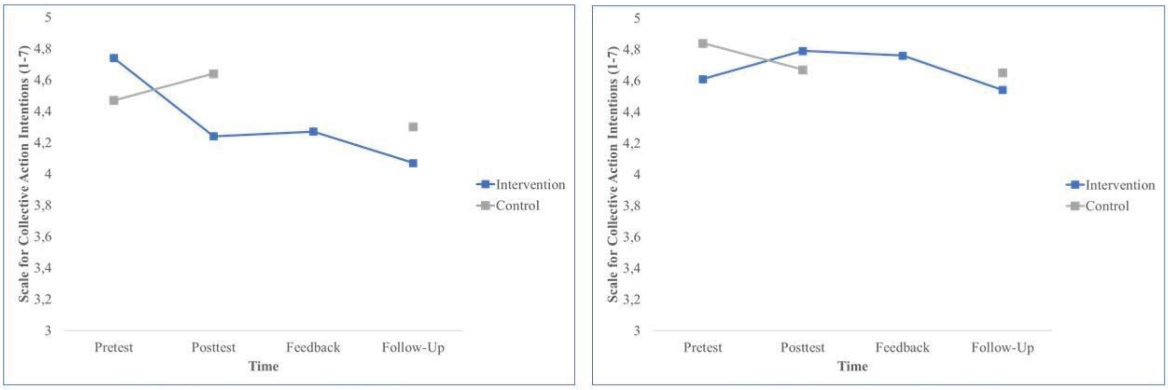


low pretest routing behavior habits (-1SD) high pretest routing behavior habits (+1SD)

Exploratory analysis: Collective action intentions to fight environmental health risks. Our next analysis explored whether our intervention would affect participants' intentions to collectively fight against environmental health risks. We tested competing assumptions about how participating in the intervention may influence collective action intentions. Specifically, participation may increase collective action intentions through increased problem awareness or risk perception. However, participation may also decrease collective action intentions by strengthening the salience of personal protection strategies. Results of mixed model analysis showed a significant decrease in collective action intentions over time, $F(3, 269) = 6.33$, $p < .001$, though there was no significant interaction effect of time and group, $F(2,269) = 1.85$, $p = .160$. To further explore our data, we included identification with the cyclist group at each measurement point as an additional moderator in the analysis. We reasoned that the negative trend might differ for participants who have no strong psychological bond with the cyclist category, as group identification is a well-established predictor of collective action (Fritsche et al., 2018; van Zomeren et al., 2008). Results showed a three-way interaction effect of time, group and identification with the cyclist category, $F(2, 265) = 5.61$, $p = .004$ (see Figure 3). Simple effects analysis revealed significant decreases in collective action intentions from pretest to posttest, from pretest to exposure feedback and from pretest to follow-up for participants with low identification in the intervention group ($M_{\text{post-pre}} = -0.50$, $t = -4.52$, $p < .001$; $M_{\text{feedback-pre}} = -0.47$, $t = -3.86$, $p < .001$; $M_{\text{follow-pre}} = -0.68$, $t = -5.90$, $p < .001$), but not in the control group (all $ps > .345$). For participants with high levels of identification, no significant effects were found, neither for participants in the intervention group nor for participants in the control group (all $ps > .173$). The current findings thus support the assumption that our intervention lowered participants' willingness to collectively engage against environmental health risks, particularly for participants with low psychological investment in their cyclist identity.

Figure 3

Collective action intentions as a function of time, group and identification with cyclists



low identification with cyclists (-1SD) high identification with cyclists (+1SD)

Other measures: Efficacy beliefs regarding exposure to environmental health risks. We also tested for within-participant changes in efficacy beliefs to protect themselves against PM, noise, and heat. Results indicated no significant intervention effects on efficacy beliefs (all *ps* > .231). This is not surprising as our feedback did not include information on how participants could reduce their exposure levels, such as information on alternative, less polluted routes.

