

Who Cares About the Air?
Inequalities in Air Pollution Information Acquisition



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Abstract

Air pollution is a pervasive global challenge responsible for one in eight deaths according to the World Health Organization (WHO). In the United Kingdom (UK), air pollution causes the equivalent of 28,000 to 36,000 premature deaths each year. In addition, exposures occur disproportionately across the population and are influenced by numerous, often interrelated factors, including but not limited to demographics, geography, profession, income, as well as an extensive array of social and behavioral patterns. Internet-connected technologies have facilitated a deluge of digitally available information about air pollution. Despite this proliferation, there is a lack of comprehensive reviews or characterization of emerging sources of air pollution information, including the varied modes for generating and delivering said information. Furthermore, aside from small-scale studies or interventions, little is known about patterns of public engagement with air pollution information and how this can affect pollution exposures or associated health outcomes at the population level.

This thesis addresses gaps in the literature surrounding the characterization of and engagement with air pollution information by presenting a series of linked studies. The first empirical Chapter introduces the term “air quality (AQ) channels” to help define a new genre of digitally enabled, real-time air quality information. An analysis of “digital trace” data demonstrates that patterns of the diffusion of AQ channels are associated with the publication of news articles about air pollution. The subsequent Chapter employs visual and computational methods to analyze the characteristics of data and information delivered across AQ channels. Findings indicate that different AQ Channels deliver varying air pollution “readings” for the same geographic location. This suggests that two individuals standing in the same place can receive varying exposure reducing behavioral advice depending on which AQ channel they consult. The final two empirical Chapters leverage a nationally representative, cross sectional survey dataset and estimate regression models to identify sociodemographic characteristics of groups that are more likely to experience the benefits of accessing AQ channels. Individuals who have or care for others with certain health conditions demonstrated greater awareness about the health impacts of air pollution. Additionally, increased concern for long-term health, as well as “response efficacy and outcome expectancy,” or belief that one’s actions can positively affect the air they breathe, are associated with greater adoption of exposure reducing behaviors. The final Chapter found that the odds of accessing digital AQ information were greater for younger individuals (below 36), those with health conditions, and those who care for some with a health condition, as compared with their counterparts. This Chapter also demonstrated that individuals are more likely to adopt a greater number of exposure reducing behaviors if they access information on a daily basis.

The thesis concludes by discussing how qualities and patterns of use of AQ channels can perpetuate existing social and informational inequalities. The research outputs from this thesis serve as a foundation for future work on how AQ channels can be used to bring benefit to those who have been previously left out of air quality research and governance.

This thesis is dedicated to those working to address pollution exposure inequality through the advancement of multidisciplinary, reflexive, and equitable environmental knowledge production and governance.

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Contents

ABSTRACT	2
ACKNOWLEDGEMENTS.....	4
INTRODUCTION.....	12
CHAPTER ONE: LITERATURE REVIEW	20
1.1 <i>The Origins & Characteristics of AQ Channels.....</i>	20
1.2 <i>Health and social inequality (disproportionate air pollution exposure risk).....</i>	26
1.3 <i>Interventions & Informational inequality.....</i>	32
1.4 <i>Drawing the literature together.....</i>	41
3. ETHICS.....	42
CHAPTER TWO: ‘REAL-TIME’ AIR QUALITY (AQ) CHANNELS: A TECHNOLOGY REVIEW OF EMERGING ENVIRONMENTAL ALERT SYSTEMS.....	44
ABSTRACT	44
1. INTRODUCTION	44
2. BACKGROUND	46
2.1 <i>Origins of AQ channels: pollution monitoring, modelling, and data generation</i>	46
2.2 CONTEMPORARY AQ CHANNEL CHARACTERISTICS: MESSAGING & ACCESS	49
2.2.1 <i>Messaging.....</i>	49
2.2.2 <i>Access</i>	53
3. METHODS	56
3.1 <i>Overview.....</i>	56
3.2 <i>Systematic technology review.....</i>	56
3.3 <i>Data selection.....</i>	57
3.4 <i>Methods of Analysis.....</i>	59
4. RESULTS	60
4.1 <i>Summary</i>	60
4.2 <i>AQ Channel Platform Specifications.....</i>	61
4.3 <i>Pollution Modelling and Forecasting.....</i>	67
<i>Spatial and temporal resolution of AQ channel pollution estimates</i>	68
4.4 <i>Messaging Characteristics</i>	69
4.5 <i>Access Patterns Across AQ Channel Case Examples.....</i>	71
5. DISCUSSION	75
5.1 <i>Summary</i>	75
5.2 <i>Limitations.....</i>	76
5.3 <i>AQ Channel Diffusion</i>	77
5.4 <i>Barriers to AQ Channel Uptake</i>	79
6. CONCLUSION	84
CHAPTER THREE: VARIATION IN REPRESENTATIONS OF AIR POLLUTION AT SIX HOSPITALS ACROSS LONDON, UK	87
ABSTRACT	87
1. INTRODUCTION	87
2. BACKGROUND	89
2.1 <i>Measuring air quality & relaying estimates.....</i>	89
2.2 <i>Representing air quality</i>	91
3. DATA AND METHODS.....	96
3.2 <i>Data</i>	96
3.3 <i>Methods</i>	99
4. RESULTS	103
4.1 <i>Summary</i>	103
4.2 <i>Numerical representations of air pollution</i>	104
4.3 <i>Visual representations of air pollution.....</i>	113
5. DISCUSSION	120
5.1 <i>Summary</i>	120

5.2 Limitations	120
5.3 Variability in numerical features, AQI, and pollutants reported	122
5.4 Temporal and spatial variability	124
5.5 Variability in visual features	125
5.6 Variability in ERB messaging	128
6. CONCLUSION	129
CHAPTER FOUR: EXAMINING PSYCHOSOCIAL, HEALTH STATUS, AND DEMOGRAPHIC PREDICTORS OF AIR POLLUTION EXPOSURE REDUCING BEHAVIORS ACROSS THE UK	132
ABSTRACT	132
3. DATA AND METHODS	140
3.1 Data and Samples	140
3.2 Measurement of Variables	141
4.3 Association between health status and concern around long term effects of air pollution	151
4.4 Association between psychosocial characteristics and exposure reducing behavior (ERB) adoption	152
5. DISCUSSION	153
4.2 Limitations	154
5.3 Association between demographic context, health status, and psychosocial characteristics	156
5.4 Psychosocial predictors of ERB adoption	157
6. CONCLUSION	159
CHAPTER FIVE: EXPLORING INEQUALITIES IN AIR QUALITY INFORMATION ACCESS AND UPTAKE OF EXPOSURE REDUCING BEHAVIORS ACROSS THE UK	162
ABSTRACT:	162
1. INTRODUCTION	162
3.1 Data	169
3.2 Measurement of Variables	170
4. RESULTS	177
4.1 UK population level general patterns of AQ channel access	178
4.2 UK population level general patterns of ERB adoption following AQ channel access	184
5. DISCUSSION	186
5.1 Overview	186
5.2 Limitations	186
5.3 Uptake of AQ Channel according to socio-demographic characteristics	187
5.4 Relationship between AQ Channel access and ERB adoption patterns	188
6. CONCLUSION	189
CONCLUSION	192
1. SUMMARY	192
2. THE AQ INFORMATION LANDSCAPE: SUSTAINING STRUCTURES THAT PERPETUATE OUTDATED MESSAGING ABOUT AIR POLLUTION EXPOSURE VULNERABILITY	194
2.1 Chapter II – Systematic review of “freely” available AQ Channels in London, UK	194
2.2 Chapter III – Variation in air pollution representations across AQ Channels at six hospital locations	196
3. STRATIFICATION IN AQ CHANNEL ACCESS AND ERB ADOPTION BY SOCIO-DEMOGRAPHIC AND HEALTH STATUS GROUP	198
3.1 Chapter IV – Psychosocial, demographic and health status predictors of ERB adoption in the UK ..	198
3.2 Chapter V – Demographic predictors of AQ channel access and ERB adoption in the UK	200
4. LIMITATIONS AND SOLUTIONS	200
5. FUTURE RESEARCH & POLICY RECOMMENDATIONS	202
6. CONCLUSION	204
LITERATURE CITED	207
APPENDICES	214
APPENDIX 1 - CHAPTER II:	214
APPENDIX 1.1: SEARCH TERM PERMUTATIONS	214
APPENDIX 2 - CHAPTER III	216
APPENDIX 2.1 – ADDITIONAL AQ CHANNEL SCREENSHOTS	216
APPENDIX 2.2 – TIMESERIES OF SPECIFIC POLLUTANT ESTIMATES BY EACH API FOR THE SIX HOSPITAL LOCATIONS	220
APPENDIX 3 - CHAPTER IV	223

APPENDIX 3.1.1 - QUESTIONS ALLOCATED TO EACH SUMMARY INDEX	223
APPENDIX 3.1.2 OPINIUM RESPONDENT WEIGHTING PROTOCOL.....	227
APPENDIX 3.2 – DESCRIPTIVE STATISTICS.....	228
3.2.1 DESCRIPTIVE STATISTICS FOR PREDICTOR VARIABLES IN NUMERICAL FORMAT	228
3.3.1 VIF MULTICOLLINEARITY TESTS	229
APPENDIX 4 - CHAPTER V	241
4.2.1 VIF MULTICOLLINEARITY TESTS	241
4.2.2 ADDITIONAL REGRESSION ANALYSES	243

List of Figures

Figure 1. Differing formats of AQI delivered by UK Defra and U.S. EPA.....	50
Figure 2. “Pipeline of online participation” (Shaw and Hargiatti, 2018).....	54
Figure 3. AQ channel metadata collection criteria.....	58
Figure 4. PRISMA flow diagram of AQ channel identification, screening, and inclusion.....	61
Figure 5. Launch years for 54 resulting AQ channels.....	62
Figure 6. Dominant platforms and technologies communicating AQ information.....	65
Figure 7. Venn diagram illustrating multiple sources of air quality “reading” across AQ channels.	66
Figure 8. Models generating air pollution estimates across 31 AQ Channels.....	68
Figure 9. Map of individuals subscribed to AirText at borough level (2007 – 2020).....	73
Figure 10. Bar plot of individuals subscribed to AirText at borough level (2007 – 2020).	73
Figure 11. Pearson correlation plot.	74
Figure 12.a Number of unique users & 12.b. Timing of visits on weekdays to London Air.	75
Figure 13.a Number of unique users visiting Breathe London pilot & 13.b Timing of visits.	75
Figure 14. Adapted figure from Chapter II showing the 7 common APIs servicing 18 unique AQ channels.	88
Figure 16. Location of 6 hospitals in London included in the analysis.....	98
Figure 17.a. AQI estimates in US EPA format from an API sampled at 6 locations over one week	108
Figure 17.b. CAQI estimates in EU format from an API sampled at 6 locations over one week.....	109
Figure 17c. Plume AQI estimates from an API sampled at 3 locations over one week.....	110
Figure 18. Proportion of AQI estimates in moderate range or higher reported by each API at the 6 hospital locations....	111
Figure 19. AQ channels from API1.....	114
Figure 20. AQ channels from API 2.....	116
Figure 21. Hybrid commercial-government AQ channel, Breathe London (API3).....	117
Figure 22. Commercial AQ channels	118
Figure 23. AQ channels from API 7.....	119
Figure 24. Capability, Motivation and Opportunity Behavior model	136
Figure 24. Number of respondents who have ever access AQ information.....	177
Figure 25. Number of respondents accessing each AQ information delivery platform	178

List of Tables

Table 1. Descriptive characteristics of resulting AQ channels (n=54).....	63
Table 2. Messaging features of AQ channels.	70
Table 3. AirTEXT summary statistics from September 2020 – 2007	72
Table 4. OLS regression estimating subscription to AirTEXT	72
Table 5. Six hospital locations in London, UK.	102
Table 6. 7 APIs queried at 6 geographic locations (Hospitals in London, UK).....	107
Table 7. Descriptive statistics for PM2.5 and NO2 across multiple APIs at each location during weekday commute.....	112
Table 9. Sample B: General descriptive statistics	145
Table 8. Sample A: General descriptive statistics	145
Table 10. Descriptive statistics for outcome variables (Samples A & B)	146
Table 11. Modelling approach.....	146
Table 12. Estimated associations between awareness and sociodemographic characteristics (H1a).....	150
Table 13. Estimated associations between concern and sociodemographic characteristics (H1b)	151
Table 14. Estimated associations between psychosocial factors and ERBs adopted (H2a - c).....	152
Table 15. Descriptive Statistics for demographic & outcome variables	175
Table 16. Modelling approach.....	175
Table 17. Odds ratios from logistic model predicting access to digital AQ channels.....	180
Table 18. Odds from logistic regression models predicting AQ channel access by health status.....	181
Table 19. Odds ratios predicting AQ channel access by carer status for someone with a specific health condition.....	183
Table 20. Coefficients from OLS model predicting adoption of ERBs by demographics and AQ channel type.....	185
Table 21. Coefficients from OLS model predicting adoption of ERBs by frequency of AQ information access....	185

Appendices

Appendix 1 - Chapter II.....	214
Appendix 1.1: Search term permutations	214
Appendix 2 - Chapter III	216
Appendix 2.1 – Additional AQ Channel screenshots.....	216
Appendix 2.2 – Timeseries of specific pollutant estimates by each API for the six hospital locations.....	220
Appendix 3 - Chapter IV	223
Appendix 3.1.1 - Questions allocated to each summary index	223
3.1.2 Opinion respondent weighting protocol.....	227
Appendix 3.2 – Descriptive statistics	228
3.2.1 Descriptive statistics for predictor variables in numerical format.....	228
3.3.1 VIF multicollinearity tests	229
Appendix 4 - Chapter V	241
4.2.1 VIF multicollinearity tests	241
4.2.2 Additional Regression analyses.....	243

Introduction

Air pollution is the greatest environmental threat to human health around the world. Pollution exposures are responsible for one in eight deaths each year globally according to the World Health Organization (WHO) and cause the equivalent of 28,000 to 36,000 deaths in the United Kingdom (UK) each year (Public Health England, n.d.). Estimates place the economic burden of air pollution on UK society at approximately 20 billion pounds per year (Royal College of Physicians, 2016). Furthermore, pollution exposures occur disproportionately across the population and are influenced by numerous, often interrelated factors, including but not limited to demographics, geography, profession, income, as well as an extensive array of social and behavioral patterns (Fairburn et al., 2019; Fecht et al., 2015; Goodman et al., 2011; H et al., 2017; Milojevic et al., 2017; Rivas et al., 2017; Rüttenauer, 2019).

Internet-connected technologies have facilitated a deluge of digitally available information about air pollution (D'Antoni et al., 2017; McCarron et al., 2022; Riley et al., 2021). In addition, a growing body of research reinforces that informational interventions can reduce air pollution exposures at an individual level and improve downstream health outcomes by acting on one or more of the factors influencing exposures that were listed above (D'Antoni et al., 2019; Neidell & Kinney, 2010; Rappold et al., 2014, 2019). Despite the proliferation of digitally available air quality (AQ) information, there is a lack of research aimed at characterizing emerging information sources, along with the varied modes through which it is generated and delivered. Furthermore, aside from small-scale studies or experimental interventions, little is known about patterns of public engagement with air pollution information and how this can affect pollution exposures or associated health outcomes at the population level.

This doctoral thesis is driven by questions about how rapidly proliferating, digitally available sources of air pollution information - or “air quality (AQ) channels” - are being constructed and consulted by the UK population and more broadly around the world (Sun et al., 2017; McCarron et al 2022). The thesis consists of linked papers, allowing a more focused application of different methods to respond to the driving research questions. Collectively it sits at the intersection of the disciplines of sociology, demography, and human geography. It builds explicitly on scholarship emerging from the subdisciplines: ‘sociology of scientific knowledge (SSK)’, socio-environmental and health inequality research, ‘science, technology, and society (STS) studies’, as well as sociology of the internet, information, and communication’.

The thesis document is structured as follows. The first Chapter is a literature review that chronicles the historical, socio-political, and environmental conditions underpinning the evolution of AQ channels, while establishing the methodological approach of the thesis. The second, third and fourth Chapters serve as the empirical Chapters of the thesis. The goal of the empirical Chapters is to define key characteristics of AQ channels, identify what drives variation in information delivered across different channels, and illustrate whether there is sociodemographic inequality in AQ channel access and associated exposure reducing behaviors. The following paragraphs describe the structure of the thesis and how each Chapter contributes to the sociology of scientific knowledge, critical data studies and digital-informational inequality literatures.

The first Chapter presents a literature review with cross-cutting themes that motivate the research contained in this thesis. It frames the thesis around Western society’s reliance on specific technologies to monitor and mitigate environmental exposures (Barry, 2002). It further

outlines discussions throughout the literature responding to the growing emphasis on self-monitoring and digital platforms to supply informational interventions to improve health outcomes at the individual level (Gabrys et al., 2016; Hubbell et al., 2018; Riley et al., 2021). It also addresses how these “internet connected technologies” or ICTs co-produce ways of understanding and governing air pollution exposures (Gabrys, 2017; Jasanoff, 2004; Whatmore, 2006). This helps establish the foundation and motivation for the mixed methods approach adopted throughout the empirical Chapters. A combination of statistical methods, computational social science data gathering and analysis techniques, as well as human geographic methods are employed throughout the four empirical Chapters. These methods are applied to fill significant gaps in the literature regarding AQ channel characteristics, sociodemographic patterns of channel access and uptake of exposure reducing behaviors across the UK. The suitability of a mixed methods approach is reinforced throughout the subsequent paragraphs, which describe the different datasets and specific methods employed to respond to the core research questions and address identified gaps in the literature.

