The role of personal air pollution sensors and smartphone technology in changing travel behaviour

Abstract

Exposure to air pollution is affected by human behaviour, and has consequences for individual and collective health. One way to lessen the health effects of air pollution is to change personal travel behaviour with the help of new information, communication and sensing technologies. Our social research tracked the experiences of participants, air quality and technology enthusiasts, based in London who financially contributed to participate in an early-stage technical trial of a new air pollution sensor and app providing individuals with air pollution information (specifically levels of NO_2 and VOCs). This paper reports the results of a before and after survey (returning respondents $n = 22$) and 12 in-depth interviews with individuals who took part in the beta test of the sensor and phone app. The survey results show that travel-related behaviours and attitudes relevant to air pollution did not change after using the technology. In contrast, expectations of technology performance and the extent it would influence behaviours were significantly lower after the trial than before. Further exploration during semi-structured interviews found that the participants, given their already high level of engagement with the topic, felt the capacity for immediate individual behaviour change was limited. As well as time and practical constraints, most people in this sample felt they were already doing what they could to avoid high levels of air pollution in their daily lives. Despite this, they had some recommendations to improve the app, such as the inclusion of real-time and historic maps, and the ability to make self and other comparisons. Overwhelmingly, people saw a broader role for the technology to engage the public with air pollution through raising awareness, and harnessing citizen science to collect diverse reliable data to inform policy and influence local policymakers to reduce air pollution levels.

1. Introduction

Consequences of high levels of air pollution such as particular matter, ozone and nitrogen dioxide has led to an estimated 7 million premature deaths worldwide (WHO, 2014). Further, research has long shown impacts also include contributing to respiratory diseases, diabetes, cognitive development (Seaton, Godden, MacNee, & Donaldson, 1995), with traffic-related air pollution being particularly harmful (Künzli et al., 2000). According to Skov et al. (1991), there are two types of behavioural responses relevant to air pollution: actions to reduce air pollution (e.g., driving less), and actions to self-protect from air pollution (e.g., avoid some outdoor activity).

As with other forms of risk communication, such as climate change (for review see Swim et al., 2009), the communication of air quality has its difficulties, e.g., abstract, scientifically uncertain and complex (van den Elshout, 2007). Further, the language used to communicate air pollution information to the public can make it difficult for engagement with the topic (Brimblecombe & Schuepbach, 2006). Observable features of air pollution (e.g., smog) and media coverage are people's main sources of information (Bickerstaff & Walker, 2001). Providing more *visible* approaches to inform the public may be useful in raising awareness of air pollution (Bickerstaff & Walker, 2001). One way to approach the 'making intangible tangible' approach is by tapping into new technologies (such as sensors) to engage people with air quality around them. Such individual air quality sensors is changing the paradigm of air pollution monitoring networks; from stationary, expensive, lagged and superficial, to versatile, (comparatively) inexpensive, real-time and portable air pollution monitoring (Snyder et al., 2013). In using a personal portable device, proximate air quality information can also be transmitted to individuals – potentially allowing people to make informed decisions to minimise their exposures and contributions to air pollution.

Research has shown some effectiveness for smartphone apps in the health behaviour context to achieve desired changes (e.g., Dennison, Morrison, Conway, & Yardley, 2013; Payne, Lister, West, & Bernhardt, 2015; Zhao, Freeman, & Li, 2016). For example, an intervention group using a smartphone application engaged people more in the 10,000 steps a day than a control group who didn't use a phone app (Kirwan, Duncan, Vandelanotte, & Mummery, 2012). This shows there may be a place for technology as a medium of communication in other decision-based contexts, such as behavioural choices related to air pollution. With 76% of adults in the UK having a smartphone (Ofcom, 2017) this is a huge potential audience to communicate directly with. While there may be benefits of real-time air pollution alerts, research has also shown there may be unintended consequences such as increased use of health services (Lyons et al., 2016).

Present study. This paper presents the social research findings from a recently completed beta test (i.e., technical trial) conducted in London, UK. After their well-publicised "Pigeon Air Patrol[1]" campaign, a start-up company, *Plume Labs*, launched a crowdfunding drive to support the development of a new sensor that measured levels of volatile organic compounds (VOCs) and nitrogen dioxide (NO_2). The novel sensor is based on metal-oxide (MOx) sensing and machine learning algorithms. The air quality information was conveyed through an accompanying smartphone app. The start-up reached their target of 100 financial contributors to fund the technology to be

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[1] e.g., https://www.theguardian.com/environment/2016/mar/14/pigeon-patrol-takes-flight-to-tackle-londons-air-pollution-crisis
http://metro.co.uk/2016/03/15/pigeons-with-backpacks-are-monitoring-air-pollution-in-london-5754054/
http://edition.cnn.com/2016/03/16/europe/pigeon-air-patrol-pollution-london/index.html

developed and participate in their "air patrol" campaign to test the sensor. The developers' stated aims is that they want to "beat air pollution". They are a commercial enterprise, however, whose primary focus is to develop and market an air quality sensor. For them the beta test was mostly about testing out that the sensor technology ran smoothly and communicated results coherently rather than aimed at changing behaviours. The app ran on iOS and Android operating systems, and each beta tester was sent instructions on how to download it from the technology company (only available to the beta testers). Participants carried the device using the leather strap that was part of the sensor. The people within the beta test were the participant pool we had access to for the social research. In partnership with *Plume Labs*, we had access to the beta testers with communication via the developers. Our research adopted a two-phase mixed methods approach to evaluate their user experiences. Phase 1 was an online survey of beta testers at two time points: this allowed us to test for any attitudinal or behavioural changes following use of the technology. Phase 2 involved semi-structured qualitative interviews with a subset of beta testers. The beta testers received their sensors in April 2017.

In-app information. There were three main sources of information within the app. Two were directly related to information from the sensor (Figures 1a and 1b). The first screen when opening the app was "My Exposure" (Figure 1a), this provided beta testers with a summary of the nearby pollution (VOC and NO_2) around them at that instant. Users could obtain more detailed information on the air quality at earlier time points by going to the "Raw Measurements" screen (Figure 1b). In both cases, levels of air pollution were communicated via an index developed by Plume Labs, rather than by providing actual concentrations. A third part in the app, labelled "Escape Pollution", provided information on where users could go to find relatively clean air in London for recreational activities (Figure 1c). This was a map pre-marked with locations of leisure activity (e.g., parks) in London which was overlaid with a map of current air pollution (derived from a spatial annual mean air pollution model (Beelen et al., 2013) combined with monitored data (London Air Quality Network, 2018): dark colours represented high pollution, light represented low pollution).
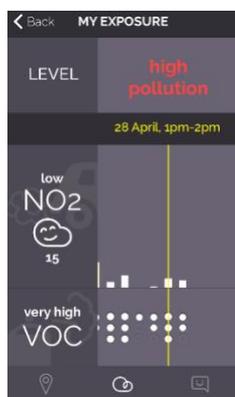

Figure 1a. Screenshot of "My Exposure"

Figure 1b. Screenshot of "Raw Measurements" indicating NO_2 and VOC levels

Figure 1c. Screenshot of "Escape Pollution"

The following sections report on a two-phase mixed-methods project examining how these technologies engaged people with air pollution. Phase 1 is described next in part of the paper (Section 2) with Phase 2 (Section 3) reporting the qualitative interviews. The paper concludes by synthesising both research perspectives and drawing insights leading to recommendations on the use of wearable technology and smart phones to engage the public towards healthy and sustainable decisions (Section 4).