Table 4

Means and standard deviations (in parantheses) of central outcome variables

	Pretest	Posttest	Feedback [a]	Follow-up
DV: Perceived PM health risk				
Intervention group	4.12 (1.46)	4.34 (1.39)	4.61 (1.33)	4.51 (1.30)
Control group	4.54 (1.37)	4.44 (1.34)	n.a.	4.42 (1.37)
DV: Perceived noise health risk				
Intervention group	3.47 (1.25)	3.70 (1.20)	3.94 (1.20)	3.92 (1.15)
Control group	3.87 (1.51)	4.10 (1.41)	n.a.	4.11 (1.39)
DV: Perceived heat health risk				
Intervention group	3.41 (1.37)	3.41 (1.36)	3.31 (1.25)	3.57 (1.41)
Control group	3.51 (1.40)	3.67 (1.43)	n.a.	3.46 (1.36)
DV: Individual action intentions				
Intervention group	3.30 (1.18)	3.60 (1.19)	3.59 (1.25)	3.44 (1.13)
Control group	3.43 (1.16)	3.53 (1.20)	n.a.	3.48 (1.25)
DV: Collective action intentions				
Intervention group	4.69 (1.11)	4.47 (1.35)	4.52 (1.31)	4.28 (1.28)
Control group	4.70 (0.98)	4.66 (1.02)	n.a.	4.51 (1.02)
DV: Efficacy beliefs PM				
Intervention group	4.42 (1.02)	4.41 (1.08)	4.51 (1.03)	4.52 (1.06)

Control group	4.24 (1.15)	4.35 (1.01)	n.a.	4.36 (1.10)
DV: Efficacy beliefs noise				
Intervention group	4.91 (0.86)	4.88 (0.94)	4.92 (0.84)	4.86 (0.96)
Control group	4.64 (0.96)	4.83 (0.88)	n.a.	4.75 (0.91)
DV: Efficacy beliefs heat				
Intervention group	4.32 (1.05)	4.32 (1.06)	4.17 (0.90)	4.28 (1.05)
Control group	3.85 (0.99)	4.13 (1.09)	n.a.	4.16 (1.11)

Note: [a]control group not surveyed at feedback

4. Discussion

Measurements with mobile sensors are becoming more important as low-cost sensors are increasingly available to the public (e.g., see plumelabs.com) and they are regularly used in research studies (Helbig et al., 2021). As these sensors are not only used to measure exposure, but also allow individuals to receive feedback on their exposure levels, it is important to evaluate the effects of carrying these sensors and receiving feedback. The measurement kit used in our experiment captured particulate matter, noise and heat and was relatively easy to use. Participants were generally satisfied with the environmental tracker device and used it regularly during the study period (see appendix for more details on usability).

Previous studies provide initial insights in the effects of feedback from wearable sensors and show mixed results regarding their effectiveness in changing individuals behavior e.g., to choose less polluted routes (Becker et al., 2021). These studies provide a glimpse into the potential effects of theses sensors but indicate that the effects of wearable sensors need to be scrutinized more as previous studies did not use an experimental approach to rigorously assess their effects. To be able to infer causal effects of carrying sensors and receiving feedback, we conducted a controlled experiment. In this experimental study, we tested psychological models of behavior change to predict participants' threat perceptions and intentions to change their routing behavior. We used Protection Motivation Theory (PMT, Rogers, 1975) to study changes in healthy routing choices. We hypothesized that carrying the sensors would lead to an increase in threat appraisals for particulate matter, heat, and noise pollution and explored effects on individual protective action (e.g., choosing less polluted routes).

The data provided partial support for the hypotheses. The intervention of carrying the measurement kit had a significant effect on threat appraisals for particulate matter, though no effects were found for heat and noise pollution. These differences between PM on the one hand and heat and noise on the other hand can be explained by the fact that the PM exposure is not perceivable directly and only the feedback of measurements allows for a more realistic assessment. For this reason, Marquart et al. (2021) proposed a more comprehensive approach to exposure assessment that includes perceptions as additional dimensions of exposure.