The second Chapter develops the concept of the “AQ channel” as an impactful, evolving innovation that enables access to location-specific, air quality information in time intervals ranging from every hour to every minute. It accomplishes this through the empirical research paper titled “*Real-time Air Quality (AQ) channels: A technology review of emerging environmental alert systems*”, which has been published in the journal *Big Data & Society*. This study examines access to “freely” available AQ channels in London, UK against the backdrop of *diffusion of innovations* theory and “information inequality” scholarship. London was selected based on the availability of high-resolution air pollution and sociodemographic data, evidence of disproportionate exposures to poor air quality and the presence of multiple channels (Tonne et al., 2008). The notion of “informational inequality”, specifically digital

informational inequality, highlights discrepancies in “access to and quality of Internet”; digital literacy or skills; and the different manners of engaging with digital technologies, including privacy concerns (Bol et al., 2018; Dimaggio & Hargittai, 2001; Hargittai, 2010; Scheerder et al., 2017; van Deursen & Helsper, 2015; van Deursen & van Dijk, 2014; van Dijk & Hacker, 2003). Access or “uptake” of AQ channels is examined using digital trace data and metadata, conceived of as material ripe for analysis that is “produced as a part of social life” (Marres, 2016; van Dijik, 2015). As individual-level demographic covariate information (age, gender, etc.) was not available, this paper focused rather on broad patterns of access with AQ channels, such as date and time of access, and borough-level geolocation.

A dataset containing metadata associated with 54 AQ channels was compiled and synthesized narratively and graphically. Digital trace data from three channels delivered in partnership with the Greater London Authority (GLA) were analyzed using regression models. The results reveal AQ channels derive air pollution estimates using common data sources, display disparate messaging, adopt variable geographic scales for reporting “readings”, and maintain psychosocial barriers to access and adoption of exposure reducing behaviors, or ERBs. The results also point to an association between the publication of a high-profile news article about air pollution and an increase visits to two specific AQ channels. These findings illuminate a need for greater transparency around how AQ channels generate personalized air pollution exposure estimates and tailor messaging. The Chapter concludes by calling for AQ channel developers to exercise co-creative methods that can support sustainable, democratic data and knowledge production around air quality, while critically approaching disproportionate patterns of both pollution and information exposure. Examples of such methods include ‘participatory mapping’ or ‘co-design workshops’, where different, affected groups can be directly involved in the design of the digital interfaces and messaging aimed at conveying

resonating information about air pollution (Whatmore and Landström 2011, Pritchard and Gabrys 2017). With respect to the overarching thesis, this Chapter serves to consolidate and systematize ways of thinking about emerging forms of air quality information and delivers both theoretical and substantive, empirical contributions to the field of information inequality dynamics amidst technological diffusion.

The third Chapter is titled *Variation in API-derived air pollution estimates at six hospitals in London, UK* and examines how AQ channel technology can contribute to information inequality at an infrastructural level. While the landscape of digitally mediated AQ information has diversified, the implications of this for quality and consistency of AQ information, and how this can affect patterns of pollution exposure reducing behavior across populations, remains unclear. Results generated throughout the first Chapter of the thesis demonstrate there is great variability in AQ information systems or “AQ channels”, from the way air pollution “readings” are generated, to the format and behavioral messaging displayed across channels. It also demonstrates that there are certain psychosocial and structural barriers to AQ channel uptake, contributing to “informational inequality” or unequal access to information that can inform health-protective behaviors at the population level. These questions are probed further throughout this Chapter, which responds explicitly to the research question: *is there variation in how air pollution is reported across AQ channels for the same geographic area, and could this affect the adoption of pollution exposure reducing behaviors?*

To respond to this question, Chapter three presents a study designed to systematically explore variability in pollution information reported across a sample of “open access” AQ channels (apps) at six hospital locations in London and determine the source of this variability. “Variability” was approached from numerical, textual, and visual standpoints. Numerical

variability was analyzed by employing statistical and graphical methods to a dataset of air pollution “readings” obtained by querying the sample of channels served by openly accessible APIs over a weeklong period in April 2022. In addition, screenshots of the sample of AQ channels were obtained and analyzed by applying visual methods rooted in semiology theory. The results demonstrate significant variation in estimated particulate matter (PM_{2.5} & PM₁₀), NO₂ and AQI for a specific latitude/longitude location. Findings suggest that different AQ channels report varying air pollution estimates for the same geographic location, which may affect ERB patterns and associated health outcomes at the population level. This work was carried out during a research visit to the Max Planck Institute for Demographic Research as a part of the Population Health and Data Science network at the Lab of Digital and Computational Demography. Beyond contributing to the literature surrounding environmental and health information variability, as well as data typologies employed across AQ channels, this Chapter proposes computational methods for generating datasets derived from internet-based platforms.

The final two Chapters address the key research question regarding whether there is sociodemographic inequality in AQ channel access and associated exposure reducing behavior (ERB) adoption at the population level in the UK. It is delivered as two separate studies across Chapters four and five. The first study, titled *Examining psychosocial, health status, and demographic predictors of air pollution exposure reducing behaviors across the UK*, has been developed in collaboration with Ben Hudson, Head of Insight and Engagement at the Global Action Plan charity. Until now, the literature has exclusively addressed the association between sociodemographic predictors and ERB uptake throughout controlled experiments involving app-based informational interventions (D’Antoni et al., 2017; Johnston et al., 2018; Rappold et al., 2019). This Chapter adds to the literature by leveraging the “Clean Air Public Insight

Tracker” (CAPIT), a nationally representative survey commissioned by Global Action Plan aimed at understanding perceptions of air pollution across the UK.

Two samples (Sample A & B) were extracted from the CAPIT dataset to support this analysis. A subset of the questions was not repeated in each wave. Sample A includes survey responses related to past voting behavior, ethnicity, and education, which were only posed during the September and December 2020 sampling waves ($n = 4,002$) (see Table 8). Sample B includes responses about presence of health conditions, which were only posed during the June 2019 and April 2020 sampling waves ($n = 4,011$) (see Table 9). Both Samples A & B include the outcome variables selected for analysis in this study. Ordinary least squares (OLS) and ordered logistic regression (OLR) models were estimated to respond to the hypotheses about whether certain groups demonstrate greater awareness and concern with respect to air pollution, and which psychosocial characteristics most strongly predict adoption of ERBs. Results show greater air pollution awareness among females, individuals with higher educational attainment, older individuals until retirement age. In addition, there was greater awareness and concern among individuals who have or care for others with certain health conditions, and the association of increased adoption of ERBs with a sense of “response efficacy/outcome expectancy”. These findings can support more targeted design of air pollution informational campaigns to address disproportionate air pollution exposure, while taking care not to place the burden to evade pollution solely on individuals.

The fifth Chapter is titled *Exploring inequalities in air quality information access and uptake of exposure reducing behaviors across the UK*. It is motivated by mounting evidence suggesting that informational interventions can play a significant role in mediating air pollution exposures for specific populations subgroups and reduce downstream adverse health outcomes (D’Antoni et al., 2019; Neidell & Kinney, 2010; Rappold et al., 2014). It addresses a major gap

in the literature around whether engagement with AQ channels correlates with increased uptake of ERBs, and whether we can observe a correlation between certain sociodemographic characteristics and greater adoption of ERBs at the population level. This Chapter is an essential complement to the findings presented in Chapter II, which rely on demographically poor “digital trace” user analytics data. The survey-based data collection and analytical methods employed in Chapter V are necessary for the delivery of comprehensive insights into patterns of AQ channel uptake.

This is accomplished in the Chapter by presenting an analysis of the March 2022 wave of the CAPIT survey ($n = 1,993$), which contains sociodemographic information and response data pertaining to AQ channel access and ERB adoption patterns. OLS and OLR models were estimated to respond to the hypotheses around which sociodemographic groups in the UK are more likely to access AQ channels, and whether certain patterns of AQ channel access correlate with adoption of more ERBs. Results estimate that 37% of the UK population have accessed air pollution information, while males, individuals in age groups below 35, and those with children under 18 are more likely to access this type of information. These findings contribute to the growing literature surrounding which population groups engage with environmental and health-relevant information channels, and whether this engagement is associated with exposure reducing behavior patterns.

The thesis concludes by summarizing the key findings emerging from the empirical Chapters and highlighting their extension of sociology, demography, and human geography scholarship.

CHAPTER ONE: Literature Review

1.1 The Origins & Characteristics of AQ Channels

1.1.1 Historical, socio-political, and environmental context informing the development of AQ channels

Concerns surrounding air quality are historic. The legacy of contemporary air quality monitoring and management can be traced back to high pollution events transpiring in the late 19th century in industrial-era UK. Thousands of Londoners died in January and February of 1880 due to air pollution exacerbated co-morbidities (Mosley, 2009). Despite efforts to centralise approaches for observing air pollution, there was an apparent lack of technical standardisation, making it difficult to evaluate results commensurably and "build public confidence in this new knowledge" (Mosley, 2009: 275). In December of 1952, London experienced what is referred to as the "Great Smog," during which cold weather conditions and emissions contributed to potentially the highest instance of air pollution exacerbated mortalities, with retrospective analyzes estimating 12,000 deaths from December through February (Bell & Davis, 2001).

This dire situation is often described as the catalyst for contemporary air quality governance (Kelly & Fussell, 2015), where public organisations and government committees established during the Victorian era called for a more coordinated response from central government towards air pollution (Mosley, 2009). The response was a standardisation of approaches for monitoring and reporting air pollution concentrations, with central government authorities calling for simple, low cost "robust and reliable" methods to deliver "uniform measurements that could be widely reproduced" (Mosley, 2009). As such, a "metrological regime" and legacy

was devised, which informed the design and production of monitoring instruments for rendering the phenomenon of air pollution politically visible and governable (Barry, 2002).

1.1.2 The onset of AQ channels

Methods for monitoring air pollution have followed the trajectory set out by the original 1953 UK Clean Air Act (CAA) which directly followed the “Great Smog” event, with monitoring instruments becoming more accurate and prevalent across the UK while under the guidance and management of central government agencies. In 1961, the UK introduced the National Survey as the world’s first coordinated national monitoring network intended for monitoring black smoke and sulphur dioxide across 1,200 sites (Defra, 2020). Advances in monitoring practices were influenced by the digital revolution, resulting in major milestones regarding the regularity of collection of air pollution data from local authorities to the central government, and its communication to members of the public. In 1987 the UK established an “automatic” urban monitoring network in response to European Union directives requiring continuous hourly, or *nowcasted* pollution measurements (Defra, 2020). By 1998, all disparate monitoring sites were consolidated to form the current automatic urban and rural network (AURN) that supplies regulatory grade air pollution data used for policy development and planning purposes, as well as health effects research (Zhang et al., 2012).

From a regulatory standpoint, the 1995 UK Environment Act tasked local authorities with monitoring air quality in their respective areas (Environment Act, 1995). For most of the UK This involves the operation of monitors in coordination with the companies Ricardo Energy & Environment and Bureau Veritas, contracted by Defra for data processing (Defra, 2022). Data products from these monitoring endeavours signals whether an area is found to be in ‘non-compliance’, where air pollution concentration are considered in violation of the Clean Air Act (LAQM Technical Guidance, 2022). Once found in non-compliance, the local authority must

declare the area as an Air Quality Management Area (AQMA) and release an air quality management plan (AQAP) to the Department of Environment, Food and Rural Affairs (Defra) and members of the public, detailing how they plan to mitigate the issue. This protocol is still in place, however technologies for measuring air pollution have evolved in different ways. The following sections describe how AQ measurement and information transmission have evolved over the past twenty years.

1.1.3 A new era for AQ measurement

Technological advances have ushered in a new era of air pollution measurement, specifically personal, portable pollution sensing devices, and advanced modelling techniques able to estimate concentrations at increasingly localised scales. This thesis presents the term *air quality (AQ) channels* as a comprehensive label for channels that deliver air pollution insights in real-time, which are essentially a convergence of three categories of innovations: advances in air pollution data generation, air pollution modelling techniques, and air quality health messaging tools.

Two key methods are employed for regulatory air quality assessment. The first is *modelling*, which relies on complex modelling techniques for blending a variety of datasets including, but not limited to, pollution emissions inventories, weather data, and hourly pollution data from government monitoring stations, land use models and roadway traffic patterns to estimate air pollution at different spatial resolutions (Daly and Zannetti, 2007).

The second method is *measurement*. Measurements can either be generated by government monitoring stations, diffusion tubes, or using lower cost sensor technology. Government monitoring stations undergo rigorous quality assurance testing, with multiple pollution measurements gathered every minute and averaged across the hour, then reported as part of the

AURN. In the UK, this pollution data is collected by 150 automatic monitors across the country for seven major airborne pollutants, including particulate matter at 10 and 2.5 micrograms (PM₁₀ and PM_{2.5}), sulphur dioxide (SO₂), carbon monoxide (CO), nitric oxides (NO), nitrogen dioxide (NO₂) and ozone (O₃), along with regional temperature, humidity, and weather data (Defra, 2020). Particle pollution can be detected using techniques involving measuring mass or through light scattering, while gaseous pollutants are measured either by examining infrared or ultraviolet wavelengths or through chemiluminescence (Snyder et al, 2013).

Lower cost air pollution sensors can be stationary or portable. Measurements derived from such sensors can vary according to a host of factors described in detail. This includes, but is not limited to: the sophistication of the instrumentation used to generate it, quality of embedded temperature and humidity sensors, and the averaging times of measurements (average number of readings per second, per minute) (Woodall et al., 2017). Common techniques employed across lower cost sensors for measuring particulate matter include lasers and electrochemical sensors for measuring gaseous pollutants such as NO₂ and O₃ (Snyder et al, 2013). In the UK, certain modelling and measurement techniques have been legally sanctioned to help evaluate when air pollution concentrations exceed statutory limits (LAQM Technical Guidance, 2022). However, stationary sensors are increasingly leveraged to generate supplemental information about air pollution conditions alongside regulatory data sources, which brings us back to our discussion of AQ channels (Singh et al., 2022).

There are two general typologies of AQ channels, rooted in the type of data and methods they draw upon to present real-time insights into air quality. The first type draws on data generated through modelling, which referred to as ‘nowcasting’ (Zhang et al, 2012). The term “nowcast” was originally used in the field of meteorology to describe the prediction of imminent weather

patterns, but has since been co-opted by other fields, mainly economics, to describe estimating some phenomenon in real-time where there is an information lag for certain model variables (Browning & Collier, 1989). In the context of this research, the term “nowcast” emphasizes this innovation’s integration of multiple streams of data (i.e. geolocation, pollution data, weather patterns, satellite data) into models that generate spatially (1 km² to 5m²) and temporally (hourly to second by second) fine-grained insights into air pollution concentrations.

The second type presents insights using data generated by measurements. There are exceptions to these general typologies, as some examples of type two AQ channels will employ models to incorporate additional datasets, often temperature and humidity, for calibration purposes. In certain cases, this is accomplished internally within the device. Within this second typology, it is necessary to distinguish whether measurement data used across an AQ channel is derived from government monitoring stations or lower cost sensors. As described previously, there is a great deal of variation in the way pollutants are measured and how the data is presented, with lower cost commercial devices presenting colour coded readings via intuitive user interfaces, while more expensive, industrial commercial sensors provide WiFi-enabled raw data feeds (Hubbell et al., 2018; Snyder et al., 2013). There are also substantial expertise and human resource costs associated with managing both sets of equipment and data.

Concerns surrounding the variability in data generated by different sensors has popularized ‘co-location’ methods, where lower cost devices are positioned alongside reference monitoring equipment and then calibrated, mechanically or in the post processing of the data (Cross et al, 2017). Calibration often relies on statistical modelling, specifically the R² or root mean squared error (RMSE), to assess bias in measurement and correct it accordingly. Findings from recent studies aimed at quantifying the utility, referred to as the ‘QUANT’ project, reinforced that

these universal metrics for assessing bias “do little to communicate the nature of the errors and the impact these errors will have in any end use application” (Diez et al. 2022). A major reason for this is because these metrics are reductionist and condense error into a single value (Tian et al, 2016). This raises important questions regarding the viability of newer pollution data employed by the second typology of AQ channels, to be used to inform exposure reducing behavior or “ERB” messaging disseminated across channels.

1.1.4 AQ Channel Platforms and Messaging

The spaces where individuals may interact with AQ channels include websites, smartphone apps, public digital “billboard” displays, television, newspapers, and radio broadcasts, with variation across cities and countries. For example, in addition to digitally available sources, the U.S. Environmental Protection Agency (EPA) AQ channel is shared via local weather channels in certain areas around the U.S, as well as on the radio and in local newspapers in certain cases (D’Antoni et al, 2017). In the UK, the Defra and Meteorological Office issued daily air quality index (DAQI) is not communicated on television or radio, however during high pollution events, certain cities such as London will broadcast readings and health messaging on digital displays located at bus and tube stops. Broadly speaking, AQ channels are delivered by government authorities, academic groups, or by commercial enterprises that sell personal pollution sensors.

Literature identifying the venues and messaging styles that exist across a broad selection of AQ channels available to lay users around the world has been limited until now. D’Antoni et al review 21 studies examining the effects of air quality warning systems (AQ channels) available across the U.S., UK, and Canada. While the design and data sources informing the AQ channels contained in the studies reviewed are not explored in detail, D’Antoni et al describe the “Air Quality Index” (AQI) format as the common format for delivering action-

oriented messaging. An AQI is an information tool for providing health advice for both sensitive and non-sensitive groups according to specific pollution thresholds (Ruggieri & Plaia, 2012). An AQI is calculated based on the highest registered concentration of each of the key pollutants. The threshold levels or color-coded “bands” are calculated differently based on which organization is reporting the AQI (see Figure 1, Chapter II) (McCarron et al., 2022).

The translation or accompaniment of a raw air pollution reading with an AQI differentiates an AQ channel that is widely publicly accessible and interpretable from the stream of nowcasted data that may be used by researchers, government agencies, or data enthusiasts. The AQI health and behavioral recommendations commonly delivered across AQ channels are structured around the understanding of vulnerable or “at risk” portions of the population informed by epidemiological research (Chen & Hoek, 2020; Orellano et al., 2020). Considering that this thesis is focused on understanding who, from a socio-demographic perspective, interacts with AQ channels, what motivates such interactions, and which ERBs and benefits are experienced by which portions of society, it is necessary to review what factors contribute to pollution exposure inequality more generally, in addition to what factors sustain digital and information inequality.