2. Phase One: Survey

The quantitative element of our research consisted of a survey administered at two time points: (1) two weeks before receiving; and (2) one month after receiving/ using the sensor and app. This approach allowed us to establish a baseline level for attitudes and behaviours before any potential influence of the new technology, and then to monitor any change after using the technology. Because the main aim of the survey work was to examine the influence of using the air pollution sensor and information provision, we will be presenting the survey results with regards to any *change* between the pre- and post- surveys.

2.1 Participants & design

The participant pool was consisted of 100 adults taking part in the *Plume Labs* beta test (these people consisted of people who financially contributed to take part in the trial). All beta testers were invited (by *Plume Labs*) to complete our online survey before and after receiving the technology. 24 people completed only the first survey; 8 people completed only the second survey; and 22 people completed both surveys. Because in this paper we are interested any potential change due to the technology, the following survey results are only the returning participants ($n = 22$). Of the people who completed both surveys, 16 are male and 6 are female, with a mean age of 42 years old. Table 1 shows the age distributions, separately for male and female participants (one female did not provide her age, hence $n = 21$ in this table). Of our sample: 4 people reported to suffer from asthma, 2 people from shortness of breath; 13 had no health issues, 3 people didn't answer. No-one in our sample was a smoker.

Table 1. Age distributions, separately for male and female participants

	Age																
	24	27	28	34	35	36	40	43	44	45	47	49	52	55	56	59	Total
Male	1	1	1	2	2	1	0	1	1	2	0	0	1	1	1	1	16
Female	0	0	0	1	0	0	1	0	0	0	1	1	0	0	0	1	5
Total	1	1	1	3	2	1	1	1	1	2	1	1	1	1	1	2	21

2.2 Measures

To understand any change in determinants of behaviour and behavioural intention, participants were asked to rate their level of agreement with a series of statements using a scale ranging from 1 "*No, not at all*" to 7 "*Yes, very much so*" for the following domains of influence.

Mode choice. Respondents were presented with the statement: "This part of the questionnaire is asking you about your current travel behaviour. Think about the most common journey you made last week. Why do you use the <u>mode</u> of transport?" They were then asked to score each of the following items: cost, speed (e.g., avoid congestion), convenience, habit (usual method of travel), minimise own contribution air pollution, minimise exposure to air pollution, for the physical activity benefits, and safety from traffic.

Route choice. Respondents were further presented with the statement "Think about this journey and the <u>route</u> you took. To what extent do the following come into consideration for you to take this route?" and asked to score each of the following items: speed (e.g., avoid congestion), convenience, habit (usual route), avoid air pollution, avoid noise, safer route, aesthetic and scenic reasons (i.e., going through green space), and no flexibility (e.g., route determined by public transport).

Attitudes to and perceptions of air pollution. To measure people's attitudes towards and perceptions related to air pollution, we drew upon various constructs that have been used in previous environment-behaviour related research. In particular, norm activation model (Schwartz, 1977), the theory of planned behaviour

(TPB) (Fishbein & Ajzen, 1975) and various extensions of these theories have been applied to ethical (Shaw & Shiu, 2002) and 'green' consumer behaviour (Sparks & Shepherd, 1992), recycling (Terry, Hogg, & White, 1999), car use (Bamberg & Schmidt, 2003), and cycling (Haddad, 2005) and active travel (Gotschi et al. 2017). We complemented constructs from TPB (attitudes, subjective norm, behaviour control) with others that have been applied in the context of travel behaviour, such as environmental concern (e.g., Nilsson & Küller, 2000; Gotschi et al. 2017); and climate change communication, such as risk perceptions, efficacy (Haddad, 2014). We added constructs we were interested in in the context of air pollution: negative consequences on health and environment; policy support; currently minimising contribution, awareness; feel effects. The series of opinion statements reflecting each of these constructs as rated by respondents in the survey, and the construct Cronbach's reliability alpha are shown in Table 2.

Expectations and experience of the technology. We additionally investigated people's expectations (Time 1) and experiences (Time 2) of the sensor and app. These are presented in Table 2 with the wording used in Time 1, keeping in mind that these were all changed into past tense when presented at Time 2, e.g., "*I expect the Air Patrol Sensor to work well*" vs "*The Air Patrol Sensor worked well*". Each measure and corresponding 2 items that constitute the measures are presented with their Cronbach's reliability alpha (measuring internal reliability) for Time 1 and Time 2 measures in Table 2.