The intervention of carrying the measurement kit and receiving feedback had no direct effect on intentions for individual self-protecting action. However, exploratory findings showed a moderation by routing habits. Only participants with low habits regarding their route choices significantly increased their individual action intentions in response to carrying the measurement kit. However, this effect was not sustainable and at the follow-up measurement after 3-4 months their individual action intentions were back to the initial levels. Participants with strong habits at the pretest measurement point were not significantly motivated by the intervention to change their everyday routes. This can be attributed to different factors. Firstly, participants with high habits regarding their routing behavior also had descriptively higher initial levels of individual action intentions. Hence, the intervention had less leverage to change these intentions. This finding is similar to previous studies, where participants reported that change was hardly possible as they were already doing their best to avoid air pollution in their everyday travel and further improvements appear impossible or too costly (Haddad & de Nazelle, 2018; Tan & Smith, 2021). Another explanation for this moderating role of habits is that highly automated habits are resistant to change (Klöckner &

Blöbaum, 2010; Matthies et al., 2006). So-called de-freezing events can open a window to make change possible (Verplanken et al., 2018). In the context of routing choices, this could result from moving one's place of residence (Ralph & Brown, 2019), a change in the local infrastructure (e.g., a large construction site that needs to be circumnavigated) or a new job in a different location (Fujii & Gärling, 2003).

Lastly, we found very interesting effects of the intervention on collective action intentions. While one may assume that the involvement with the topic of environmental pollution could motivate participants to show more collective action (i.e., go to demonstrations, talk to others, sign petitions), we found that there was a decrease in motivation to show collective action throughout the study period. This may be explained by the very individualized framing of the study and wearable sensors in a more general sense. Measuring exposure levels and finding individual ways of adapting to them is a very individualized approach – much like other health-monitoring applications such as heart rate measures or step counters, this can be seen in the wider context of self-optimization, or as Tan & Smith (2020) put it, a way to create "the optimal environment for our optimal selves" (p. 359). This may move the focus away from the broader collective problem of environmental air and noise pollution and rising temperatures in urban areas. This is important to consider with the increase in individualized sensor measurements as it is crucial to keep the broader collective goals in mind – last but not least environmental crisis are a collective problem, that can only be addressed effectively when individuals see their contributions embedded in the greater effort of a collective (Fritsche et al., 2018). The finding that participants who were highly identified with the group of cyclists were not demotivated to participate in collective action supports this assumption, as identification with a group (particularly one with pro-environmental goals and norms) can motivate pro-environmental action in a collective (Fritsche et al., 2018).

We found no effects of the intervention on coping appraisals (i.e., efficacy beliefs). This is not surprising given that participants were not provided information on steps they could take to reduce their exposure to environmental stressors. This was also a result in previous work on feedback on air pollution where many people felt that they had limited capacity to meet the threat posed by air pollution with adequate actions to reduce their exposure (Haddad & de Nazelle, 2018; Heydon & Chakraborty, 2020; Marquart, 2022; Oltra et al., 2017; Tan & Smith, 2021). This resulted in frustration or resignation for some participants (Heydon & Chakraborty, 2020). Future studies should investigate the effects of wearable sensors when providing participants with information on how to effectively reduce their exposure. For example, alternative route suggestions could potentially raise coping appraisals and thereby raise intentions to change their routing behavior to healthier route choices. A mobility app providing suggestions for pleasant routes with low pollution levels was also suggested by citizens in a qualitative focus group study (Marquart, 2022). A visualization of pollution levels in different areas of the city could also help participants identify healthier routes. Such a visualization in an immersive virtual reality environment was created for the data collected in this study and could be used in future applications (Helbig et al., 2022).