1.2 Health and social inequality (disproportionate air pollution exposure risk)

1.2.1 Air pollution exposures and health outcomes in the long and short term

Seminal cohort studies following residents of six cities in the U.S. revealed “statistically significant and robust associations between air pollution and mortality,” specifically for exposure to “fine” particles smaller than $2.5\mu\text{m}$ or complex mixtures containing fine particulates (Dockery, Pope, Xu, et al., 1993: 1753). These findings spawned an expanding body of research aimed at identifying health endpoints and disease outcomes linked with

exposures to a variety of air pollutants (Kelly and Fussell, 2015). Since the publication of these foundational studies, massive amounts of research on the health effects of air pollutants have been reviewed and underpin regulation, health messaging and identification of individuals who are at an increased risk for more adverse effects following pollution exposures. Recent meta-analyses have confirmed that all-cause mortality, cardiovascular disease, respiratory disease and lung cancer are each causally associated with long term PM₁₀ and PM_{2.5} exposure (Chen & Hoek, 2020; Orellano et al., 2020). Further research reinforces a relationship between pre-existing conditions including asthma, obesity, diabetes, cardiovascular and cardiopulmonary disease with increased hospital visits and mortality, while the explanatory biological mechanism includes - but is not limited to - vascular deterioration, inflammatory responses, and pulmonary obstructions (Koman et al., 2018). Notably, findings from a recent study by Swanton and others clearly establish a physiological mechanism by which PM exposure initiates cancerous tumors (ESMO, 2022).

Low socioeconomic status (SES) has been linked to increased instances of adverse health outcomes (Brunekreef & Holgate, 2002; Fairburn et al., 2019). This evidence aligns with theory presented across the broader sociology and population health literatures, which highlight “diverse underlying causal mechanisms” that link SES and lifestyle factors relating to health (Pampel et al., 2010; Phelan et al., 2010). Strong and significant associations have also been found between socioeconomic status (SES) and likelihood for increased air pollution exposure associated with neighborhood effects (Pasetto et al., 2019; Rüttenauer, 2019). The public health focused literature reinforces the augmented vulnerability of certain population sub-groups to both increased exposures and exacerbated effects of air pollution.

Research approaches to short term versus long term pollution exposures greater than one year (Hoek et al., 2013) have grown more sophisticated with recent epidemiological studies now

able to measure increased inflammatory effects exhibited across specific biomarkers collected at hourly, weekly, and monthly intervals (Tsai et al., 2019). As large episodic high pollution events become rarer in developed areas, epidemiological research has trended towards time-series approaches for examining the effects of lower, prolonged exposure (Brunekreef & Holgate, 2002). Nevertheless, the growing body of biological and epidemiological research reinforces the correlation between air pollution exposures at any concentration above zero and negative effects on the human physiological system, with the WHO clearly stating that there is no healthy level of air pollution exposure (WHO, 2018). While everyone in the world is exposed to air pollution and at risk of suffering from associated negative health outcomes, certain population sub-groups and intersections are at greater risk for increased exposures, as well as associated adverse downstream health outcomes.

1.2.2 Estimating the health impacts of air pollution from macro to micro level

This section links the literature on methods of air pollution measurement with advances in understanding disproportionate pollution exposures and downstream health outcomes. At the macro level, the global assessment of air pollution exposures and burden of disease estimated approximately 9 million deaths per year are attributable to outdoor exposures (Fuller et al., 2022). To generate this figure, outdoor exposures were estimated at the city or town level, using population data, average annual ground level PM₁₀ and PM_{2.5} data, as well as modelled estimates of PM_{2.5} using the Data Integration Model for Air Quality (DIMAQ) at a resolution of 11km² (Global Burden of Disease, 2019). The health impacts or “burdens of disease” were determined through an integrated exposure-response function using country-level population attributable fractions (PAF) of air pollution exposure induced for acute lower respiratory infections (ALRI), lung cancer, chronic obstructive pulmonary disease (COPD), stroke and ischaemic heart disease (IHD) according to age and sex group (Global Burden of Disease,

2019; Burnett et al., 2014). From there, the attributable burden was calculated by multiplying PAF by the health outcome of interest such as death, or another standardized measure of life lost such as disability adjusted life years (DALYs), years of life lost (YLL) or years of life lived in disability (YLD). Uncertainty intervals were obtained at the 2.5 and 97.5 percentiles to account for bias surrounding exposure estimates, relative risks, and the use of proxy measures for PM_{2.5} to address data gaps, rendering the final approximation of 3 million deaths attributable to ambient air pollution exposures in 2012, with 87% occurring in low to middle income countries.

At the meso- or country-level, large-scale analyzes completed by the Royal College of Physicians in 2016 estimate approximately 40,000 deaths a year are attributable to outdoor air pollution exposures in the UK (Royal College of Physicians, 2016). Microsimulation modelling estimates that the total cumulative costs of the burden of PM_{2.5} and NO₂ pollution on the UK National Health Services (NHS) and social care amounted to £5.37 billion pounds after 18 years of no increase in pollution from 2015 baseline levels (Pimpin et al., 2018). This cost estimate increased to £18.57 billion when lesser researched diseases were factored into the model. Alternative estimates place the economic impact of air pollution at approximately 20 billion pounds per year across the UK (Royal College of Physicians, 2016). Figures pertaining to the health and economic burden of air pollution generated by the UK's Committee on the medical effects of air pollutants (COMEAP) reported by the Royal College of Physicians do not differentiate how the burden impacts different socioeconomic or demographic groups throughout the UK. This thesis generates insight into which population groups at the UK national and city level are potentially able to mitigate burdens caused by air pollution exposure through engagement with AQ channels. Furthermore, it uncovers whether such groups fall within, or outside conventional health, demographic and socioeconomic population groups

empirically proven to be at greater risk to the effects of poor air quality exposures. This can help illuminate whether certain groups are being left out or cut off from ERB messaging through non-engagement with AQ channels.

Focusing in on the city of London, the Greater London Authority (GLA) commissioned reports in 2013 and 2016, which analyzed air pollution exposures across London's 32 boroughs with specific attention to demographic and geographic inequalities (Aether, 2017). They reviewed estimated annual mean concentrations of PM₁₀, PM_{2.5} and NO₂ generated via ADMS modelling techniques at a resolution of 20m², alongside annual ONS datasets index for multiple deprivation datasets and ethnicity proportions for the population of London. Their analysis concluded that more deprived communities in London experience higher exposures to NO₂ and PM_{2.5} than less deprived communities do. For areas that exceeded EU annual mean limits for NO₂ (40µm /m³), lower super output statistical areas (LSOAs) with a higher proportion of white residents experienced lower registered concentrations of NO₂ than those with less white residents. City and local authority level interventions to mitigate traffic-related sources of NO₂ include Ultra Low Emission Zones (LEZ) and Low Traffic Neighborhoods (LTNs), which restrict specific types of vehicles or emissions in certain areas. Evidence of the impact of LEZ and LTN interventions on public health outcomes is mixed and nascent, with studies unable to conclusively link these interventions to physiological or objective health outcomes (Royal College of Physicians, 2016). Considering the widespread and complex nature of air pollution exposures, researchers often rely on observational, natural experiment evidence to examine the association between exposure and health outcomes (see: Neidell et al, 2011; Rappold et al., 2014; Keivabu et al., 2022). It is necessary to note that observational data is subject to biases arising from confounding variables, which can generate false or inaccurate estimates of the effects in question (Hammerton & Munafò, 2021). While keeping this in mind, computational

social science methods present a promising approach towards examining social and behavioral mechanisms that can contribute to differential air pollution exposures. A strong example of this is work by Keivabu and Rüttenauer, which found significantly lower numbers of absences at schools with larger proportions of low SES students in areas of London where ULEZ schemes were implemented (Keivabu et al., 2022).

Micro scale estimates of individual level exposures rely on more granular pollution measurement and modelling, layered with data pertaining to patterns of behavior and “effective inhalation doses.” Rapidly proliferating portable air pollution sensing technologies are being used to generate insights into personal exposures from both a research and personal standpoint (Hubbell et al, 2018; Snyder et al, 2013). For example, Cepeda et al present a systematic review of 39 studies that measure and compare the personal exposures of active commuters (pedestrian or cyclists) and passive commuters (car, bus, motorcycle, train, subway, metro) (Cepeda et al., 2017). This review of a modal comparison pollution exposure study confirmed important and consistent results that the benefits from active transport outweigh those of passive modes.

This insight has not yet appeared widely in research on the delivery of ERB messaging from AQ channels, perhaps being a function of their predominant research focus on “at risk” groups assumed not to be engaged in active modes of transport. Despite increasingly spatiotemporally granular estimates of exposure risk being communicated across AQ channels, they neglect to incorporate any measures for social and demographic contributors to exposure risk. This raises questions as to why this is the case, and how AQ channels can better account for potential socio-demographic disparities across exposures and possibly risk messaging.

1.3. Interventions & Informational inequality

1.3.1 Knowledge production & AQ channels as mediators of air pollution exposures

Despite the presence of ample, freely available information on local air quality conditions, disparate exposures to air pollution are still apparent (Aether, 2017), and there is yet to be any comprehensive evaluation of the role of “freely available” AQ channels in reducing pollution exposures at the population level. Nor has there been an attempt to leverage insights from trace data emerging through such digitally enabled interactions. In addition, the social inequality literature highlights the role of education throughout the processing and gathering of technical information (Pampel et al, 2010). To disentangle the role of the interplay of scientifically derived conceptions of air quality perpetuated through AQ channels, alongside the lived experiences and socially constructed conceptions of air quality, it is necessary to turn towards the limited literature that has examined engagement with these innovations. This portion of the literature review introduces research on digital engagement and the use of “digital trace data” to examine socio-digital patterns. It then presents an overview of existing research on the efficacy of AQ channels at mediating pollution exposures via behavioral advice, while examining the mechanisms driving observed outcomes in the form of health benefits.

1.3.2 The digital divide

In the past decade, there has been a proliferation of information communication technologies (ICTs), such as digital sensors and personal tracking devices, designed to feedback information to their users and support behavioral transformations (Karppinen & Oinas-Kukkonen, 2013). Many ICTs, including Google, Facebook, Twitter, and AQ channel platforms generate “digital trace” data which is now being repurposed across the fields of communication studies, demography, and computational social sciences to further research on previously unobservable processes and associated socio-demographic patterns (Alburez-Gutierrez et al., 2019). This

form of data is yet to be considered as an approach towards empirical research aimed at better understanding who interacts with AQ channels, what motivates such interactions, and whether exposures can be effectively reduced. Furthermore, the many ways that an individual can interact with an AQ channel is yet to be characterized in the literature, reinforcing a gap in understanding of whether interactions with the innovation are intermittent or continuously maintained, and whether this plays a role in exposure reductions.

Shaw and Hargittai approach online participation in terms of a “pipeline” by modelling awareness and behavior conducive with becoming a contributor to the open source, internet-based encyclopedia, Wikipedia (Figure 2, Chapter II) (Shaw & Hargittai, 2018). The goal of this is not to neglect the sample of individuals that may be “cut off” in prior stages of potential engagement as a contributor. Much like Wikipedia, most freely available AQ channels require internet access and a level of participation or engagement for individuals to arrive at that final stage of implementation or confirmation identified by Rogers. In his theory on *diffusion of innovations*, Rogers defines a model for the “innovation-decision process” that traces individuals through the process of learning about an innovation and whether they ultimately implement and reinforce the ideas or practices put forth by said innovation in their lives (Rogers, 2003: 169). Considering the AQ channels that are theoretically available to individuals across all populations through internet-based channels, it is important to examine whether certain structural or digital inequalities might limit these interactions.

Marres describes digital trace data as something “produced as a part of social life” and has the potential to “establish continuities... between sociality, technicity and knowledge” (Marres, 2017; van Dijik, 2015). While AQ channel trace data presents a promising opportunity to examine the artefacts of patterns of interaction with air quality information, key ethical and

interpretive issues that emerge alongside these new forms of data and warrant careful methodological consideration (Amoore, 2011; Kitchin, 2014; Neff et al., 2017). To address these concerns, it is necessary to turn to the psychological and socio-cultural barriers that may inform engagements with AQ channels.

1.3.3 Mechanisms contributing to AQ channel mediated exposure reductions

AQ channels may supply messaging aimed at helping individuals reduce their exposures and ultimately to improve downstream health outcomes. However, it is important to note the limitations associated with ‘exposure reducing’ messaging or informational interventions. There is currently a lack of empirical evidence linking explicit behaviours or behavior change with measured exposure reductions, and with improved health outcomes. Key areas for evaluating the effects of behavior on pollution exposures include transportation or movement patterns, activities conducted in indoor environments, such as cooking, cleaning or ventilation practice, and digital or mobile-app based interventions (Kelly & Fussell, 2019 and McCarron et al, 2022).

When evaluating exposure to air pollution, it is necessary to consider the difference between *exposure* and *inhaled dose*. Exposure refers to the concentrations of ambient or outdoor air pollution an individual comes into contact while undertaking certain activities, whereas or ‘inhaled dose’ requires the calculation of one’s ventilation rate to determine the volume of air pollution one ingests (Cepeda et al, 2017). This thesis is concerned with exposure as opposed to inhaled dose, as the existing air pollution and behavior literature focuses largely on exposure rather than inhaled dose, which is comparatively easier to measure.

Variation in air pollution exposures according to mode of transport have been documented in the literature. 70% of studies included in a systematic review found that commuters traveling by car experienced higher pollution exposures than those traveling via other modes, including bus, motorcycle or by active travel (Cepeda et al, 2017; [Karanasiou et al., 2014](#)). This systematic review also found that active commuters' inhaled dose is higher than those adopting motorised transport methods (car, bus, motorcycle, metro). Findings from this review reinforced that adopting motorised transport methods results in lowering life expectancy by up to one year in comparison with cyclists (Cepeda et al, 2017). These findings have been reinforced across other studies, which conclude that the health benefits of adopting active travel outweighed the potential effects of having greater inhaled air pollution doses ([de Hartog et al., 2010](#); [Tainio et al., 2016](#)). Additional studies that leverage portable air pollution sensors have demonstrated that adopting active travel modes and choosing quieter, back streets are associated with lower pollution exposures (Emissions Analytics, 2021; Grieve, 2017; DeNazelle et al 2017). These findings represent a component of a growing literature aiming at associating specific behavioural patterns or shifts with reduced air pollution exposures.

The majority AQ channels do not provide messaging recommending transport modifications, apart from the CityAir app, which plots the route 'lowest pollution' (McCarron, 2022; Schulte, 2022). AQ channels do provide recommendations on whether individuals should avoid exercising outdoors or opening windows if pollution levels are high (Breezometer, 2022 and AirVisual, 2022). Significant amounts of research have been conducted to examine the effect of cooking practices on domestic air pollution exposures in developing countries ([Bartington et al., 2017](#); [Pope et al., 2017](#); [Gordon et al., 2014](#); [Jetter et al., 2012](#)), however, research about variation and sources of domestic air pollution exposures throughout developed countries is lacking. The air pollution and health literature outlines the need for additional research around

indoor environments to further understandings of how exposure to air pollution across microenvironments contributes to individual health profiles (Kelly & Fussell, 2019).

While there are a range of studies examining differential exposure according to commuter or domestic behaviors, the body of evidence demonstrating a causal relationship between behavior modification and exposure reduction, and then with improved health outcomes is disparate and nascent. It is also necessary to note the subtleties between exposure reducing behaviors and *emissions* reducing behaviors. Exposure reducing behaviors can also be emissions reducing, for example, choosing to walk or cycle instead of traveling via motorized transport or switching to electric technology can directly eliminate sources of emissions. Another category of exposure reducing behavior are those where pollution exposures are avoided, such as choosing to travel on less crowded streets or avoiding going outdoors when pollution levels are higher (Whitmarsh, 2009). These examples help draw attention to potential risk-benefit trade-offs that must be considered when developing behavioural interventions, such as increasing pollution exposure due to increased time in indoor settings, reducing levels of physical activity, increasing anxiety, and potentially impairing access to healthcare services.

Fundamentally though, behaviors that fall into the ‘emissions reduction’ category have the potential to reduce personal exposure to pollution. Whether this is the intention driving the adoption of the behavior, or merely a side effect, is important to consider when aiming to understand motivations behind patterns of behavior that can affect exposure to air pollution (Clayton et al., 2016). The current state of the research in this domain, as well as the nuance of exposure versus emissions reduction, must be held in consideration as this thesis examines access to and engagement with AQ channels that supply ERB recommendations, and whether certain behaviors are taken up as a result.

Emerging research surrounding what guides interactions with AQ channels, and more specifically sustained adoption of exposure reducing behaviors (ERBs), draws upon socio-demographic, psychological and behavioral theory to explain observed results (McCarron et al., 2022; Riley et al., 2021). The experimental design presented across the existing literature on AQ channels is focused on evaluating the effects of interactions with a single channel. It is worth noting that none of the studies included ERBs associated with specific indoor based activities that might contribute to exposures, including failure to use an extraction hood during cooking or opening windows, as well as wood burning fires.

D'Antoni et al approach ERBs through the COM-B theoretical framework in their study (N = 82). This framework considers an individual's a.) capability, b.) motivation and c.) opportunity to adhere to the behavioral advice (D'Antoni et al., 2019; Eliasson et al., 2014). A similar approach is adopted by Rogers throughout his presentation of the diffusion of innovation theory, and the notion of "compatibility," "where an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 1995:240). More recent work from D'Antoni examined the effect a series of perception-rooted variables on the (likelihood) of considering permanent exposure reducing behavior changes (D'Antoni et al., 2019). The variables "worry" ($b = 0.40$, $CI = 0.01 - 0.80$) "severity," ($b = 0.44$, $CI = 0.04 - 0.87$) "response efficacy," ($b = 0.38$, $CI = 0.02 - 0.71$) and "self-efficacy" ($b = 0.44$, $CI = 0.08 - 0.77$) were found to have a statistically significant effect on actual behavior change measured after four weeks ($R^2 = 0.48$). Furthermore, a mediation analysis demonstrated that "perception of not having enough time" had a significant and positive indirect effect on whether participants considered permanent changes ($b = 0.16$, $CI = -0.19 - 0.45$) (D'Antoni et al., 2019).