1 *Table 2.* Measures, their items that constitute the measures, and the Cronbach's reliability alpha. Respondents were asked to rate their level of
2 agreement using a scale ranging from 1 "*No, not at all*" to 7 "*Yes, very much so*"
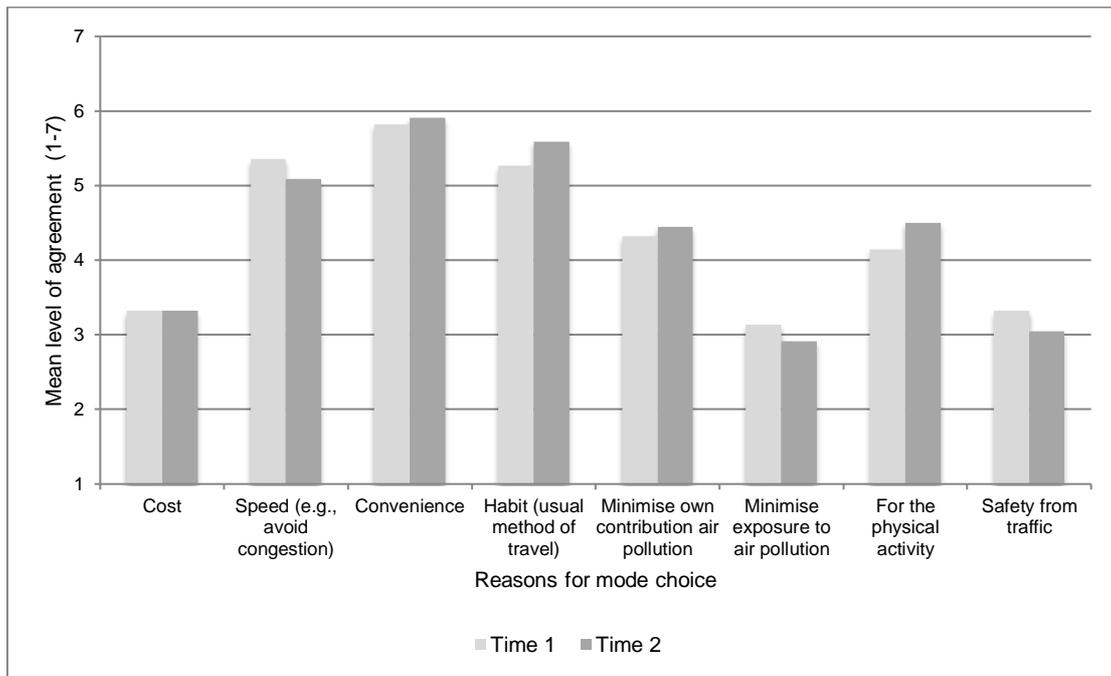
Measure	Items	Cronbach's α Time 1	Time 2
Attitudes to air pollution Awareness	Generally speaking, I feel well-informed around the issue of air pollution; I don't feel aware of the issue of air pollution (reversed)	0.78	0.59
Feel effects	I am aware when air pollution is high (e.g., feel differences in the air, see smog); I am personally aware when pollution is high (e.g., throat hurts more than usual, sneezing a lot); I don't feel any effects of air pollution (reversed)	0.72	0.85
Risk perceptions	I believe there is a global risk of the consequences of air pollution; I feel personally at risk from the consequences of air pollution	0.72	0.72
Moral norms	I feel it is my duty to the environment to reduce my level of pollution as much as possible; I feel a personal obligation to reduce my contribution towards air pollution	0.97	0.91
Efficacy	I believe my actions have an influence on air pollution; There is nothing that I do specifically in response to air pollution levels (reversed)	0.64	0.77
Environmental concern	I am concerned about the state of the environment generally; I care about the environment	0.97	0.75
Negative consequences on health and environment	I understand that high levels of air pollution can have effects on human health; I understand that levels of air pollution can have effects on the environment	0.95	0.74
Policy support	I would like to see more regulation of air pollutants; I would be supportive of the government introducing policy to reduce the levels of air pollution (e.g., low emissions zones); I don't think that we need public policy to control levels of air pollution (reversed)	0.70	0.82
Currently minimising contribution	I already do what I can to reduce my contribution to air pollution; I am currently minimising my air pollution contribution as much as possible	0.44	0.44
Individual intentions	I intend to change my travel behavioural (more) to reduce my contribution to air pollution in the future; My intention to change my travel behaviour to reduce my impact of air pollution is (low to high)	0.89	0.82
Expectations of the technology (Expected) Sensor performance	I expect the Air Patrol Sensor to work well; I think the Air Patrol Sensor will be easy to use	0.73	0.66
(Expected) Perceived Understanding	I think I would understand the information provided by the app; I don't think I will understand what the App information is supposed to mean (reversed)	0.79	0.88
(Expected) Trust	I trust the information in the app will be accurate; I trust the information provided by the app will be reliable	0.96	0.92
(Expected) Influence on journeys & activities	I think I will be motivated to take into account the information provided by Plume Labs App when planning my journeys and activities; I don't think the information provided by the app will influence my journeys and activities (reversed)	0.68	0.63
(Expected) Behaviour change to avoid air pollution	I feel having a personal sensor and app will enable me to alter my behaviour to avoid high levels of air pollution; I don't think having an air pollution sensor and app will help me avoid high levels of air pollution (reversed)	0.67	0.77

3

4 2.3 Results
5   Our sample was highly aware and concerned about air pollution, supportive
6 of policies, generally felt they were doing what they could and had little intention to
7 change behaviour[2]. To test if there were any differences on scores at Time 1 and
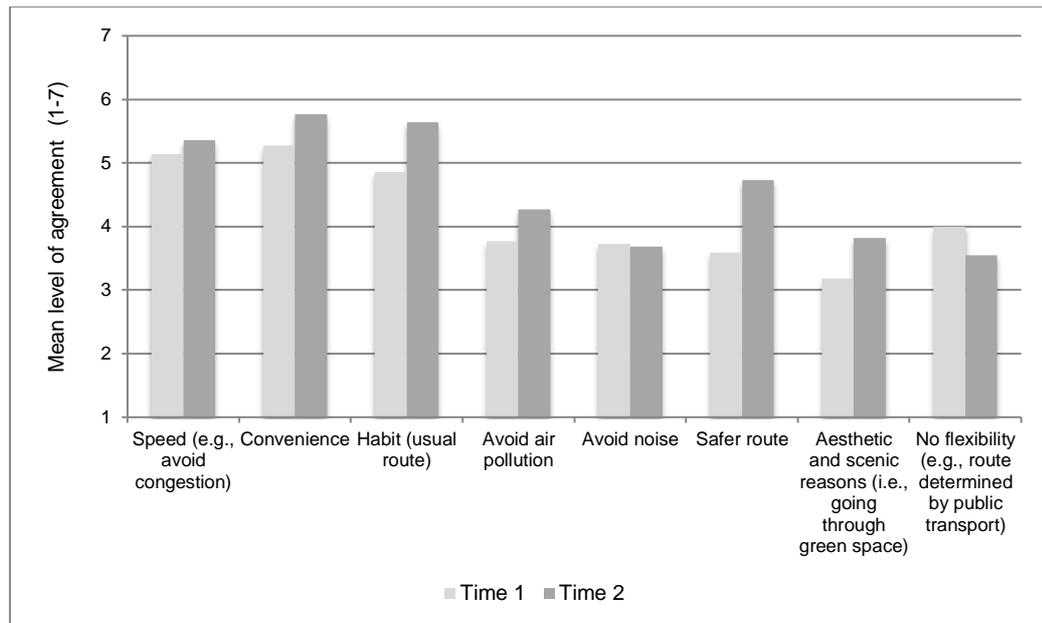8 Time 2, a series of paired samples t-tests were conducted.
9   *Mode and route choices.* There were no significant differences in any
10 motivations of mode and route choices between times one and two, as evidenced by
11 p-values (p) all well-above any level of significance ($p>0.31$) and low t-values
12 ($t<1.04$). Patterns are shown in Figures 2 and 3.
13