Policymakers could also foster city infrastructure that provides options for cyclists and pedestrians to bypass locations with high pollution levels. Air pollution can also be reduced by introducing urban vegetation such as green walls, green roofs, hedges, or trees which absorb pollutants (Abhijith et al., 2017). However, these measures require careful planning as trees can inhibit ventilation and trap pollution in street canyons (Abhijith et al., 2017) or emit allergens (Kumar et al., 2019). Green and blue (water) infrastructure can also reduce noise pollution via absorption of noise or by creating space for a pleasant noisescape including bird sound (Yildirim et al., 2022). Beyond a reduction in noise and air pollution, greenspaces such as parks can have positive effects on physical activity and mental health (Kumar et al., 2019).

A stronger focus on raising collective efficacy beliefs should also be aimed at in the future, for example by framing individuals' measurements as part of a broader project and highlighting the collective efficacy of the citizen science approach, for example in communicating needs to policy makers through citizen science projects (Ottinger, 2010). Joint workshops or coaching events for participants to find solutions to high pollution levels may also be a way of heightening collective efficacy as well as individual coping appraisals (Hamann et al., 2021).

4.1. Limitations

The presented study has some limitations that should be taken into account when interpreting the results. Firstly, the sensors used in the measurement campaign did not give feedback about current exposure levels directly. Participants were only provided with an overview of their accumulated exposure levels throughout the measurement phase. Instantaneous feedback would allow users to connect the information about exposure levels directly to their current routes. Furthermore, the study highlights the necessity not only to provide information on possible health threats of environmental stressors, but also to equip participants with feasible alternatives for them to avoid these high exposure levels. Previous studies have shown that information provision without possibilities for protective action can lead to resignation and feelings of powerlessness (Becker et al., 2021; Marquart, 2022). Alternative route suggestions might help to motivate behavior change in future studies.

Another limitation of this study is that the feedback on particulate matter may have been hard to understand as participants had no clear reference of what levels of exposure should be considered unhealthy. Hence, future studies could aim to make the measurement results more relatable for example by showing how the exposure to PM relates to the health impacts of more commonly known risks such as smoking cigarettes (Marquart, 2022; Riley et al., 2021).

Another limitation of this research lies in the fact that we could only measure personal protection intentions, rather than monitoring participant's actual behavior and whether it reduced their exposure to environmental stressors. Future studies could target not only intentions, but also tap into measured behavior changes by looking at GPS tracks and exposure levels before and after the feedback intervention.

Furthermore, future studies could further investigate the demotivating effect of individualized feedback on collective action intentions and test ways to avoid this. For example, framing the collection of data as a joint effort of many participants contributing to a shared dataset may motivate further collective action. Alternatively, the feedback report could include suggestions on collective activities to fight pollution (Riley et al., 2021).

Lastly, as a longitudinal study, there was some dropout and though dropouts did not differ from those who completed all questionnaires on important variables, we cannot be sure that the dropout was not selective. Furthermore, we must be aware, that participants willing to participate in a study that requires some effort such as carrying a sensor kit on their everyday routes may be different from the general public in that they have a particular interest in the topic and may be very motivated to avoid environmental stressors. The extent to which study results can be generalized may also be limited when working with so-called weird (western, educated, industrialized, richa, and democratic) samples in the behavioral sciences (Henrich et al., 2010) and volunteered georaphic information (VGI) is mostly produced by privileged groups (Elwood et al., 2012). This is particularly problematic, given that people with a socioeconomic disadvantage are exposed to higher levels of air pollution (Fairburn et al., 2019) and noise pollution (Dregner et al., 2019). While the sample in this study was self-selected, future research should aim for a representative sample.

Lastly, a limitation of our study design is that the control group filled out only the pre- and post- as well as the follow-up questionnaires, while the intervention group also filled out a questionnaire after the feedback. While there are practical reasons for this, a fully parallel use of the questionnaires would have been beneficial.

4.2. Conclusion

Increased proliferation of wearable sensors highlights the necessity to evaluate their potential for healthy mobility more rigorously. Taken together, the presented findings highlight the potential of wearable sensors in changing individuals' perceptions of environmental stressors and their routing behavior intentions. Our research allows policy makers to make informed decisions about the design and implementation of interventions using wearable sensors to foster healthy mobility.

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