Other studies examining interactions with AQ channels and the adoption of exposure reducing behavior highlight the contribution of “extreme” pollution events to increased app downloads. A 2018 study of the uptake of an AQ channel app known as “AirRater” observed spikes in app downloads during major bushfire events, simultaneous with media reports (N = 3,443) (Johnston et al, 2018). Additional studies have confirmed exceptional air pollution event-induced download spikes, with 80% of downloads for the U.S. EPA “SmokeSense” app taking place during smoke events (N = 5,598) (Rappold et al., 2019). The AirRater and SmokeSense studies also reported a significant proportion of those accessing the channel as having pre-existing health conditions. In the case of AirRater, 48% of registered users reported having asthma, 65% with allergies (allergic rhinitis) and 34% with both, while SmokeSense reported 51% of their channel users having pre-existing health conditions (Johnston et al., 2018; Rappold et al., 2019). Findings from the SmokeSense study revealed that adoption of ERBs was correlated with the presence of physical symptoms, so while initial interactions with AQ channels were prompted by perception of health risk, continued engagement and adoption of ERBs was driven by the presence of physical symptoms.

The studies mentioned above raise questions regarding the timing and frequency with which individuals might engage with an AQ channel. Certain AQ channels can be programmed to send daily forecasts in the morning or evening, while others do not have this. Others, including SmokeSense app and one other London-based app focusing on the borough of Hackney “gamify” pattern shifts or ERBs in response to app-delivered information. For certain channels, individuals can opt out from receiving any notifications and rely solely on their own motivations for checking the channel. The controlled nature of AQ channel message delivery points to a gap in the literature towards considering differences in frequency and degrees of

engagement individuals can have with AQ channels, and what motivates self-sustained engagement.

The literature reviewed here on the responsiveness to health advice and ERBs from air quality warning systems (AQ channels), alongside the work of Shaw and Hargittai on Wikipedia, reinforces how demographic factors did not always predict adherence. Both sets of research did however point to several “psychosocial facilitators” correlated with adherence. In the case of D’Antoni’s research these included: knowing where to find air quality information and advice, having received advice from health care professionals, perceiving air pollution as an issue, and believing that symptoms are tied to exposure (D’Antoni et al., 2017). D’Antoni’s work specifically cites “reliance on sensory cues” as a barrier to adherence of advice to reduce exposures and protect health. These findings reinforce the importance of the “subjective, perceived” conceptualizations of air quality. D’Antoni’s review also concluded that existing research shows “suboptimal” adherence to the messaging put forth by those AQ channels warrants further examination as to whether there is something about the dichotomous, perhaps divergent presence of both “objective, statistical” and “subjective, perceived” understandings of risk associated with air quality contained within in an AQ channel (Bickerstaff & Walker, 2003; Gabrys, 2017). Apart from Neidell and Kinney’s work, the research reviewed up until this point from Johnston, Rappold, and D’Antoni, which focus on AQ channel mediated behaviors, has relied exclusively on self-reported behaviors to hypothesize exposure reductions. There has yet to be any systematic approach to examining exposure reductions stemming from AQ channel interactions that does not rely exclusively on self-reported adoption of exposure reducing behaviors following engagement with a singular channel.

1.3.4 (Re)framing Air Pollution Risk

Research on risk perception reveals that higher levels of registered air pollution are not always associated with increased perceptions of risk (Brody et al, 2004). Observed instances of perception of risk associated with air pollution were found rather to be a function of local, situated knowledge, including everyday experience and social-cultural factors, particularly those more closely associated with perceptions of pollution (Bickerstaff & Walker, 2001; Brody et al., 2008; D’Antoni et al., 2019). The reverse has also been well documented, where concern in relation to air pollution risk is not cited as a top priority by those who are most vulnerable according to scientific measures (BMG, 2018 and Brody et al, 2004). This discrepancy suggests that there is more to be learned from a social standpoint regarding what motivates engagement with air quality information in general, and how risk is framed.

At present, the framing of risk by AQ channels appears to be restricted to scientific interpretations of risk for “healthy” and “unhealthy” individuals. This final section of the literature review points to increased levels of engagement with both ERBs and AQ channels in general, coming from individuals with pre-existing conditions or physical symptoms (Neidell & Kinney, 2010; Rappold et al., 2019). It is possible that this is a function of messaging that targets these groups, rather than others who also experience high exposures and health impacts in the short or long term. Several AQ channels now include messaging specifically for individuals who are pregnant and for allergy sufferers, which points to technical feasibility of tailored risk messaging. However, as discussed in the second section of the literature review, the current scope for presentation of risk across AQ channels does not incorporate well documented evidence of socio-demographic associations with increased exposures, despite being a major focus of academic research on air pollution exposure (Koman et al., 2018 Aether, 2017).

1.4 Drawing the literature together

This thesis is motivated by evidence from the literature that air pollution exposure inequality and associated health burdens persist throughout the UK and beyond. The sparse literature surrounding how the AQ channel innovation is impacting informational exchange and exposure mitigation at the population level prompted a systematic review of ‘freely’ available channels to individuals in London, which is presented in Chapter II. The historic measurement and pollutant-focused representations of air pollution adopted from a regulatory standpoint in the UK inspires a critique of how these representations have been carried into contemporary, AQ channel technology. Chapter III therefore looks across a sample of AQ channels resulting from Chapter II and examines whether there is visual and numerical variation across the channels, particularly when they are communicating about exposure risk.

While the evidence base linking AQ information to behavioral changes and subsequent reductions in individual level exposure is nascent and lacks high-quality, large-scale studies, AQ channels continue to issue ERB recommendations. Considering this, alongside the need to understand how air pollution perceptions, risk, and vulnerability map onto patterns of ERB adoption, Chapters IV and V analyze the CAPIT dataset. These Chapters challenge conventional notions of air pollution exposure ‘risk’ by identifying which sociodemographic and health groups engage the least with AQ information and adopt the fewest ERBs. Additionally, Chapter V builds on discussions throughout the literature surrounding digital inequality and explores whether patterns of disproportionate access observed in other contexts are mirrored throughout AQ channel access. These final two Chapters aim to uncover whether AQ channels may “shape or magnify biases in judgement or processes of societal discrimination” occurring in the form of ERBs being selectively adopted by different groups in a population (Neff et al, 2017:90). This ties in with the overarching, title question: who cares

about the air? Or more specifically, who is engaged with information and technology surrounding air quality and is most likely to experience exposure reducing benefits.

Finally, the trend towards personalised information delivery made possible through AQ channels contradicts traditional, centralized air pollution data production for regulatory and governance purposes that persist today throughout the UK. This raises important questions as to where AQ channels fall within the broader scope of air quality governance, whether the onus is being placed on individuals to safeguard against the impacts of air pollution, and how engagement with AQ channels may be socio-demographically stratifying knowledge production surrounding air quality and patterns of exposure reduction.

3. Ethics

Social science scholars of data caution against the non-critical reaggregation of big data and the “operationalization of citizens as nodes for data collection” (Pritchard & Gabrys, 2016); (Kitchin, 2014). The ethics surrounding the employment of computational methods and digital trace data demand an augmented commitment to consent and transparency (Neff et al., 2017). It also warrants the inclusion of the voices of the subjects of the research to help frame the study design and variables of interest. To achieve this, the study is designed to be flexible by allowing survey respondents to include additional fields, specifically pertaining from open ended responses about patterns of AQ channel use, and types of ERBs adopted. While this study is not “participatory” in the sense established across literature on “community modelling” by Whatmore, Landström and others, it aims to adopt a similar spirit by establishing these opportunities for survey respondents to be more than just “respondents,” by enabling them to guide the parameters for analysis and model development (Whatmore & Landström, 2011).

To ensure data security, the analysis of the user analytics trace data will be conducted offline and unique identifiers will be kept on a password protected hard drive at the University. Data will be aggregated at the LSOA or borough level in any presentations or publications. For more details on ethical considerations and data security, please reference the DREC approved CUREC form Ref. SOC_R2_001_C1A_20_07.

CHAPTER TWO

‘Real-time’ Air Quality (AQ) channels: A technology review of emerging environmental alert systems¹

Abstract

Poor air quality is a pressing global challenge contributing to adverse health impacts around the world. In the past decade, there has been a rapid proliferation of air quality information delivered via sensors, apps, websites, or other media channels in near real-time and at increasingly localized geographic scales. This paper explores the growing emphasis on self-monitoring and digital platforms to supply informational interventions for reducing pollution exposures and improving health outcomes at the individual level. It presents a technological case study that characterizes emerging air quality information communication mechanisms, or “AQ channels”, while drawing upon examples throughout the literature. The questions are posed: which air quality channels are “freely” available to individuals in London, UK, and when and where are they accessed? Digital trace data and metadata associated with 54 air quality channels are synthesized narratively and graphically. Results reveal air quality channels derive air pollution estimates using common data sources, display disparate messaging, adopt variable geographic scales for reporting “readings” and maintain psychosocial barriers to access and adoption of exposure-reducing behaviors. The results also point to a clear association between the publication of a high-profile news article about air pollution and increased air quality channel access. These findings illuminate a need for greater transparency around how air quality channels generate personalized air pollution exposure estimates and tailor messaging. The paper concludes by calling for air quality channel developers to exercise co-creative methods that can support sustainable, democratic data and knowledge production around air quality, while critically approaching disproportionate patterns of both pollution and information exposure.

1. Introduction

This paper characterizes the landscape and features of a new paradigm of digitally enabled information designed to present air quality conditions in real time at local or individual levels. It introduces the term: *air quality information channels*, or “AQ channel” as a label for proliferating internet-enabled air quality information sources. AQ channels blend personal information like geolocation, age, and presence of pre-existing health conditions, alongside real-time air quality estimates, to provide tailored recommendations for reducing exposure to

¹ A previous version of this Chapter was published as: Schulte, K., 2022. “Real-time” air quality channels: A technology review of emerging environmental alert systems. *Big Data & Society*, 9(1), p.20539517221101346.

pollution (di Bella et al., 2018a). Air pollution causes the equivalent of 28,000 to 36,000 premature deaths in the UK each year, with the burden disproportionately falling on more vulnerable groups throughout the population (PHE, 2018). Research reinforces that AQ channels may reduce burdens of adverse health outcomes via informational interventions which can contribute to widespread adoption of exposure reducing behaviors (ERBs) during high pollution events (D’Antoni et al., 2017; Kelly et al., 2012; Neidell & Kinney, 2010; Rappold et al., 2014). AQ channels and other individual-level digital health interventions become increasingly prevalent, yet limited work so far has systematized these emerging environmental alert systems and this growing digital informational landscape of air pollution. This Chapter addresses this gap and asks: *which AQ channels are freely available to individuals, and when and where are they accessed?*

This paper presents a literature review chronicling the development of the AQ channel innovation and a technology review of a sample of channels available to individuals in London, UK. London was selected based on its standing as a major international city with high population density, consistent evidence of disproportionate air pollution exposures, major health and social inequality, and availability of additional sociodemographic datasets for analysis of patterns of access to AQ channels (Fecht et al., 2015; Rivas et al., 2017). A lack of linked individual-level demographic data connected to the digital analytics data available on platform use of specific AQ channel use limits this paper from generating granular insights around who in a population engages with AQ channels and what motivates such engagement. This gap is addressed more directly in the next Chapters where survey data are used to examine these questions. Instead, it explores uptake of AQ channels through the “diffusion of innovations” theoretical framework proposed by Rogers, while adopting digital trace data as a unit for quantifying broad uptake of AQ channels in London, UK. *Diffusion* is understood here

as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1995:5). This study focuses on AQ channels – a hybrid of air quality information or data and the communication mechanisms by which it diffuses through a population. Existing literature is referenced to show how AQ channels emerged, their characteristics, and how they have “diffused” throughout population groups.

Digital trace data and metadata are units of analysis “produced as a part of social life” throughout interactions with digital technologies (Marres, 2017; Ruppert et al., 2015). They were derived through the technology review process, which included web and app store searches to identify AQ channels accessible to individuals in London at no additional cost (beyond device ownership) and manually harvesting metadata, as well as acquiring additional, more spatial and temporally granular user analytics data from certain AQ channel providers. Questions surrounding what it means for a channel to be truly “free” or “open access”, alongside whether “digital inequality” may be exacerbating existing health and environmental inequalities rather than democratizing protective action against air pollution, are examined in greater detail throughout this paper (Cruz, 2020; Hargittai, 2010). The following sections outline why studying AQ channels is important for understating air pollution inequality, as a function of both access to information and associated downstream exposure reducing practices.

2. Background

2.1 *Origins of AQ channels: pollution monitoring, modelling, and data generation*

AQ channels are technological descendants of historic air pollution monitoring, modelling, and communication mechanisms. Over the 20th century, technologies were standardized to collect policy-relevant data so that governments could build knowledge about air pollution concentrations. This occurred in response to pressures from government authorities for simple,

low cost “robust and reliable” methods to deliver “uniform measurements that could be widely reproduced” (Mosley, 2009). A “metrological regime” was devised, informing the design and production of monitoring instruments for rendering air pollution politically visible and governable (Barry, 2002). The digital revolution drove advances in monitoring practices resulting in increased frequency at which air pollution data was collected and communicated by local authorities to central government². This marked a transition whereby access to air pollution information was extended beyond government actors and made directly available to the public³ (Bickerstaff & Walker, 2001).

Air pollution modelling also expanded access to AQ information during the 20th and 21st centuries. Multi-national and multi-institutional enterprises⁴ that have been in place since the 1970s draw on a variety of land-based and satellite datasets to deliver publicly available data on concentrations for different pollutants at the mesoscale (1-12km²) and at hourly intervals (Simpson et al, 2012). More recently, a method known as “nowcasting” has gained traction. It uses historical data trends for pollution concentrations and weather patterns, among other data sources, to generate statistical, predictive models, or “*nowcast*” air quality conditions in “real-time” (Browning & Collier, 1989). One example of nowcasting is Imperial College London Environmental Research Group’s (ERG) employment of the CMAQ-Urban model to oversee hourly air quality conditions across London at a geographic resolution of 20m², alongside regulatory data gathered across the London Air Quality Network (LAQN). Another trend facilitating access to air pollution information are application programming interfaces (APIs).

² Channels delivered information twice daily through free telephone and broadcast services CEEFAX and TELETTEXT in 1986, then hourly via the AEA Technology plc www.AEAT.co.uk.netcen website in 1995.

³ The modern Automatic Urban and Rural Network (AURN) was instituted in 1998 in the UK, enabling hourly digitized data transfers and supplying regulatory grade air pollution data (Defra, 2020). The UK’s monitoring network’s current and historic air pollution data are available via Defra data archives (see: <https://uk-air.defra.gov.uk/data/>).

⁴ Examples include the EMEP MSC-W model emerging from the 1979 UN convention on long-range transboundary air pollution, the Community Multi-Scale Air Quality Model (CMAQ) developed by the U.S. Environmental Protection Agency (EPA), Copernicus Atmospheric Monitoring Service (CAMS) by the European Centre for Medium-Range Weather Forecasts (ECMWF), and the Unified Model (AQUUM) deployed by the UK Meteorological Office (Met Office).

APIs enable data to be piped into other applications, ranging from publicly available AQ channels, vehicle displays, and mobile apps developed by companies or large-scale urban planning initiatives (Breezometer, 2021).

Modelling and sensing practices have advanced over the past two decades alongside growing computational capacity, miniaturization, and machine learning, further expanding opportunities for information access (Snyder et al., 2013). In this study, a “sensor” is a lower cost technological instrument that measures multiple pollutants simultaneously (~£50 – 7,000) compared with more expensive regulatory monitors that generate data for specific pollutants at latitude-longitude point locations (Morawska et al., 2018). Commercially available sensors produce air pollution data of variable quality due to a host of factors, including sophistication of instrumentation; quality of temperature and humidity sensors, and measurement averaging times (average number of readings per second, per minute); which pollutants they measure, spatial resolution, lack of adjustment for meteorological conditions and many additional features (Woodall et al., 2017). California’s South Coast Air Quality Monitoring District (SCAQMD) in the USA compiles systematic field and laboratory assessments commercially available sensors’ accuracy, precision, and bias. Assessments are publicly available via Air Quality Sensor Performance Evaluation (AQ-SPEC) web platform (SCAQMD, 2021). The commercialization of air sensors, and how this affects access to air quality information, warrants further investigation.

Regulatory pollution limits vary across countries and underpin what constitutes as legally actionable evidence of air pollution, reinforcing notions of air quality being synonymous with the specified pollutants, monitoring methods, and acceptable concentration thresholds (COMEAP, 2010; Dockery, Pope, Xu, et al., 1993). Evolving mobile sensing technology

continues to disrupt the exposure monitoring and health effects evaluation space, pointing to how data generation practices render pollution a barometric “technology” for evidencing acceptable environmental states and guiding parameters for change (Gabrys, 2020). Furthermore, the World Health Organization (WHO) recently released stricter air pollution concentration guidelines for nitrogen dioxide (NO₂), particulate matter (PM), sulphur dioxide (SO₂), and Ozone (O₃) and NO₂ in 2021 (Global Air Quality Guidelines). While these are guidelines, and not legal mandates, they are based on evidence from the health literature and help serve as a political lever for establishing stricter regulation of air pollution across the UK. This elevates questions about the types of air pollution guidelines and messaging individuals can access via “open” AQ channels, how individuals are encouraged to respond to this information, and whether access is uniform across populations.

2.2 Contemporary AQ Channel characteristics: Messaging & Access

2.2.1 Messaging

This section presents the limited literature surrounding message construction and how it can inform patterns of access to AQ channels and adoption of ERBs. Existing literature focuses on channels tailored for research purposes, as opposed to commercial AQ channels. Examples include an adaptation of Imperial ERG’s CityAir app, U.S. EPA’s Smoke Sense app, AirForU app by University of California Los Angeles, and the University of Tasmania’s AirRater app. Samples of individuals in these studies demonstrated certain biases, with approximately half of participants possessing pre-existing health conditions, and individuals with University degree level education or above, as well as white individuals, being overrepresented in the Smoke Sense and CityAir studies (D’Antoni et al., 2019; Rappold et al., 2019).