15 *Figure 2.* Reasons for mode choice at Time 1 and Time 2

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[2] Due to the small sample size non-parametric tests were also carried out and results were consistent with the parametric repeated measures tests. For presentation ease, we are presenting the parametric results and means scores.
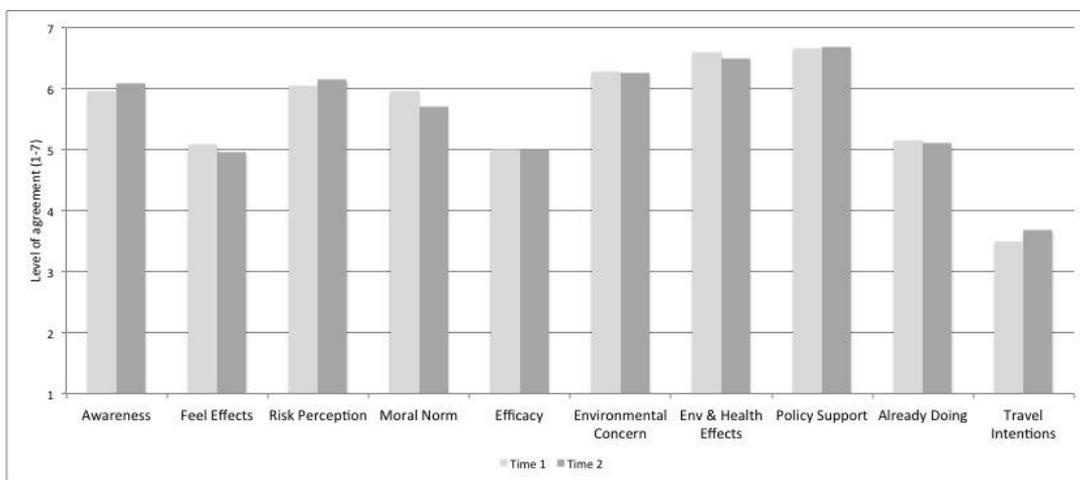
Figure 3. Reasons for route choice at Time 1 and Time 2

Attitudes towards air pollution. Further, there were no significant differences in people's attitudes and perceptions related air pollution at Time 1 and Time 2, $t < 1.60$ $p > 1.15$. See Figure 4 for the patterns of results.
We further checked if having an air pollution related illness affected results and found no difference between the group with air pollution-related health issues ($n = 6$) and the group of participants who did not ($n = 13$).

Figure 4. Attitudes towards air pollution at Time 1 and Time 2

Expectations and experience of the technology. The only measures with significant differences between pre and post surveys were the expectation and experiences of the technology. The sample started out with high expectations on how they perceived the sensor would perform, how they would understand and trust the technology, and how the technology might influence any travel-related behaviour. All these expectations dropped significantly after having trialled the app and sensor for 2 to 4 weeks ($t > 3.89$, $p < 0.01$ for all statements, Figure 5). These patterns were identical for the two air-pollution related health illnesses groups when considered separately.
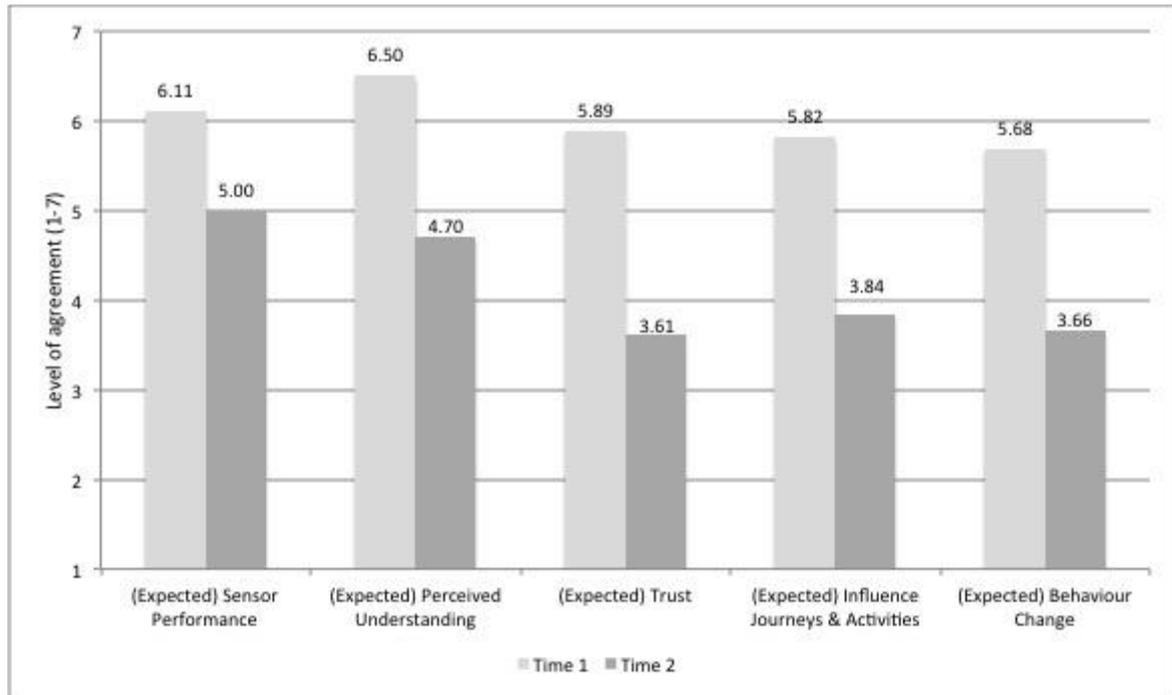
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Figure 5. Expectations and Experience of the technology at Time 1 and Time 2

3. Phase Two: Semi-structured interviews
The second phase of social research consisted of a series of qualitative in-depth interviews.

3.1 Procedure
During June and July 2017 (about two months after participants received the sensor) we conducted 12 in-depth semi-structured interviews with people taking part in the beta test (11 males, 1 female). One of our interviewees was asthmatic. The interviews were carried out at a mutually convenient time and location in London, UK, and lasted up to an hour each.
Based on the information from the survey work, we developed broad aims of the interview research that helped frame the topic guide: to obtain further information on areas, such as people's motivations for joining the beta test; what they were expecting and what were their experiences with the technology; how the technology may have influenced behaviour, and if it hadn't, how it could be changed to do so.
Given the amount of data collected from 12 in-depth interviews, we used a structured matrix mapping process to help manage the data. The topic guide provided us with an initial template: this allowed data to be compared and also allowed for further elaboration or adaptation of the templates (Miles & Huberman, 1994; Silverman, 2006). Thematic analysis (see Braun & Clarke, 2006) helped in identifying the subthemes within our main themes of interest as framed by the interview aims and topic guide. In some cases, subthemes were developed as a result of an expansion of pre-identified (a-priori) themes, and in other cases themes were created on the contrary by collapsing very similar pre-identified subthemes together. The subthemes are not fully separate: instead there was overlap and linkage both within and between the broader themes. Matrix mapping helped manage the data and assess commonalities and differences between interviewees (see Haddad, 2014; Lyons & Haddad, 2008; Musselwhite, Avineri, & Susilo, 2014 for details on this approach).