Literature identifying characteristics of messaging across non-research AQ channels is limited. The “Air Quality Index” (AQI) is a common format for delivering targeted messages encouraging ERBs (D’Antoni et al., 2019). An AQI is an informational tool for providing health messaging according to specific pollution thresholds (Ruggieri & Plaia, 2012). AQIs are calculated according to the highest registered concentration of key pollutants over a set geographic area and vary by reporting organization or state institution, as do threshold levels, or color-coded “bands” (see Figure 1) (Woodall et al., 2017a). ERBs also vary across AQIs, with the most common examples including the U.S. EPA’s AQI, the UK’s Daily AQI (DAQI) the European Union’s Common AQI (CAQI).

Air Pollution Banding	Value	Accompanying health messages for at-risk individuals*	Accompanying health messages for the general population
Low	1-3	Enjoy your usual outdoor activities.	Enjoy your usual outdoor activities.
Moderate	4-6	Adults and children with lung problems, and adults with heart problems, who experience symptoms, should consider reducing strenuous physical activity, particularly outdoors.	Enjoy your usual outdoor activities.
High	7-9	Adults and children with lung problems, and adults with heart problems, should reduce strenuous physical exertion, particularly outdoors, and particularly if they experience symptoms. People with asthma may find they need to use their reliever inhaler more often. Older people should also reduce physical exertion.	Anyone experiencing discomfort such as sore eyes, cough or sore throat should consider reducing activity, particularly outdoors.
Very High	10	Adults and children with lung problems, adults with heart problems, and older people, should avoid strenuous physical activity. People with asthma may find they need to use their reliever inhaler more often.	Reduce physical exertion, particularly outdoors, especially if you experience symptoms such as cough or sore throat.

Daily AQI Color	Levels of Concern	Values of Index	Description of Air Quality
Green	Good	0 to 50	Air quality is satisfactory, and air pollution poses little or no risk.
Yellow	Moderate	51 to 100	Air quality is acceptable. However, there may be a risk for some people, particularly those who are unusually sensitive to air pollution.
Orange	Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is less likely to be affected.
Red	Unhealthy	151 to 200	Some members of the general public may experience health effects; members of sensitive groups may experience more serious health effects.
Purple	Very Unhealthy	201 to 300	Health alert: The risk of health effects is increased for everyone.
Maroon	Hazardous	301 and higher	Health warning of emergency conditions: everyone is more likely to be affected.

Figure 1. Differing formats of AQI delivered by UK Defra and U.S. EPA

Language across the main Defra webpage with DAQI messaging, which is intended to serve as a short-term informational intervention, identifies “at-risk” individuals as adults or children with heart or lung problems (COMEAP). This “at-risk” classification doesn’t incorporate mounting evidence of socio-demographic and spatiotemporal factors contributing to increased vulnerability including place of residence, work, or school; characteristics of commute; socioeconomic status, race, and ethnicity, or pregnancy (Kim & Kwan, 2021; Koman et al., 2018). The tendency towards standardization at the expense of incorporating situated context throughout air quality messaging has been addressed across science, technology and society

(STS) and critical social theory research (Gabrys et al., 2016; Haraway, 1988), while challenging whether predominantly scientific, sterile representations of air quality are most effective at making air pollution visible or actionable from a personal, non-technical standpoint (Barry, 2002; Whatmore, 2006; Whatmore & Landström, 2011). Furthermore, it raises questions about how this affects access to and engagement with AQ channels, and whether certain population groups are alienated, such as individuals with disabilities or low to no internet access.

The focus of AQ channel experiments on “at-risk” individuals prompts consideration of the relationship between definition of risk, risk perception, and AQ channel uptake. Evidence points to “risk perception” being a function of local, situated knowledge, involving daily experiences, sensations, and social-cultural factors (Bickerstaff & Walker, 2001; Brody et al., 2008; D’Antoni et al., 2019; Elliott et al., 1999). The D’Antoni study, Smoke Sense, and AirForU confirmed increased levels of engagement with both ERBs and the AQ channel by individuals with pre-existing conditions, particularly after experiencing intrinsic, physical symptoms (Delmas & Kohli, 2019; Johnston et al., 2018; Rappold et al., 2019). Extrinsic factors, such as notifications or messages, and environmental incidents like high pollution wildfire events have also been shown to increase AQ channel access (Johnston et al., 2018; Rappold et al., 2019). This helps focus attention towards how AQ channel messaging conceptualizes risk, and how the interplay of intrinsic and extrinsic factors informs who accesses AQ channels.

Each AQ channel reviewed delivered pre-crafted messages, mirroring existing models of AQI information delivery. The AQI is designed according to the “deficit model”, that is, the notion that providing more, “factual” information, will eliminate scepticism or translate into adoption

of certain pro-environmental behaviors (Hart & Nisbet, 2012b). This model is commonplace across environmental science and health communication endeavors. It is critiqued, particularly within the context of climate change, for misrepresenting the complex nature of knowledge production and behavior change (Moser & Dilling, 2009). The theory of co-production reinforces how knowledge is a product of interactions across society, science, and technology (Jasanoff, 2004; Whatmore, 2006). Reviewing AQ channels can support understandings how individuals interact with these infrastructures, and how this informs the co-production of information and knowledge about air quality.

Participatory approaches such as “citizen science” that involve non-technical or “lay” individuals through experimental practice have been proposed to further democratize knowledge, information and data-generation surrounding environmental challenges (Lave, 2015). Examples of endeavours across London demonstrating participatory elements include the Citizen Sense “Dust Box”, the SmartCitizen sensing kit, and the second phase of the Breathe London project. These examples, along with several others identifying as participatory, “citizen science” or “do-it-yourself” (DIY) projects, involve the design and deployment personal sensors to co-create air pollution data (Pritchard et al., 2018). Participation and knowledge co-creation occurs in varying degrees, and certain projects may only involve non-technical participants at specific, convenient stages of the research process to maintain control over how results are produced and communicated (Lezaun & Soneryd, 2007). While some of the participatory sensing projects reviewed here also deliver a publicly accessible AQ channel, not all of them provide widespread, real or near-real time access to air pollution data, therefore falling outside of the scope of this study. This study proposes a framework focusing on patterns of access to AQ information, how this affects diverse participation and co-production of knowledge about air pollution, and ultimately how this translates into ERBs.

2.2.2 Access

This section explores mechanisms contributing to AQ channel access, paying close attention to the notion of “digital or informational inequality”. Spaces where individuals interact with AQ channels include websites, smartphone apps, public digital “billboard” displays, television, newspapers, and radio broadcasts across cities and countries. For example, in addition to digitally available sources, the U.S. EPA’s AQ channel is shared via local weather channels, radio, and newspapers (D’Antoni et al., 2017). The UK DAQI is communicated on television or radio when there is an “exceptional” pollution event. When pollution concentrations exceed the moderate DAQI range, certain cities including London will broadcast readings and health messaging across Transport for London (TfL) digital displays located at bus and “Tube” stops (COMEAP, 2010). Broadly speaking, AQ channels are delivered by government authorities, academic groups, or commercial enterprises selling personal pollution sensors. Increasingly, air pollution information is communicated via social media platforms. Aside from Twitter, communication of air quality information via social media, as well as “smart home” devices such as Amazon’s “Alexa” or “Nest”, are beyond the scope of this study.

The most recent UK Office of National Statistics (ONS) survey on internet and computer use (2014) showed 94% of London residents have access to the internet at home and 74% have internet-connected mobile devices (London Datastore, 2021). A 2019 Global Action Plan (GAP) survey found that when asked where individuals would like to find information about air pollution, “the internet” was ranked highest, followed by TV and radio adverts (n=262) (Global Action Plan, 2019). The following paragraphs review factors contributing to unequal access to, and subsequent uptake of internet-based innovations, along with how studying AQ channels can supply important insights into processes of digitally mediated exposure inequality.

Notions of digital inequality, or the “digital divide” are intertwined with systemic sociodemographic inequalities. Three levels have been identified across the literature: discrepancies in “access to and quality of Internet”; digital literacy or skills; and the different manners of engaging with digital technologies, including privacy concerns (Bol et al., 2018; Dimaggio & Hargittai, 2001; Hargittai, 2010; Scheerder et al., 2017; van Deursen & Helsper, 2015; van Deursen & van Dijk, 2014; van Dijk & Hacker, 2003). In their work associated with the internet-based encyclopaedia, Wikipedia, Shaw and Hargittai approach online participation in terms of a “pipeline” by modelling awareness and behavior conducive with becoming involved in the production and proliferation of information (Figure 2) (Shaw & Hargittai, 2018).

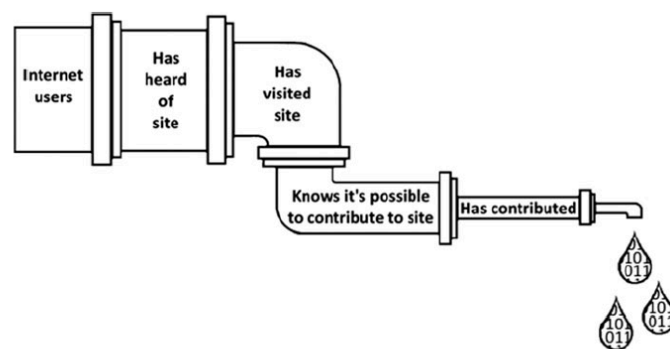


Figure 2. “Pipeline of online participation” (Shaw and Hargittai, 2018).

Like Wikipedia, most freely available AQ channels require internet access and a level of participation or engagement for individuals to arrive at that final stage of “implementation” or “confirmation” described in *diffusion of innovations* theory. Rogers defines a model for the “innovation-decision process” that traces individuals through the process of learning about an innovation and whether they ultimately implement and reinforce ideas or practices put forth by said innovation in their lives (Rogers, 2003: 169). Acknowledging digital and information inequalities are likely to exist, it is necessary to consider how AQ channels may “shape or

magnify biases in judgement or processes of societal discrimination occurring in the form of ERBs being selectively adopted by groups in a population (Neff et al, 2017:90).

Alongside proliferating internet-connected technologies, there has been a deluge of big “digital trace” data (Marres, 2017). Digital trace data is being repurposed across the fields of communication studies, demography, and computational social sciences to further research on previously unobservable processes and associated socio-demographic patterns (Alburez-Gutierrez et al., 2019). This form of “transactional” data has yet to be considered as an approach towards empirical research aimed at understanding who interacts with AQ channels, what motivates such interactions, and whether exposures can be reduced. The different ways individuals can interact with AQ channel infrastructure has yet to be characterized in the literature, reinforcing a gap in understanding around whether access and engagement are continuous and consistent over time, or intermittent, and how this might contribute to ERBs. While AQ channel trace data presents a promising opportunity to examine artefacts of patterns of interaction with air quality information, key ethical and interpretive issues arise that warrant careful methodological consideration (Amoore, 2011; Kitchin, 2014; Gina Neff et al., 2017).

Bowker stresses “Raw data is both an oxymoron and a bad idea; to the contrary, data should be cooked with care,” signalling research involving digital trace data warrants a critical and ethical undertaking (Bowker, 2005: 184). This advice is retained alongside Roger’s concept of “selective exposure”, whereby digital trace data associated with AQ channel uptake is likely to be biased to reflect the patterns and characteristics of “early adopters” of the innovation (Rogers, 1995). These critical insights are carried throughout this study’s methodology as metadata and user analytics digital trace data are leveraged as units of analysis for examining how technological specifications, messaging characteristics, and modes of access contribute to AQ channel uptake patterns across London.

3. Methods

3.1 Overview

Addressing the first research question, this paper presents a technology review and structured content analysis to identify and characterize existing AQ channels “freely” available to individuals in London. To answer the second research question and elucidate patterns of where and when channels are accessed in London, user analytics “digital trace” data is examined from three AQ channel examples associated with the Mayor of London’s office, including London Air, AirText and the Breathe London pilot. In the context of this study, with attention to diffusion of innovation theoretical principles, user analytics data serves as a unit to help examine uptake of the AQ channel innovation. This represents a preliminary investigation of whether there are discernible patterns of access to AQ channels at the population level. The goal is to establish an empirical foundation for further research into what motivates or hinders patterns of access and engagement with AQ channels across different sociodemographic groups, while acknowledging certain groups may be more or less likely to reap potential health benefits associated with specific patterns of access.

3.2 Systematic technology review

As demonstrated in the literature review, research discussing AQ channels is sparse due to the novelty of the innovation. This, in addition to a lack of clearly reported, publicly available information on AQ channels patterns of access along with device availability, drove a technology review leveraging online research methods (ORMs). ORM included constructing search terms to conduct systematic web searches using the Google search engine, as well as across the Apple app and Android Google Play stores. Traditional bibliographic database searches were inappropriate given the novelty of this innovation. The search protocol is described in Appendix 1.1 to support “reproducibility and transparency” (Briscoe, 2015).

3.3 *Data selection*

The dataset was generated through a combination of web and app store searches in February 2021 according to a clear set of inclusion criteria. Searches included the terms “air quality” or “air pollution,” “forecast” or “nowcast,” and “London UK.” For a complete list of search term permutations see Appendix 1.1. Browser IP addresses were manually set to a London location. Results from the search were extrapolated from the first three pages of Google searches for each search term. All AQ apps resulting from the searches were initially retained. The resulting list was refined according to specific criteria to best reflect prominent AQ channels available to individuals in London. These criteria were selected in response to this paper’s core research questions, while also aligning with characteristics of AQ channels demonstrating evidence of reducing exposure to air pollution (see Johnson et al, 2015, D’Antoni et al, 2019 and (Hano, Prince, et al., 2020).

To be included in the final dataset, channels had to be accessible without additional charge, aside device ownership, in alignment with this work’s commitment to understand uptake barriers associated with this informational innovation. Channels must provide pollution “readings” at a minimum daily frequency to remain within the scope of the near “real-time” feature of the innovation. Furthermore, channels must possess a user interface displaying an AQ reading in line with the descriptions outlined in the literature review. To maintain focus on access patterns of individuals in London and conduct additional demographic analyzes with the available data, channels had to supply ambient readings at the local authority level or below. Metadata was gathered to aid the refining process. Each metadata field was chosen to support insights into the novelty, popularity, messaging characteristics, and technological approach for generating pollution estimates adopted across each AQ channel (Figure 3).

1. *General information*
 - a. Channel name
 - b. Provider/developer
 - c. URL
 - d. Total downloads since inception
 - e. Launch date
 - f. Latest update date
2. *Air pollution 'reading' technical specifications*
 - a. Method of pollution estimate
 - a. Nowcast (modelled), monitor or sensor (measured)
 - b. Pollutants reported
 - c. Model used for forecasting/nowcasting
 - d. Geographic resolution
3. *Messaging*
 1. Frequency of reading
 2. Forecast provided (yes/no)
 3. Is it tailorable (yes/no)
 4. ERBs (exposure reducing behavioural recommendations)
4. *Accessibility features*
 1. Platform of access (website, app, email, TV, radio, newspaper)
 2. Sensor (yes/no)
 3. API (yes/no)
 4. Push/automatic notification option (yes/no)

Figure 3. AQ channel metadata collection criteria

The resulting list catalogued AQ channels in the order of highest to lowest access or downloads according to user analytics data obtained from the channel provider or via Google Play store metadata. The range was between $\geq 100,000,000$ and 1. Channels in the upper third portion, as well as channels specifically catering to London, were retained. Channels for which the search was unable to return a figure indicative of volume of access or downloads were retained only if they specified a connection with the city of London. AQ channels in the final dataset were examined in detail and manually mined for metadata to populate each of the fields listed in Figure 3 with numerical or categorical data where possible. For the three channels involved in the in-depth analysis, additional metadata was gathered to help respond to key research questions on patterns of where and when individuals in access AQ channels. This supported the development of principle summary measures including time series graphs and linear regression modelling.

For the in-depth analysis of patterns of access expressed across three sample AQ channels, AirTEXT provided anonymized datasets on subscribers to the service, and London Air and the Breathe London pilot exported data in csv file format from the Google Analytics platform from 1 July 2019 through 1 December 2020. This date range represents the entire period during which the Breathe London pilot was operational and the decision was made to examine access to the London Air web platform during the analogous date range for comparability. AirTEXT data represents the entire time the channel was operational. Data were selected based on their availability, status as official AQ channels provided in partnership with the London Mayor's office, and the fine-grained temporal resolution at which the data is recorded.

3.4 *Methods of Analysis*

A structured content analysis (SCA) was conducted to examine characteristics expressed across the final AQ channel dataset. SCA supports the distillation of key technological features to help group examples of an innovation into categories (Elo & Kyngäs, 2008). Results from the manual metadata mining exercise were recorded in labelled columns associated with each specific AQ channel. Metadata was used to generate summary statistics for year of channel launch, total downloads, mechanism for generating pollution “reading”, and “messaging” features for the entire dataset.

Boroughs and outer postcode areas showing highest and lowest access across the AirTEXT channel was examined further. Additional datasets including 2018 London population estimates, 2019 Index of multiple deprivation and most recent annual mean air pollution estimates from 2016 were obtained via the London Datastore. These data, along with user analytics datasets, were combined with shapefiles obtained from the ShareGeo open repository to generate insight into patterns of access alongside demographic factors (PM_{2.5}, PM₁₀, and NO₂) at the borough level using ggplot2 3.3.2 and cowplot 1.1.0 in R Studio 1.3.959. A linear

model was generated using AirTEXT subscriber data to examine the relationship with mean annual NO₂ pollution levels at the outer postcode level. It included coefficients for usual resident population, average income, index of multiple deprivation and the interaction between mean annual NO₂ concentration and usual resident population, averaged across the outer postcode level.

4. Results

4.1 Summary

The systematic technology review resulted in a dataset containing 54 AQ channels (Table 1), refined from a total of 274 (Figure 4). This section presents details about the resulting channels in terms of respective launch dates, platforms of information delivery (website, app, text message, etc.), technical means for generating air pollution estimates or “readings”, messaging and accessibility characteristics, and volume and patterns of access. The final section on volume and patterns of access focuses on the three AQ channels for which user analytics datasets were obtained. These results help build a picture of openly available, real-time AQ information, along with groups most likely to access with such information and experience ERBs.

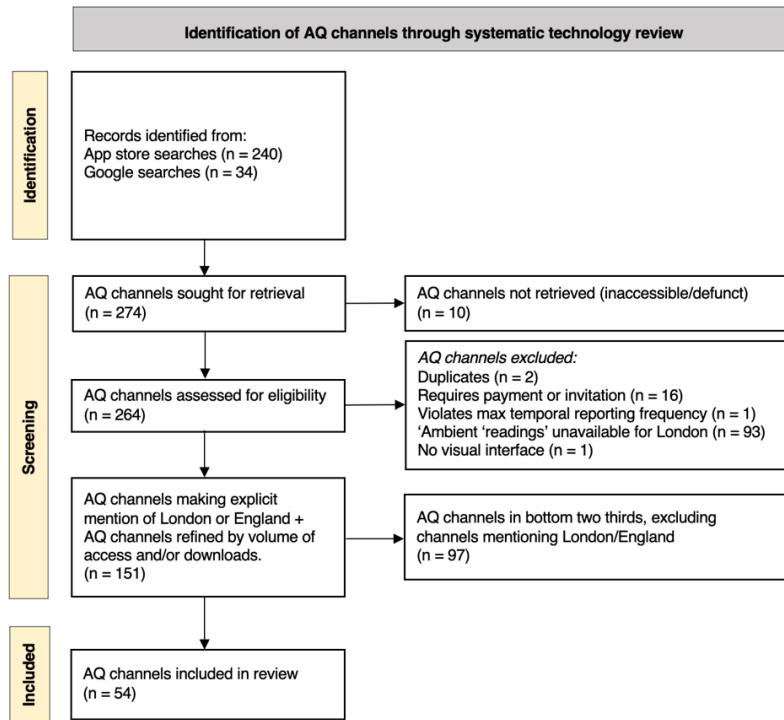


Figure 4. PRISMA flow diagram of AQ channel identification, screening, and inclusion.

4.2 AQ Channel Platform Specifications

The resulting 54 AQ channels were launched between 1995 and 2020. The year presented here indicates when the first platform was launched, or when AQ information was first added to an existing service or platform.

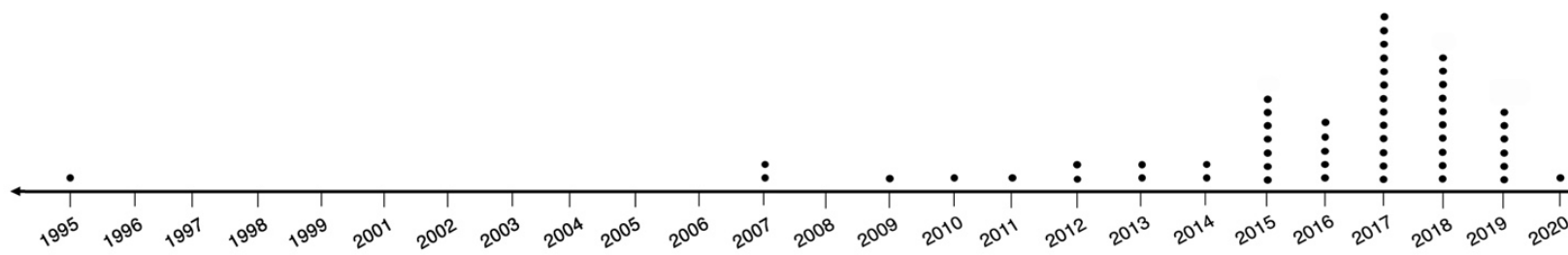


Figure 5. Launch years for 54 resulting AQ channels.

Table 1. Descriptive characteristics of resulting AQ channels (n=54).

#	Channel Name	Channel & Data Provider(s)	Launch/inclusion of AQ info	Worldwide downloads/visits since platform creation (user analytics OR Google Play Store) *in 2019	Frequency of reading ^not disclosed	Pollution Forecast Available?	Forecast Resolution ^not disclosed	Pollutants reported	Web App ?	Mobile App?	API?	Paired personal sensor?
1	Accuweather	Plume Labs	2020	≥100000000	Hourly		1x1km	AQI, O3, PM2.5, PM10, NO2, SO2, CO	X	X	X	
2	Air Pollution	Weblim	2017	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
3	Air pollution around you	Urbanandroid, WAQI	2018	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
4	Air Pollution Check	evolution technologies	2017	≥50000	Hourly		Point	AQI, PM10, PM2.5, SO2, NO2, O3		X		
5	Air quality	FFZ	2018	≥100000	Hourly	X	Point	AQI, O3, PM2.5, PM10, NO2, SO2, CO, Benzene		X		
6	Air Quality Checker	YEAHH	2017	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
7	Air Quality England	Ricardo E&E	2011	15410	Hourly	X	12 x 12km	AQI, PM10, NO2, NO, NOx	X			
8	Air Quality Index - Ambee	Ambee	2019	≥50000	Hourly		^	AQI, PM2.5, NO2		X	X	X
9	Air Quality Index - Real time AQI	App aspect	2019	≥100000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
10	Air Quality Index by TheVillageGuy	TheVillageGuy	2019	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
11	Air quality index near me	Appstronaut Studios, AirVisual	2017	≥50000	Hourly	X	^	AQI, PM10, PM2.5, NO2, O3		X		
12	Air Quality meter	Gaia consulting	2017	≥10000	Instantaneous		Point	PM10		X		
13	Air quality near me	labmatic, WAQI	2018	≥10000	Hourly	X	Point	PM2.5, PM10, NO2, O3		X		
14	AirCare	Gorjan Jovanovski, PurpleAir	2015	≥100000	Hourly		Point	AQI, PM10, PM2.5	X	X		
15	Airlief	Luftdaten, WAQI, SYNGEOS, Sofia Air, Smog, OpenAQ	2018	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
16	Airly	Airly sp. z o.o., PurpleAir, Defra	2017	≥100000	Hourly	X	Point	AQI, PM10, PM2.5, NO2, NO	X	X	X	X
17	AirMatters	Purple Air, Luftdaten, UK Air, Pollen Info, Phillips, Kaiterra	2013	≥100000	Hourly		Point	AQI, PM10, PM2.5, NO2	X	X		X
18	airTEXT	Cambridge Environmental Monitoring Group	2007	16097	Daily	X	7 x 7m	AQI	X			
19	Airveda	AQICN (WAQI)	2016	≥50000	Hourly		Point	AQI, PM2.5, SO2, NO2	X	X		X
20	AirVisual	IQ Air	2015	≥5000000	Hourly	X	^	AQI, PM10, PM2.5, NO2, O3	X	X	X	X
21	Airy	Hyung-Taek Lim	2017	≥100000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
22	BBC Weather	MetOffice	2013	≥10000000	Hourly	X	10 x 10km	AQI	X	X		
23	Breathe London Pilot	EDF, Cambridge Environmental Monitoring Group	2018	70728	Hourly		Point	PM2.5, NO2	X		X	
24	Breezometer	Breezometer	2014	≥100000000	Hourly	X	5 x 5m	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X	X	
25	CityAir	Imperial College London ERG, City of London	2014	≥5000	Hourly	X	20 x 20m	AQI, PM10, PM2.5, NO2, O3		X		
26	Clean Air Hub by Global Action Plan	LondonAir	2019	94000	Hourly		Point	AQI, PM10, NO2	X			
27	CleanSpace - Air Pollution App	Drayson Technologies Ltd., Imperial ERG, Sustrans, Earthwatch	2015	≥10000	Hourly	X	20 x 20m	CO		X		X
28	ClimaCell - Weather Assistant	ClimaCell	2019	≥500000	Hourly	X	^	AQI	X	X	X	
29	Ealing Air	Imperial College London ERG	2009	12165	Hourly	X	Point & 20 x 20m	AQI, PM10, NO2	X			
30	eWeather HDF	Elecont software	2018	≥100000	Hourly		12 x 12km	AQI, PM2.5, PM10, NO2, SO2, CO, NO, O3		X		
31	Geco air : air quality and mobility	IFP Energies Nouvelles	2017	≥10000	Hourly		Regional	PM2.5, O3, NO2		X		
32	Lewisham Air	Imperial College London ERG, Lewisham Council	2018	≥500	Hourly	X	20 x 20m	AQI, PM10, PM2.5, NO2, O3		X		
33	Live Air by Kaiterra	Kaiterra Global	2016	≥10000	Hourly	X	^	AQI, PM2.5, PM10, NO2, O3, SO2, NO		X	X	X
34	Londair - Pollution in London	InnerCircle Software	2017	≥100	Daily	X	20 x 20m	AQI, PM10, PM2.5, SO2, NO2, O3		X		
35	LondonAir	Imperial College London ERG, Mayor of London	2010	5068634	Hourly	X	20 x 20m	AQI, PM10, PM2.5, NO2, O3	X	X	X	
36	Met Office	UK Air (Defra)	2016	≥1000000	Hourly	X	10 x 10km	AQI	X	X		
37	Meteoblue	University of Basel, Meteoblue	2018	≥1000000	Hourly	X	12 x 12km	AQI, PM10, PM2.5, SO2, NO2, O3	X			
38	OpenAQ	UK Air (Defra), Purple Air	2015	484*	Hourly		Point	PM2.5, PM10, NO2, SO2, CO, O3, BC	X		X	
39	Plume Labs: Air Quality App	Plume Labs	2015	≥100000	Hourly	X	1x1km	AQI, PM2.5, PM10, NO2, O3	X	X	X	X
40	Purple Air	Purple Air, LLC	2016	≥1000000	2-min		Point	PM2.5, PM10	X		X	
41	Sensio Air	WLAB	2018	≥10000	^	X	^	AQI, PM10, PM2.5, NO2, O3		X	X	
42	Sh**t!l Smoke	Amaury M, Marcelo S. Coelho, WAQI, OpenAQ	2018	≥50000	Hourly		Point	PM2.5, PM10, NO2		X		
43	Smog Alert	Kacper Dziubek	2017	≥50000	^		Point	PM2.5, PM10, NO2, SO2, O3		X		
44	Smog Map	cgKim	2019	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, O3		X		
45	The Weather Network	UK Air (Defra)	2015	≥100000	Hourly	X	10 x 10km	AQI	X			
46	Today Weather - Widget & Alert	Tho Tran	2017	≥1000000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
47	Transport for London	LondonAir	2016	47177*	Hourly	X	Regional	AQI	X		X	
48	UBreathe	Ricardo E&E, UK Air (Defra)	2012	≥50000	Hourly	X	10 x 10km	AQI		X		
49	UK Air (formerly AEAT)	Ricardo E&E, Defra	1995	83120	Hourly	X	10 x 10km	AQI	X		X	
50	UKAir	Envitech LTD	2015	≥100	Hourly		Point	AQI, PM2.5, PM10, NO2, O3, SO2	X	X		
51	Weather	The Weather Channel, IBM, Copernicus	2017	≥100000000	Hourly		5 x 5m	AQI	X	X		
52	WeatherBug	Breezometer	2012	≥10000000	Hourly	X	5 x 5m	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X		
53	World AQI	jp2n, Defra, Imperial ERG, uradmonitors, insdio	2007	≥500000	Hourly	X	Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X	X	X
54	Wunderground	The Weather Channel, IBM, Copernicus, PurpleAir	2017	≥5000000	Hourly	X	12 x 12km	AQI, PM2.5, PM10, NO2, SO2, CO, O3	X	X		X

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2	Air Pollution	Weblim	2017	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
3	Air pollution around you	Urbanandroid, WAQI	2018	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
4	Air Pollution Check	evolution technologies	2017	≥50000	Hourly		Point	AQI, PM10, PM2.5, SO2, NO2, O3		X		
5	Air quality	FFZ	2018	≥100000	Hourly	X	Point	AQI, O3, PM2.5, PM10, NO2, SO2, CO, Benzene		X		
6	Air Quality Checker	YEAHH	2017	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
7	Air Quality England	Ricardo E&E	2011	15410	Hourly	X	12 x 12km	AQI, PM10, NO2, NO, Nox	X			
8	Air Quality Index - Ambee	Ambee	2019	≥50000	Hourly		^	AQI, PM2.5, NO2		X	X	X
9	Air Quality Index - Real time AQI	App aspect	2019	≥100000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
10	Air Quality Index by TheVillageGuy	TheVillageGuy	2019	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
11	Air quality index near me	Appstronaut Studios, AirVisual	2017	≥50000	Hourly	X	^	AQI, PM10, PM2.5, NO2, O3		X		
12	Air Quality meter	Gaia consulting	2017	≥10000	Instantaneous		Point	PM10		X		
13	Air quality near me	labmatic, WAQI	2018	≥10000	Hourly	X	Point	PM2.5, PM10, NO2, O3		X		
14	AirCare	Gorjan Jovanovski, PurpleAir	2015	≥100000	Hourly		Point	AQI, PM10, PM2.5	X	X		X
15	Airlief	Luftdaten, WAQI, SYNGEOS, Sofia Air, Smog, OpenAQ	2018	≥10000	Hourly		Point	AQI, PM2.5, PM10, NO2		X		
16	Airly	Airly sp. z o.o., PurpleAir, Defra	2017	≥100000	Hourly	X	Point	AQI, PM10, PM2.5, NO2, NO	X	X	X	X
17	AirMatters	Purple Air, Luftdaten, UK Air, Pollen Info, Phillips, Kaiterra	2013	≥100000	Hourly		Point	AQI, PM10, PM2.5, NO2	X	X		X
18	airTEXT	Cambridge Environmental Monitoring Group	2007	16097	Daily	X	7 x 7m	AQI	X			
19	Airveda	AQICN (WAQI)	2016	≥50000	Hourly		Point	AQI, PM2.5, SO2, NO2	X	X		X
20	AirVisual	IQ Air	2015	≥5000000	Hourly	X	^	AQI, PM10, PM2.5, NO2, O3	X	X	X	X
21	Airy	Hyung-Taek Lim	2017	≥100000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
22	BBC Weather	MetOffice	2013	≥10000000	Hourly	X	10 x 10km	AQI	X	X		
23	Breathe London Pilot	EDF, Cambridge Environmental Monitoring Group	2018	70728	Hourly		Point	PM2.5, NO2	X		X	
24	Breezometer	Breezometer	2014	≥100000000	Hourly	X	5 x 5m	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X	X	
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28	ClimaCell - Weather Assistant	ClimaCell	2019	≥500000	Hourly	X	^	AQI	X	X	X	
29	Ealing Air	Imperial College London ERG	2009	12165	Hourly	X	Point & 20 x 20m	AQI, PM10, NO2	X			
30	eWeather HDF	Elecont software	2018	≥1000000	Hourly		12 x 12km	AQI, PM2.5, PM10, NO2, SO2, CO, NO, O3		X		
31	Geco air : air quality and mobility	IFP Energies Nouvelles	2017	≥10000	Hourly		Regional	PM2.5, O3, NO2		X		
32	Lewisham Air	Imperial College London ERG, Lewisham Council	2018	≥500	Hourly	X	20 x 20m	AQI, PM10, PM2.5, NO2, O3		X		
33	Live Air by Kaiterra	Kaiterra Global	2016	≥10000	Hourly	X	^	AQI, PM2.5, PM10, NO2, O3, SO2, NO		X	X	X
34	Londair - Pollution in London	InnerCircle Software	2017	≥100	Daily	X	20 x 20m	AQI, PM10, PM2.5, SO2, NO2, O3		X		
35	LondonAir	Imperial College London ERG, Mayor of London	2010	5068634	Hourly	X	20 x 20m	AQI, PM10, PM2.5, NO2, O3	X	X	X	
36	Met Office	UK Air (Defra)	2016	≥1000000	Hourly	X	10 x 10km	AQI	X	X		
37	Meteoblue	University of Basel, Meteoblue	2018	≥1000000	Hourly	X	12 x 12km	AQI, PM10, PM2.5, SO2, NO2, O3	X			
38	OpenAQ	UK Air (Defra), Purple Air	2015	484*	Hourly		Point	PM2.5, PM10, NO2, SO2, CO, O3, BC	X		X	
39	Plume Labs: Air Quality App	Plume Labs	2015	≥100000	Hourly	X	1x1km	AQI, PM2.5, PM10, NO2, O3	X	X	X	X
40	Purple Air	Purple Air, LLC	2016	≥1000000	2-min		Point	PM2.5, PM10	X		X	
41	Sensio Air	WLAB	2018	≥10000	^	X	^	AQI, PM10, PM2.5, NO2, O3		X	X	
42	Sh**tl Smoke	Amaury M, Marcelo S. Coelho, WAQI, OpenAQ	2018	≥50000	Hourly		Point	PM2.5, PM10, NO2		X		
43	Smog Alert	Kacper Dziubek	2017	≥50000	^		Point	PM2.5, PM10, NO2, SO2, O3		X		
44	Smog Map	cgKim	2019	≥10000	Hourly		Point	AQI, PM10, PM2.5, NO2, O3		X		
45	The Weather Network	UK Air (Defra)	2015	≥100000	Hourly	X	10 x 10km	AQI	X			
46	Today Weather - Widget & Alert	Tho Tran	2017	≥1000000	Hourly		Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3		X		
47	Transport for London	LondonAir	2016	47177*	Hourly	X	Regional	AQI	X		X	
48	UBreathe	Ricardo E&E, UK Air (Defra)	2012	≥50000	Hourly	X	10 x 10km	AQI		X		
49	UK Air (formerly AEAT)	Ricardo E&E, Defra	1995	83120	Hourly	X	10 x 10km	AQI	X		X	
50	UKAir	Envitech LTD	2015	≥100	Hourly		Point	AQI, PM2.5, PM10, NO2, O3, SO2	X	X		
51	Weather	The Weather Channel, IBM, Copernicus	2017	≥100000000	Hourly		5 x 5m	AQI	X	X		
52	WeatherBug	Breezometer	2012	≥10000000	Hourly	X	5 x 5m	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X		
53	World AQI	jp2n, Defra, Imperial ERG, uradmonitors, insdio	2007	≥500000	Hourly	X	Point	AQI, PM10, PM2.5, NO2, SO2, CO, O3	X	X	X	X
54	Wunderground	The Weather Channel, IBM, Copernicus, PurpleAir	2017	≥5000000	Hourly	X	12 x 12km	AQI, PM2.5, PM10, NO2, SO2, CO, O3	X	X		X

A subset of AQ channels supply their information across multiple platforms, for example via websites, mobile applications (apps), or APIs. Apps were the most common AQ channel platform, followed by web applications, then APIs accessing the channel’s backend database. The least amount of AQ channels shared their readings through Twitter, followed by voice, email, and text messaging. Some of the channels include some platforms that don’t offer AQ information. These platforms weren’t registered in the dataset.