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78　3.2 Findings
79　　　　We report on four overarching themes: motivations; expectations and
80　experiences; (potential for) behaviour change; and role of the technology.
81
82　*3.2.1 Motivations for joining the beta test.* Everyone interviewed expressed high
83　awareness of air pollution as a big issue in London. Most participants became aware
84　of the beta test due to the Pigeon Air Patrol campaign and the media coverage that
85　came with it. There were two distinct motivations for joining the beta test:
86　　　　*Curiosity.* A common explanation for joining the beta test was that people
87　were curious about levels of air pollution around them. Some people also wanted to
88　be able to compare levels of air pollution for places they visit, both comparing places
89　*within* London, and comparing cities *to* London. One person reported joining the trial
90　due to personal health concerns as an asthma sufferer. Even for this this person
91　curiosity (about NO_2 exposure levels) was the main driver for joining the trial:
92　"I have a general interest in how current exposure levels are around me" (Participant
93　　　　　　　　　　　　　　　　　　　　　　3)
94　For a small number of people, it was a technical curiosity that motivated them to
95　become a beta tester: they had a desire to help develop the technology and
96　understand issues around the trial. For example,
97　　　　"I'm interested in [the] technical/ gadget perspective, I'm interested in new
98　　　　　　　　　　　technologies" (Participant 2)
99　　　　*Citizen Science & Crowdsourcing.* Many of our interviewees wanted to
100　contribute to datasets that can be used by others to inform policy and decision
101　makers around air pollution They felt it was important to help build up a network of
102　'on the ground' air quality data points. They wanted to be actively involved in a
103　project that seeks to improve our understanding of air pollution, raise awareness
104　within their local community and present to local authorities. For example,
105　　"Let's see if we can get better air quality predictions and readings" (Participant 2)
106
107　*3.2.2 Expectations and experiences*
108　　　　*Technology.* Everyone interviewed understood they were taking part in a
109　technology beta test; they were not expecting a 'ready to market' product, for
110　instance,
111　　　　"It's a prototype. I expected it to be a little unreliable" (Participant 5)
112　That said, some participants did have concerns with the quality of both the sensor
113　and app. This may in part help explain the differences in perceived performance
114　technology scores from the two surveys. Firstly, most people interviewed had
115　technical difficulties in pairing their sensor with the smartphone app using the
116　Bluetooth connectivity. Secondly, a number of the interviewees said they expected
117　the device to measure ozone levels – mainly because it was initially advertised as
118　such, and its absence led to disappointment for some. Finally, the sensors did not
119　appear to function in windy conditions.
120　　　　*Pollutants of interest.* Of the two pollutants measured, most people were
121　interested in levels of NO_2 as they felt this was the major pollutant they were exposed
122　to when travelling. People said they were not as interested in VOCs: either because
123　they considered NO_2 had more significant health impacts, or because they didn't feel
124　they knew enough about VOCs to form a strong opinion of its importance. Most
125　interviewees were keen to also have measurements of particulate matter (PM)
126　because of their perceived negative impact on human health. For example,

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127   "I would also be interested in PM_{10}. This is found within diesels and also on the
128   Tube[3]. Showing the level of particulate matter would give the bigger picture of air
129   pollution exposure" (Participant 2)
130   "I was surprised that particulate matter wasn't being measured as it's a bit of a hot
131   topic. I sometimes take the Tube: and on the Tube the NO_2 is really low but the
132   particulate matter you would expect to be high. So I suppose currently this doesn't
133 give you a completely representative picture of the quality of the air because it makes
134 it look like the Tube is a low pollution option when actually is just a different form of
135 poor air quality that you're likely to be experiencing. Generally, health concerns focus
136   on PM and NO_2, not VOC" (Participant 4)
137   *In-app information.* The majority of users said they broadly understood the
138 information presented in the app. However, when further probed about the detail of
139 what each piece of information represented, some did not seem to have a clear
140 understanding of what the details actually meant – often making assumptions and
141 saying: 'Well, it's pretty obvious this means that…,'. This was particularly the case for
142 the NO_2 "Raw measurements" (the information they were most interested in, shown
143 in Figure 1b). People felt the app would be better if the presentation of NO_2
144 information were consistent with standardised measures used to communicate air
145 pollution information (e.g., used by the World Health Organisation), rather than the
146 company's own index. People felt this would be more meaningful and allow them to
147 make comparisons with legal levels that they could provide to their local authorities.
148 The two quotes below illustrate this,
149   "The app uses the developer's own scale [and] gives no way of relating it to standard
150   units of measuring air quality. It would be good if they used what the EU uses"
151   (Participant 11)
152   "I would prefer it to use a comparable scale of measurement for NO_2 readings, such
153   as the World Health Organisation uses" (Participant 12)
154   All of the participants were most interested in the outdoor pollutants,
155 especially those they may be exposed to during their commute; people most used
156 the NO_2 "raw measurements" screen (Figure 1b). The Escape Pollution map (Figure
157 1c), places within London with low air pollution, was not utilised – either because
158 they didn't know it was there, or they did but felt it just wasn't useful. Interviewees felt
159 that location suggestions were irrelevant because of their own constraints regarding
160 activities they had to engage in. This was the only map contained within the app.
161 Most participants felt a real-time map (with suggested low pollution travel routes)
162 would have been useful. In addition to this, people would have preferred a personal
163 historic map showing where they had travelled in the day and what had been their
164 exposures during that time, rather than the history presented as a list organised by
165 time of day (see Figure 1b). This presentation "list" style was not seen as user-
166 friendly, especially as it depended on the user's memory to link specific location with
167 certain time. The two quotes below are indicative of the sample's thinking towards
168 the information content and its presentation in this context,
169   "I was expecting the presentation of information to be more sophisticated, such as
170   maps, and having a more detailed output" (Participant 9)
171   "It doesn't provide you with the location…just times and values. There is no
172   forecasting function. I find this unhelpful" (Participant 8)
173   *Perceived reliability of data.* Generally, people felt that they could get a sense
174 of the level of air pollution around them and therefore they made judgements about
175 how reliable they felt the sensor to be. Views were mixed on the perceived reliability
176 of the data. For some people, readings seemed consistent with their perception of
177 the local air quality. However, often people would say they did not trust the data from
178 the sensor to be accurate. See the quotes below for examples,

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[3]The tube is the common term for the underground railway system in London.
https://en.wikipedia.org/wiki/London_Underground