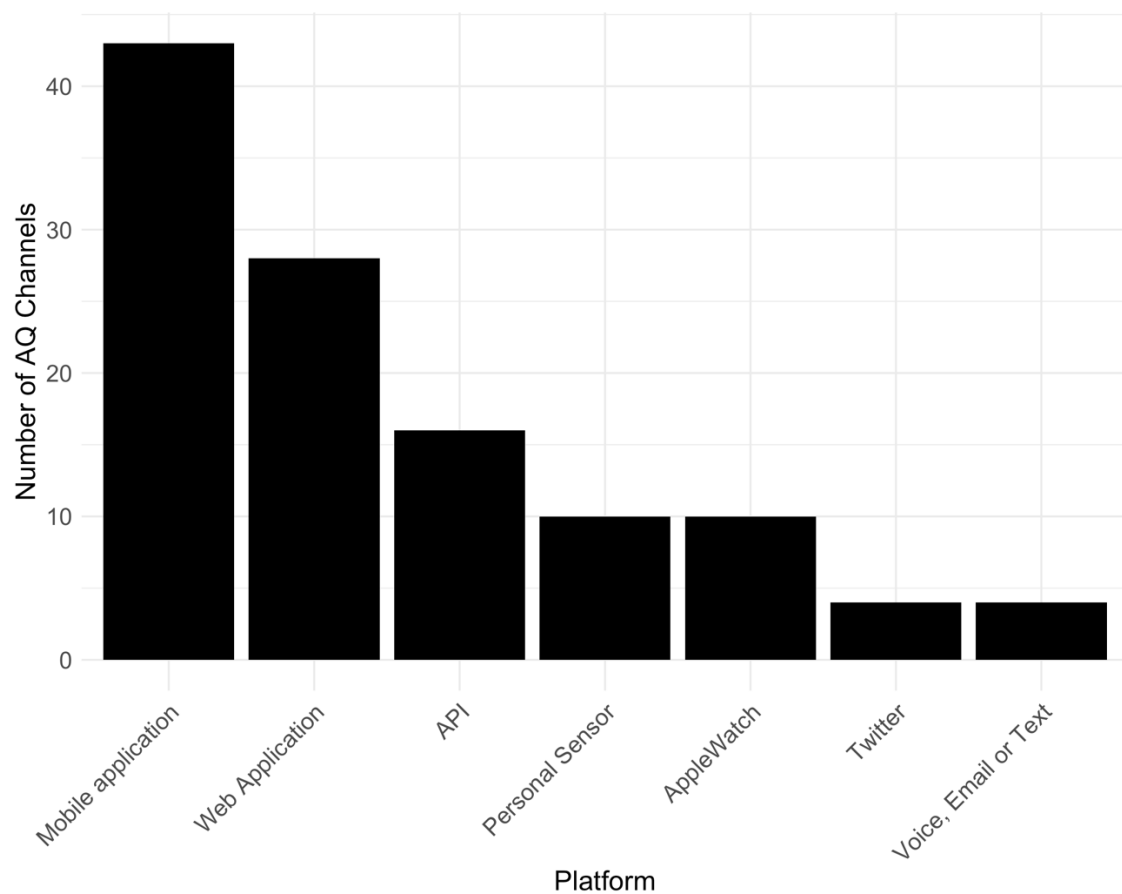


Figure 6. Dominant platforms and technologies communicating AQ information.

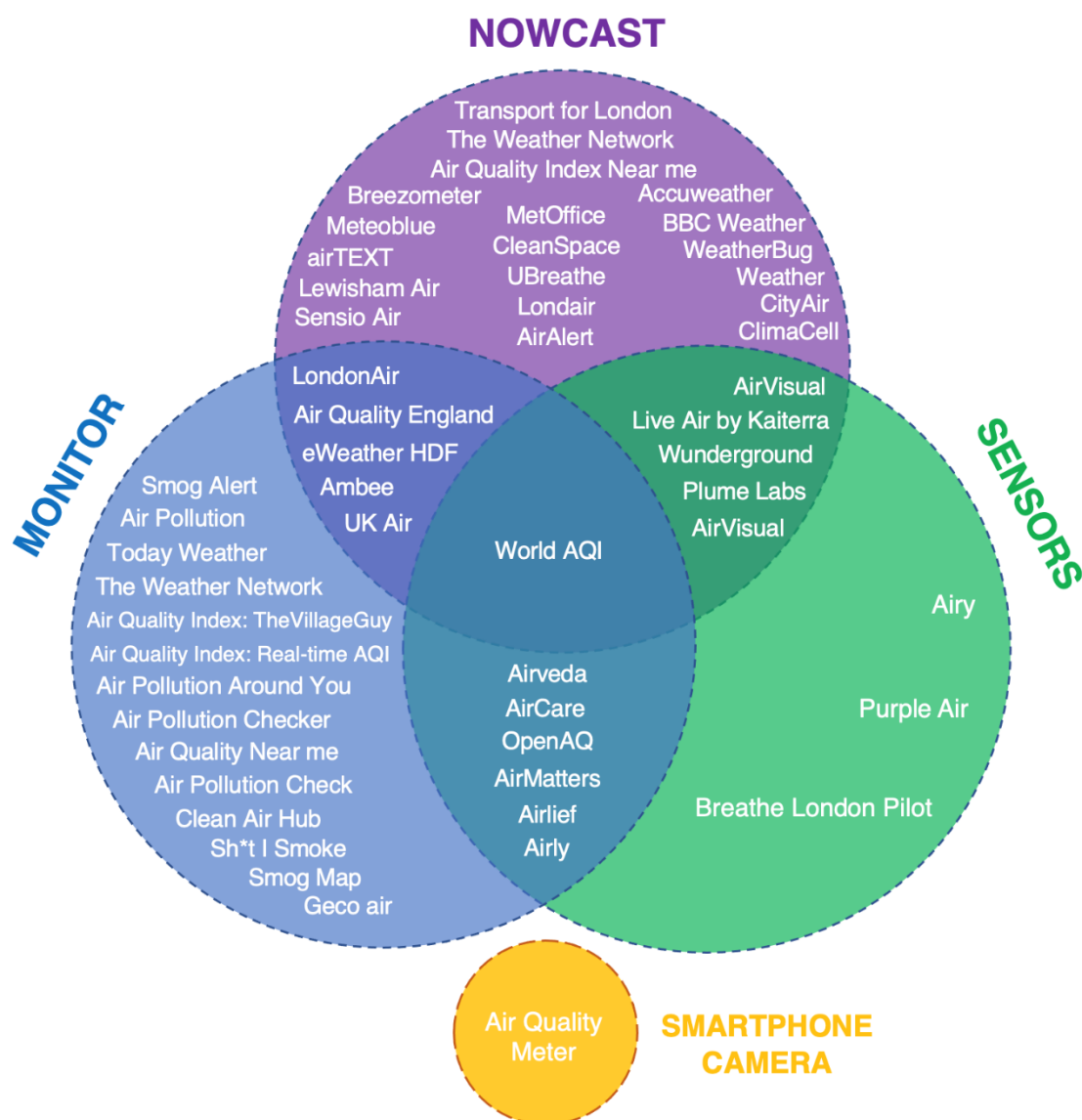


Figure 7. Venn diagram illustrating multiple sources of air quality “reading” across AQ channels.

Overall, nowcasted models were the most common method for deriving air pollution estimates (56% of channels). This was followed by a total of 52% channels relying on regulatory monitoring data to deliver air pollution estimates. Of the 35 AQ channels deriving pollution estimates from regulatory monitors or non-regulatory sensors, the majority present pollution estimates derived from AURN or LAQN monitoring stations (80%), followed by Purple Air sensors (11%), then other personal, commercially available sensors. Three channels display pollution estimates gathered from multiple sensors or monitors, while the rest present estimates

from only one type of sensor or monitor, or a combination of one sensor or monitor alongside nowcasted pollution estimates. Several channels enabled individuals to connect or “pair” their personally owned air quality sensor with that channel platform, thus recording and displaying data registered by the sensing device. Most channels connect and display data exclusively for their or their partner’s proprietary sensor. AirMatters and Airleif, were exceptions, allowing users to “pair” or sync sensors and display data from various sensor providers including PurpleAir, Luftdaten and Kaiterra.

4.3 *Pollution Modelling and Forecasting*

11 of the 31 nowcast channels rely on proprietary models, specifically those developed by Breezeometer, Plume Labs, IQ Air, WLAB and ClimaCell. While proprietary models may implement government or other common modelling techniques, it was not clear which underlying models were implemented. Seven of the nowcasted channels employ the CMAQ-urban model run by Imperial ERG. Of the remaining thirteen, five derive estimates from the CMAQ model implemented by Ricardo E&E for UK Air (Defra), six drawing on ECMWF model outputs from CAMS and EMEP (three using CAMS explicitly), one using the ADMS-urban model and one on the AQUM model also implemented by Ricardo E&E (Figure 8).

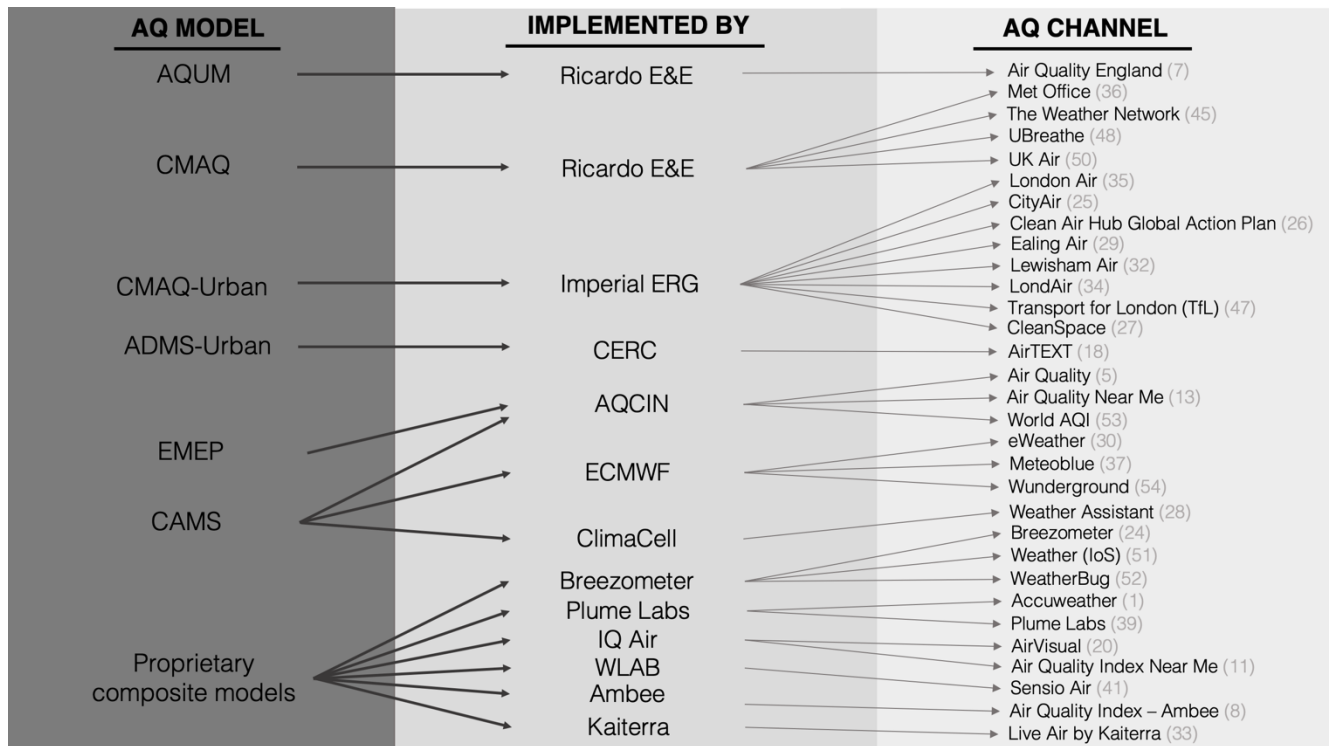


Figure 8. Models generating air pollution estimates across 31 AQ Channels.

Spatial and temporal resolution of AQ channel pollution estimates

The 33 AQ channels reporting readings derived from monitors and sensors correspond to measurements obtained and averaged over 1 to 60 minutes at latitude-longitude point locations. The 29 channels drawing on nowcasted modelling techniques generate estimates of air pollution concentrations projected onto a geospatial grid at varying timescales. The geographic resolution of air pollution nowcast models range from 12km² to 5m² (Table 1). Information on geographic projection resolutions for the IQAir, ClimaCell and Sensio Air nowcasting models wasn't publicly available.

All but four of the 54 channels report air pollution estimates on an hourly basis. While gathering metadata, “Air pollution around you” and eWeather HDF appeared to have AQ reading delays of 3+ hours. AirTEXT delivers a daily text, email, or voice message when pollution concentrations enter the DAQI moderate range. One channel relying on smartphone camera equipment to estimate PM₁₀ concentrations delivered its reading immediately. It was unclear

the frequency at which pollution estimates were updated for two of the channels (Sensio Air and Purple Air), however metadata collection estimates suggested at least daily, thus meeting the study's inclusion criteria. 28 AQ channels provide a forecast of air pollution, ranging from one day to one week into the future.

4.4 *Messaging Characteristics*

49 of the 54 channels present an air pollution “reading” alongside an AQI (Table 2). 28 of the 54 channels provided messaging targeted at specific groups either through the AQ channel interface or AQI description. The most common distinction was between “general population” and “at-risk” individuals, however only 10 channels defined “at risk”. Some of these channels distinguish pregnant women, babies, and athletes. Channels developed by Imperial ERG contain messaging specifically geared towards different categories of commuters, such as pedestrians, cyclists, and drivers, while also providing advice on how to reduce personal contributions to air pollution. The only channels offering email, voice or text message options are managed by government departments or their sub-contractors.

Table 2. Messaging features of AQ channels⁵.

Channel Name	Mobile App?	IoT	Android	API	AppleWatch	Manually tailorable?	Push Notification	AQI Format
Accuweather	X	X	X	X	X			Plume AQI
Air Pollution	X		X					US AQI
Air pollution around you	X		X				X	CAQI (EU)
Air Pollution Check	X		X					US AQI
Air quality	X		X					CAQI (EU)
Air Quality Checker	X		X					US AQI
Air Quality Index - Ambee	X	X	X	X		X	X	US AQI
Air Quality Index - Real time AQI	X	X	X					CAQI (EU)
Air Quality Index by TheVillageGuy	X		X					CAQI (EU)
Air quality index near me	X		X					US AQI
Air Quality meter	X		X					US AQI, CITEAIR, CITEAIR24
Air quality near me	X	X	X			X	X	AQI (percentage of norm)
AirCare	X	X	X			X	X	AQI (US), AQI (EU)
AirLief	X	X	X			X	X	CAQI (EU)
Airly	X	X	X	X	X	X	X	CAQI (EU)
AirMatters	X	X	X		X		X	DAQI (UK), CAQI (Europe), AQHI (Canada), AQI (NL), AQI (US), AQI (India)
Airveda	X	X	X			X	X	AQI (India)
AirVisual	X	X	X	X	X		X	AQI (US)
Airy	X	X	X			X	X	Airy AQI (WHO, 6 levels), KR AQI, US AQI
BBC Weather	X	X	X					DAQI
Breezometer	X	X	X	X	X	X	X	DAQI, BAQI
CityAir	X	X	X			X	X	DAQI
CleanSpace - Air Pollution App	X	X	X					high, moderate, low
ClimaCell - Weather Assistant	X	X	X	X		X	X	US AQI
eWeather HDF	X		X					CAQI (EU)
Geco air : air quality and mobility	X	X	X					N/A
Lewisham Air	X	X	X			X	X	DAQI
Live Air by Kaiterra	X	X	X	X				AQI (US), AQI (China), AQI (India), AQI (Australia)
Londair - Pollution in London	X		X				X	DAQI
LondonAir	X	X	X	X			X	DAQI
Met Office	X	X	X		X			DAQI
Plume Labs: Air Quality App	X	X	X	X	X	X	X	Plume AQI
Sensio Air	X	X	X	X		X	X	AQI (unique)
Sh**!! Smoke	X	X	X				X	CAQI (EU)
Smog Alert	X	X	X		X	X	X	CAQI (EU), AQI (China), AQI (Polish), AQI (USA)
Smog Map	X		X					US AQI
Today Weather - Widget & Alert	X	X	X					US AQI
UBreathe	X	X	X					DAQI
UKAir	X	X	X					DAQI
Weather	X	X	X		X			DAQI
WeatherBug	X	X	X					BAQI
World AQI	X		X	X				US AQI
Wunderground	X	X	X		X		X	DAQI
Air Quality England								DAQI
airTEXT							X	DAQI
Breathe London Pilot				X				N/A
Clean Air Hub by Global Action Plan								DAQI
Ealing Air						X		DAQI
Meteoblue								CAQI (EU)
OpenAQ				X				N/A
Purple Air				X				CAQI (EU)
The Weather Network								DAQI
Transport for London				X				DAQI
UK Air (formerly AEAT)				X				DAQI

⁵ Push notification: an automated message sent by an application to a user when the application is not open (OUP, 2021)

4.5 Access Patterns Across AQ Channel Case Examples

User analytics data from the London Air website, AirTEXT and Breathe London pilot study generated further insights into patterns of when and where individuals access AQ channels across London. Location of AirTEXT subscribers, since the channel's inception in 2007, is presented below as univariate maps and bar graphs identifying the boroughs showing the highest and lowest levels of access (Figure 9). Colour gradients indicate volume of access as lower, middle, and upper proportions of total AirTEXT users. Subscriber metadata indicates 86% have a pre-existing condition, while the greatest number of subscribers were born in the decade of 1970 (Table 3). A linear regression model estimated with robust standard errors showed a positive, statistically significant association between AirTEXT subscriptions and mean annual NO₂ concentrations in 2016 at the outer postcode level, with usual resident population demonstrating a significant effect on model outcome (Table 4). Additionally, a Pearson correlation plot illustrated a positive association between mean annual NO₂ concentrations in 2016 at the outer postcode level and volume of AirTEXT subscribers (Figure 11). Postcodes with numbers of subscribers greater than two standard deviations above the mean ($25.63 + 61.92$) were removed as outliers during sensitivity analyzes, however the correlation between the two variables remained positive.