179   "Seems accurate. But not during or after charging" (Participant 4)
180   "Not sure on the accuracy of the thing. Often it didn't look correct! Sometimes I get
181   surprising readings….like when I was driving round the M25[4] with my window open
182   and it said there was no NO_2, and that seems unlikely" (Participant 8)
183   "I was disappointed with the accuracy: doesn't make sense. The numbers aren't
184   intuitively right. It just didn't look correct, when it is working I do find it really
185   interesting I don't always totally trust the readings then I lost interest" (Participant 5)
186   For some people, the lack of trust in the data had negative implications on their
187   engagement with the technology.
188
189   *3.2.3. (Potential for) Behaviour change.* The context of behaviour was usually
190   discussed in the context of travel, particularly the commute. On the whole, people felt
191   *immediate* individual behaviour change was limited. As well as time and practical
192   constraints, most people felt they were already doing what they could to avoid high
193   levels of air pollution in their daily lives.
194   *Information.* People also felt that the information provision wasn't sufficient to
195   enable them to change their behaviour. People were expecting real-time low-
196   pollution alternative travel routes on a map (see 3.2.2). They said this might not
197   necessarily make them change their behaviour immediately (see below quote for an
198   example), but the ability to see potential alternatives and to be able to reflect on
199   one's own travel behaviour in the context of air pollution may be the first step to
200   behaviour change.
201   "I was interested in [my] personal air pollution exposure. I wanted to see a map with
202   my own daily history. I was interested in the new technology, the air pollution data -
203   but I'm not interested in how I can create healthy and sustainable behaviours from
204   the information as I'm already as healthy and sustainable as I can be" (Participant 7)
205   "I was surprised there wasn't a map" (Participant 8)
206   Some of our interviewees often likened the air pollution sensor and app to
207   fitness watches/app, perceiving these as successful in maintaining user engagement.
208   Some people suggested the app should enable making comparisons with friends, or
209   others (who are not necessarily friends) that might be travelling a similar route. They
210   saw this as a successful approach in fitness apps that could be applied in this
211   context. For example,
212   "Need to keep people's attention once the novelty has worn off. Like connect with
213   friends using the device, making social comparisons - something like fitbit does"
214   (Participant 1)
215   While most felt their *immediate* behaviour change was limited, some people
216   felt that the information could inform *medium to long-term* changes. For example, air
217   quality considerations would be important to factor in with a wider *quality of life* in a
218   long-term life plan. Some people felt that their current life and work commitments
219   meant they couldn't move, but in a future moves, the local air pollution level is
220   something they would consider,
221   "I haven't changed my behaviour. But it's a process. For example…when I am in the
222   process of changing location, then I can think about comparing places and making
223   choices on this" (Participant 7)
224   "I could see this sensor helping me to find a particular house or area that is exposed
225   to air pollution" (Participant 8)
226   *Trust.* The perceived lack of reliability in the data (see 3.2.2.) was also used
227   as a reason for not wanting to change behaviour. The below quote illustrates the
228   perceived practical (route) constraint, as well as the lack of trust in the data to allow
229   for behaviour change,

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[4]The M25 is the London Orbital Motorway known for its frequent traffic jams,
https://en.wikipedia.org/wiki/M25_motorway#Popular_culture

230 "I don't have an alternative route to work. And I'm not motivated to find alternative
231 [routes] because I can't base a hard behaviour change on something I don't trust"
232 (Participant 5)
233
234 *3.2.4 Role of the technology.* While the role of the technology as a source of
235 behaviour change was perceived to be limited, people felt there is an important place
236 for this kind of air pollution technology and the information it produces.
237 *Informing and influencing policy.* This aspect is closely related to people's
238 *motivations* to join the beta test (see 3.2.1): being part of citizen science and
239 crowdsourcing data to help inform and influence policy. People generally felt that at a
240 larger scale, this approach to air quality monitoring would add richness and diversity
241 to the existing monitoring system. For example,
242 "This approach would allow for mobile and micro monitoring stations with small
243 devices. This would show the variability on roads, for example. This would build up a
244 network of air quality" (Participant 12)
245 "More devices like this would provide more granular data of air quality" (Participant 9)
246 Overwhelmingly, people felt (a reliable version of) the sensor and app had an
247 important role to play to inform policy and also to give credibility to policies when
248 presented to the public.
249 "Through the citizens providing data, this could lead to policy change. For example,
250 the data could be sold to governments" (Participant 9)
251 *Public awareness and acceptability of policy.* People felt that this kind of thing
252 can raise people's awareness of the air pollution issue. For example,
253 "This kind of approach makes air pollution more visible, makes easier for mayor to
254 introduce policy" (Participant 12)
255 Some interviewees reported that the device often became a talking point
256 among their peers leading to discussion around air pollution. The potential to engage
257 the wider public with air pollution through social interaction could be facilitated by the
258 visible presence of a device.
259
260 **4. General discussion & conclusions**
261 *Recap on key survey and interview findings.* Results from our survey of beta-testers
262 of a newly developed sensor and app showed there were no differences between
263 before and after the use of the device in people's travel behaviours, motivation to
264 change behaviours, or attitudes towards air pollution. However, people's
265 expectations and perceptions of the sensor/ app's performance and ability to
266 influence behaviours all dropped significantly during that period. Follow-up in-depth
267 interviews gave us a chance to explore this expectation-experience gap. People
268 were generally motivated to use the technology out of curiosity and to engage in
269 citizen science, though on the whole they did not join the beta test to change their
270 own behaviour. They felt opportunities for immediate behaviour change were limited -
271 in part because they felt they were doing as much as they could already, and in part
272 because they saw the sensor as unreliable and the in-app information as limited.
273 Interviewees had some recommendations to improve the app, such as including:
274 real-time low pollution maps, historic maps of personal travel and exposures, and the
275 ability to connect with other users (similar to fitness apps). Generally, people saw a
276 broader role for the technology to engage the public with air pollution through raising
277 awareness and through harnessing citizen science to collect diverse, street-level
278 data to inform policy and influence local policymakers to reduce levels of air pollution.
279 Albeit within a very select group of people, this work shows that within some pools of
280 society motivation to engage in issues related to air pollution exists.
281
282 *Crowdsourcing & Citizen science.* Citizen science (the public participation of
283 non-scientists in scientific research) is a tool used for monitoring environmental
284 change and engaging citizens with science (Bonney et al., 2009; Johnson et al.,

285 2014). Such scientific engagement can facilitate public understanding and
286 communication of science, with the caveat that the targeted audience will often
287 already be engaged with the topic (Martin, 2017).
288   Among our sample, people felt they were taking part in a citizen science
289 project. This gave them opportunity fulfilling some personal motivations (e.g.,
290 curiosity), and the desire to contribute to science and policy needs (i.e., collecting
291 reliable and diverse data to better our understanding of air pollution knowledge and
292 to add credibility to policy decisions). Previous research has also shown a sense of
293 personal and social benefits to be associated with participation in citizen science
294 (Hobbs & White, 2016).
295   There are many examples of citizen science projects with "low-tech"
296 approaches to monitor air pollution (NO_2 passive samplers, lichens), however new
297 developments in real-time wearable sensor technology is seen as presenting a
298 potential paradigm shift in air pollution science and engagement (Snyder et al, 2013).
299 Our trial suggests this view of a *potential* for public support and meaningful data
300 collection could be useful in developing evidence-based policy through new sensor
301 technology. It also provided new and critical insights on the importance of the sensor
302 to be perceived as providing reliable data, for fear of disengaging the public
303 otherwise. This is lends further support to scholars' recent call for researchers to test
304 the accuracy of low-cost monitoring devices before regulators are overwhelmed with
305 low air-quality data (Lewis & Edwards, 2016).
306
307   *Towards behaviour change.* To our knowledge, the beta version of the app
308 and its trial by the developer were primarily aimed at testing the smooth interaction
309 between the sensor, the app and the user. The app content was therefore not
310 deliberately based on any theoretical underpinnings of behaviour change. In effect,
311 the app in part took the approach of the deficit model: the view that providing
312 information to its users, seen as empty vessels waiting to be filled with knowledge,
313 will lead to change (Gross, 1994; Nisbet & Scheufele, 2009). But, this model of
314 science communication has received a number of criticisms as it assumes implicitly
315 that providing information is sufficient to enact behaviour change, and it fails to take
316 into account the role of context and individual differences in shaping communication
317 strategies (Sturgis & Allum, 2004; Wynne, 1991). Although the app did provide
318 personalised feedback to participants about their exposures (providing index values
319 derived from concentrations measured by the wearable sensor), it didn't go beyond
320 this mere information provision. It didn't contextualise the feedback by giving for
321 example exposures on alternative travel routes, it didn't include any user preference
322 or characteristic to tailor feedback, it didn't empower the user with concrete
323 recommended actions, and it didn't attempt to nudge users into any behavioural
324 change (e.g. giving an account of potential gains from specific alternative
325 behaviours).
326   The findings from our survey and interview work jointly point to a lack of effect
327 of the information provided by the app and sensor to change travel behaviour. A
328 similar lack of behavioural change was found by Chatterton, Coulter, Musselwhite,
329 Lyons, and Clegg (2009) in the context of travel behaviour and personal information
330 provision of carbon dioxide emissions using "carbon calculators" (tools that allow
331 people to assess how their personal behaviour impacts the environment). They found
332 that while people liked the carbon monitors and said it made them think more about
333 environmental issues, it didn't fundamentally change travel behaviour. The
334 researchers concluded by saying travel behaviour was a difficult and substantial
335 behaviour compared with other lifestyle changes (e.g., due to habits, socio-affective
336 appraisals).
337   As in our study, Chatterton et al (2009) appeared to take a deficit approach to
338 communication and did not tap into psychological constructs that may assist
339 behaviour change. Similarly, their trial did not provide behavioural advice on *how* to

14

340 change behaviour alongside emissions information. While information about a topic
341 can be interesting, it has been shown in other settings that providing actionable
342 behavioural advice is essential to effectuate desired behaviour changes. For
343 example, Haddad (2014) conducted experimental research in the context of
344 communicating climate change information showed that, in comparison with an
345 absence of behavioural advice, the presence of advice in addition to the topic
346 information, leads to higher intentions of environmentally friendly behaviour (such as
347 to recycle more, consume less household energy). A recent similar recent study by
348 Varaden, McKevitt and Barratt (in press) engaged school children by monitoring air
349 pollution with a sensor in London; but instead of an app, participants received
350 tailored advice from the researcher. They found that this participatory approach
351 encouraged individuals to think about reducing their own air pollution exposure. This
352 suggests that the type, mode, and level, of information provision is important for
353 users considering behaviour changes.
354   A review of top-ranked physical activity apps (indicating a measure of
355 success in engaging the public) revealed that the most commonly used intervention
356 techniques included the provision of clear instructions on how to perform behaviour
357 (Conroy, Yang, & Maher, 2014). Our respondents clearly echoed these research
358 findings on the need for actionable information when indicating the need for the app
359 to provide maps that would enable them to identify alternative routes to minimise air
360 pollution exposures. The Conroy et al. (2014) review also identified other
361 characteristics of top ranking apps relevant for our current study, including the use of
362 personalised and motivational feedback such as feedback on performance, goal-
363 setting for behaviour, planning social support/ change, information about others'
364 approval, and goal-setting for outcome. Stroulia et al. (2013) similarly identified
365 personalised feedback mechanisms as influential in leading to long term health
366 behaviour changes in an analysis of physical activity and diabetes monitoring apps,
367 specifically: personalisation, interactive reviewing, and subtle notifications (reminders
368 and personalised information). Mobile-health research to reduce alcohol
369 consumption also showed the provision of personal feedback as effective in
370 influencing behaviour (Garnett, Crane, West, Brown, & Michie, 2015). Respondents
371 from our study sensed the need for the type of clear and detailed personalised
372 feedback e.g., from personal historic travel behaviour and exposure maps, which
373 were shown to be effective in these health-behaviour settings. Such an integration
374 would allow people to make self-comparisons (i.e., assessing their behaviour once
375 they have made changes (Shakya, Christakis, & Fowler, 2015). Our trial participants
376 also highlighted the opportunity of an air pollution app to generate social support, or
377 to contribute to a network approach, also identified in the previous examples as key
378 to success. Social comparisons has been shown to be more effective than simply
379 providing information in other contexts of environmental behaviours, for example in
380 reducing towel use in hotels (e.g., Goldstein, Cialdini, & Griskevicius, 2008).
381 An example of a comprehensive approach to designing transport- and
382 environmentally-related behaviour change interventions can be found in the 'Four
383 Dimensions of Behaviour' (4DB) (Chatterton and Wilson, 2014). For Chatterton and
384 Wilson, behaviour and behaviour change is far more complex than a one-directional
385 communication and behaviour relationship and comprises of layers and contextual
386 complexities. Our work lends support to the use of such frameworks, with our
387 findings on air pollution engagement and new technologies fitting the 4DB framework
388 (using 4DB terminology for dimensions and sub-components - in *italics*):
389   *Actor*. Choice of air pollution responsiveness is usually driven by the
390 *individual* but may also involve a local *community* or action group. As highlighted
391 from our interviewees, *interpersonal networks* (e.g., friends, family) may play a social
392 influence role in engagement with air pollution and new technologies that may be
393 relevant. Like us, Varaden et al (in press) found that school children taking part in
394 their study also thought about ways to influence other people's behaviour, such as

395 proposing anti-idling campaigns, and pledged to persuade their parents to walk or
396 cycle to school instead of the using the car. While the population as a whole more
397 widely could be engaged with air pollution (and of course it would be more fruitful to
398 do so), it is more likely that *segments* of the populace will have a heightened sense
399 of engagement and respond to air pollution issues (in particular those with pre-
400 existing health issues, or with concerns for young children).
401   *Domain.* A range of *psychological* processes are involved in engagement of
402 and acting in response to air pollution – such as rational decision making, attitudes,
403 norms. *Technology* is key to air pollution engagement in the context of sensing
404 innovations and smartphone apps. As shown in our research, reliability, longevity,
405 connectivity, and accuracy, are all important features to engage people with air
406 pollution sensors and apps. *Institutional* domains are also essential in this context, as
407 people won't be able to engage without the supply of the technologies.
408   *Durability.* The engagement of, and behavioural responses to, air pollution
409 information is potentially something incorporated to daily activity to have the best
410 effects to avoid and reduce air pollution, therefore is a *repeated activity*. Engagement
411 in air quality information may also be *dependent* on occasions e.g., when preparing
412 for a long-distance run, or when the weather is particularly prone to worsen the air
413 quality. There are also *norm-setting* features where the actors may influence their
414 social networks towards supportive attitudes to air pollution and air quality monitoring
415 technologies.
416   *Scope.* The extent to which an actor is engaged with air pollution and its
417 communication will determine the scope of *interrelated* with other behaviours. As
418 suggested from our interviewees, if information provision is adequate, it could
419 facilitate behavioural alternatives e.g., different travel routes. Air quality engagement
420 and responsiveness could also be considered as *bundled* meaning that the ability to
421 act in response to the app may be constrained by the need to take certain routes, at
422 certain times, and to do certain chores.
423   More specifically in the area of air pollution communication, a recent
424 systematic review showed that air quality alerts need to be accompanied by health
425 advice to effectively change behaviour (D'Antoni, Smith, Auyeung, & Weinman,
426 2017). In the particular context of travel behaviour, communicating on the health or
427 environmental risks of air pollution, and in particular focusing on potential gains
428 rather than losses from mitigating or not air pollution, has been shown to affect
429 intentions to change behaviours (Mir, Behrang, Isaai, & Nejat, 2016). Although this
430 wasn't something highlighted by our study participants, the app used in our trial failed
431 to provide the needed health-related context as feedback.
432   Reflecting upon *medium to long-term* changes, some people interviewed said
433 that this technology may help them when assessing air quality when considering a
434 house move. In relating this to travel behaviour, previous research has shown that
435 new travel habits can form following a residential relocation (e.g., Bamberg, 2006;
436 Stanbridge & Lyons, 2006): this may provide an opportunity to develop new (air
437 pollution friendly) travel habits.
438
439 *Strengths, Weaknesses & Future research and Recommendations*
440   *Strength & weakness.* This social research made the most of a technical trial
441 of a new and unique app and sensor. In utilising this real life 'intervention' we were
442 able to examine behaviours and attitudes before and after usage of the new
443 technology. The mixed methods approach allowed us to probe and understand
444 survey results. As well as providing an evaluation of user-experiences in a real-life
445 setting, our results add to the broader literature and theory of communication and
446 behaviour change. There are downsides that came with this quasi-experimental
447 method. Firstly, we had no control over the content of the app. Secondly, we had
448 biased sample: people's attitudes skewed towards already being highly engaged with
449 the topic of air pollution, everyone in our sample made a financial commitment to

450 help develop the technology, and participants were mostly male, technologically-
451 inclined individuals. This may in part explain the null effect of the intervention in
452 terms of behaviour change. Thirdly, though we had access to 100 beta testers, our
453 survey sample size was small.
454
455 *Future research.* Future research can help app developers better target potential
456 users and help policymakers better understand the impact of this technology-based
457 intervention. For instance, sample segmentation by (medical problems absent or
458 present, and nature of medical problems, respiratory, etc) would be useful, though it
459 would be necessary to have a larger sample size to do this thoroughly and a
460 reasonable expectation of statistically significant results if such differences exist
461 between these groups.
462   Further research testing the ability of air pollution apps to enact behaviour
463 change should trial an app which has firm theoretical grounding on how to change
464 behaviour. It also needs to incorporate a larger, more diverse sample. The diffusion
465 of innovations (Rogers, 2010) could help frame future sampling. This segments
466 (potential) consumers of innovations and new technologies as the extent to which
467 they adopt a new idea. The categories of adopters are: innovators, early adopters,
468 early majority, late majority, and laggards. The people taking part in this beta test can
469 be seen as *innovators* and *early adopters*. Future work could explore the role each
470 potential consumer may have influencing and being influenced by another. With
471 some of our interviewees highlighting how the presence of the sensor led to
472 discussions among their peers about air pollution, there could be a social influence
473 role that *innovators* and *early adopters* can have in encouraging the uptake of new
474 technologies, among their peers. It may be that the *early majority* are more
475 influenced by *early adopting* peers close to them, with *late majority* and *laggards*
476 more influenced by outside groups (e.g., policymakers, stakeholders) and contextual
477 determinants (e.g., prices, policies, infrastructure).
478   While the current real-world setting using an actual app and sensor are ideal,
479 mocked-up websites/apps presenting the desired intervention (i.e., manipulation) are
480 also good alternatives, often used in social and environmental psychology to assess
481 any influence on attitudes and intentional behaviours with more opportunity to vary
482 communication strategies (Haddad 2014).
483   Future research may also want to get the perspectives of the developers:
484 what are they basing the app information on, and why; what behavioural changes do
485 they expect, and why? In addition to this, it would be wise to consider a wider
486 audience engaging with new technologies for air pollution monitoring and
487 communication, such as decisionmakers and policymakers.
488
489   *Recommendations.* Learning from previous communication research
490 suggests that the provision of information alone will unlikely change attitudes/
491 behaviour. If the purpose of the app is to influence its users in this way, perhaps a
492 further development of the air pollution app could include messages that go beyond
493 information provision of the level of air pollution – and to provide feedback. We
494 believe that there is some potential to change behaviour here, however some
495 modifications are advised. For example, to allow people to see how their own travel
496 behaviour choices affect their air pollution exposure, simple personalised self-
497 comparison prompts may be useful.
498   Because reducing excessive air pollution depends on a holistic approach that
499 relies on societal attitude and behaviour change, it is important to also *engage* the
500 *disengaged*. Our interviewees did say that the presence of the sensor did engage
501 those around them as a talking point, leading to a broader discussion about air
502 pollution. To further engage those who may not have pre-existing motivation science,
503 the use of incentives may attract the attention of a wider pool. For example, local and

504 transport authorities may wish to invest in devices, offering these to residents in
505 exchange for a bus pass, or credits for hire bikes at docking stations.
506   To conclude, if developed and implemented correctly, this kind of technology
507 can offer a tri-functional way of collecting data (to inform and influence policies),
508 communication of air pollution information and changing behaviour. For this package
509 to be effective, the technology must be and be seen to be reliable, trustworthy and
510 accurate to maintain engagement and make the data useable and the
511 communication must provide personalised and actionable information to effectuate
512 behaviour change. In terms of the human interaction aspects: human communication
513 scenarios and behaviour is complex and dynamic, thus it makes *changing behaviour*
514 very difficult. Future interventions that seek health and environmental behaviour
515 changes may be more successful with grounding in theory or previous research.
516
517

531
532

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