Table 3. AirTEXT summary statistics from September 2020 – 2007

	<i>Number of subscribers</i>	<i>Percentage of subscribers</i>
Health conditions n=13035		
Asthma	6386	42%
Bronchitis	3786	25%
Heart Disease	2863	19%
N/A	2192	14%
Year of Birth n=7648*		
1910	23	0.3%
1920	161	2%
1930	399	5%
1940	779	10%
1950	1009	13%
1960	1185	15%
1970	1453	19%
1980	1317	17%
1990	1074	14%
2000	238	3%
2010	10	0.1%

*not all subscribers supplied year of birth (Total subscribers = 15,227)

Table 4. OLS regression estimating subscription to AirTEXT

	<i>Estimate</i>	<i>Confidence intervals</i>
Intercept	−0.97 (1.87)	(−4.64, 2.70)
Mean NO ²	0.07*** (0.02)	(0.02, 0.11)
Number of usual residents	−0.001*** (0.0004)	(−0.002, −0.001)
Index of Multiple Deprivation (IMD)	0.0001 (0.0001)	(−0.0001, 0.0003)
Mean NO ² * Number of usual residents	0.0001*** (0.0000)	(0.0000, 0.0001)
Observations	289	
R ²	0.78	
Adjusted R ²	0.77	
Residual Std. Error (df = 284)	7.41	

Note: Robust standard errors shown *p<0.1; **p<0.05; ***p<0.01

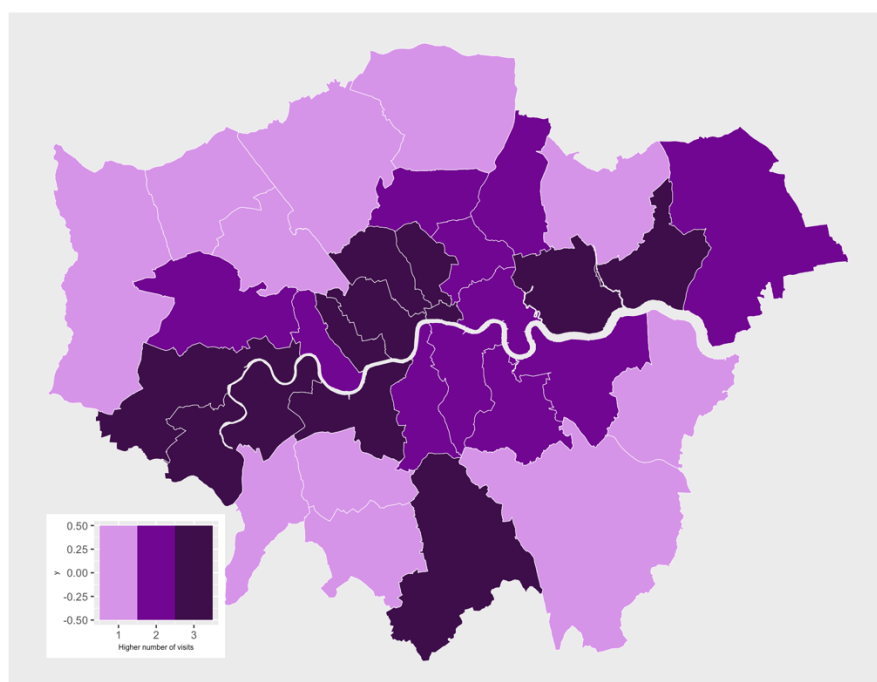


Figure 9. Map of individuals subscribed to AirText at borough level (2007 – 2020) in lower, middle and upper proportions of total AirTEXT users

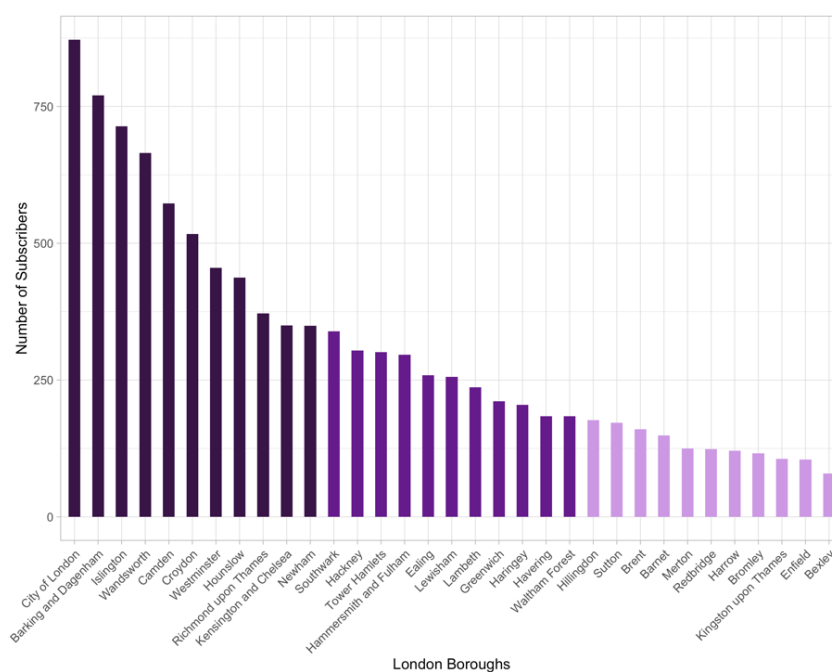


Figure 10. Bar plot of individuals subscribed to AirText at borough level (2007 – 2020).

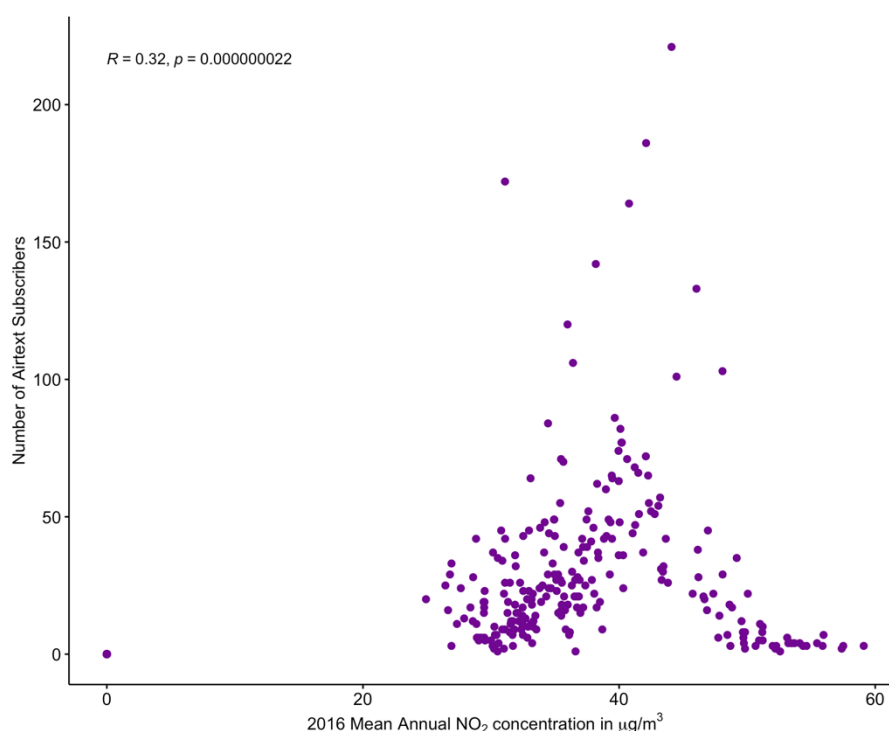


Figure 11. Pearson correlation plot showing AirTEXT subscribers and 2016 annual mean NO₂ concentrations in µm/m³ at the London outer postcode level.⁶

User analytics data from the London Air website, Breathe London and AirTEXT were examined for temporal patterns of access. Access to London Air increased between 9:00 and 16:00, peaking at 10:00 (Figure 12b). Breathe London access increased from 8:00 to 16:00, peaking at 14:00 (Figure 13b). London Air's mean daily access was 669 visits during the sampling period. Weekday mean daily access was higher at 725 visits. Access exceeded 2000 visits on three days: September 18th and 19th 2019, and April 9th 2020. Mean daily access to the Breathe London pilot was 136 visits, with higher weekday access at 155 visits. The three days with the highest access to the Breathe London pilot platform were July 24th 2019, October 19th and 21st 2020.

⁶ Further investigation of apparent curvilinear trend revealed that the outer postcode areas appearing in the data tail are central London postcodes (W and WC), known to have lower usual residents and high air pollution. Recall that the strongest predictor of number of subscribers to AIRTEXT was number of residents in postcode area.

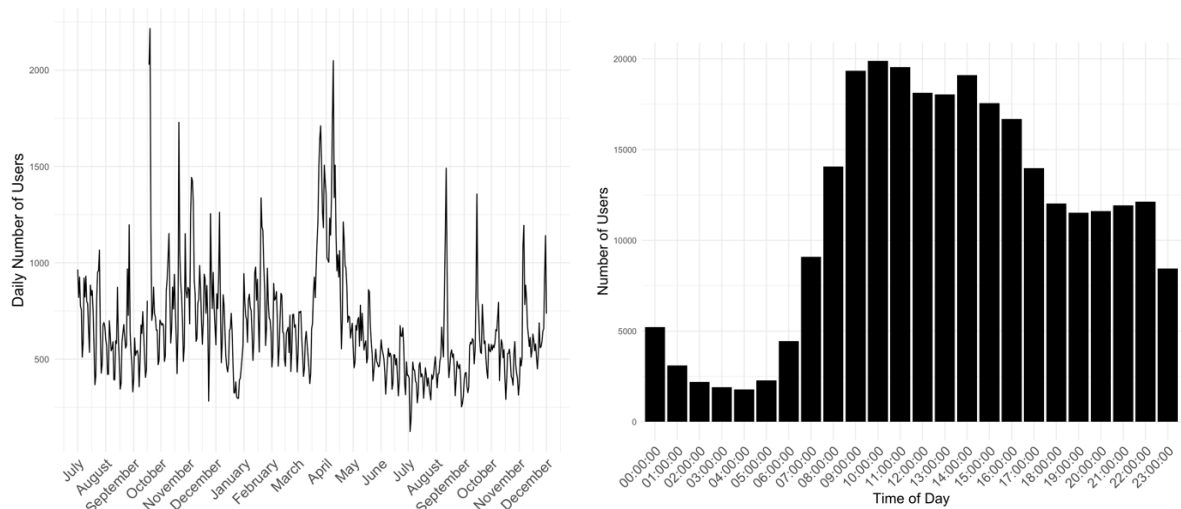


Figure 12.a Number of unique users visiting London Air from 1 July 2019 through 1 December 2020. 12.b. Timing of visits on weekdays to London Air.

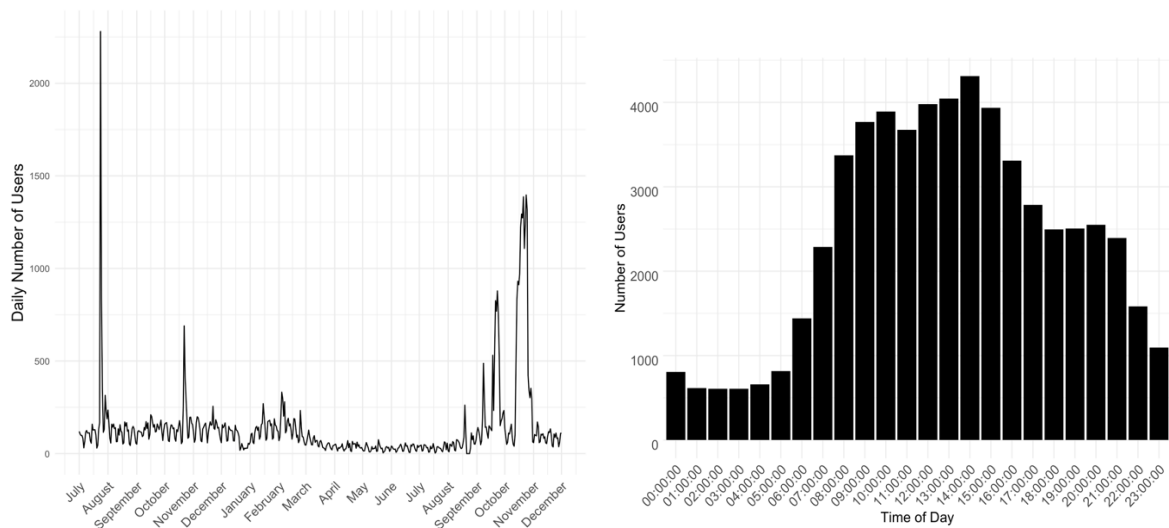


Figure 13.a Number of unique users visiting Breathe London pilot from 1 July 2019 through 1 December 2020. 13.b Timing of visits on weekdays to Breathe London pilot.

5. Discussion

5.1 Summary

Results from the systematic technology review process reveal patterns of how air pollution estimates are derived and communicated across the 54 AQ channels “freely” available to individuals in London. These channels represent a subset of AQ information communication systems, the limitations of which are discussed throughout this section. The three channels

where digital trace user analytics data was available were explored in greater depth, focusing on access across the London population. This section discusses the results of the technology review while considering the evolution of the AQ channel paradigm, along with messaging and technological barriers to uptake associated with the innovation. Additionally, it explores the potential for participatory, co-creative methods to address inequality in AQ channel access.

5.2 Limitations

This research is limited to the city of London. AQ channels use has increased in Asia, particularly China and India, where a greater number of individuals are exposed to dangerous concentrations of air pollution (Sun et al., 2017). Further research in these regions is warranted and should involve close partnerships with local institutions. Research design should be harmonized with socio-cultural patterns and contexts present in those parts of the world. Additionally, more detailed, socio-demographically linked user analytics data is necessary to uncover whether patterns relating to education, caretaking or personal health bias can be observed at the population level. Digital traces alone are demographically poor. Future research should consider designing surveys on these platforms to understand user characteristics better through eliciting self-reported demographic information.

Inclusion criteria limited the final list from featuring all AQ channels one could consult in London. One excluded channel was the GLA's coordination of AQ alerts displayed at bus shelters and London Underground stops. This delivery of AQ information and ERBs reaches a diverse portion of the London population, and additional research into what motivates engagement with AQ information and adoption of ERBs in such cases is warranted.

5.3 *AQ Channel Diffusion*

In response to the first research question regarding what AQ channels are freely available to individuals across London, the results include channels that don't require additional payment and have demonstrated uptake across the city. The diffusion of innovations theory approaches innovation development as a step-by-step process. Results from this study reinforce how digital innovations aren't static entities. Discussions across critical data studies literature place strong emphasis on the co-productive encounters occurring among technology and individuals, which recasts the innovation-diffusion process as one of constant iteration and creation. This is apparent across the resulting AQ channel dataset, which matches the timeline and evolution described throughout the literature review. It reinforces that AQ channel diffusion commenced in 1995 with UK-Air (formerly AEAT). Older AQ channels captured in the dataset (UK Air, AirTEXT, World AQI, and London Air) are all government issued apart from World AQI, which also draws directly on government generated pollution estimates. This aligns with traditional emphasis on air pollution data and information standardization, which was disrupted by digital and computational developments throughout the 2000s, thus resulting in the case whereby government institutions are no longer the exclusive communicators of AQ information.

The dataset demonstrates how AQ channels rely on common sources for estimating air pollution concentrations. The 29 channels relying on nowcasted estimates can be reduced to outputs from five models operated by the UK or the European Union. These data generation practices leverage popularized "open access" mechanisms like APIs leading to the syphoning of government-generated pollution data across a growing number of independently operated, commercial AQ channels. While at the foundation, these channels can be linked to common pollution data sources, the subsequent layering of algorithms and proprietary specifications

shift the appearance of the data underpinning the messages they deliver. In the case of channels relying on monitor or nowcast derived pollution estimates, the user interface may be different, but the “insides” retain standardized elements.

From 2013 onwards we see multiple AQ channels associated with personal AQ sensors or other commercial products such as masks or air filtration devices emerge. This suggests the commodification of the pollution problem, where pollution exposure is framed as a challenge that can be mitigated by a consumer purchase (Graham, 2015). The diffusion of innovations framework treats this as an inherent component of the innovation development process, defining “problems” or “needs” as precursors to the creation of an innovation. The case of AQ channels, and complex socio-political, environmental and health inequity landscape in which they operate, warrants critical attention towards which groups are defining said problem or need. Participatory methods present an opportunity to approach air pollution whereby lived experiences of affected individuals, and diverse understandings of the “problem”, become materialized throughout AQ channel sensing, data handling and display infrastructures.

A recent commercial trend is the provision of highly localized, forecasted and nowcasted air pollution estimates via paid subscriptions to APIs (Breezometer, 2021). Similarly, despite not charging a fee, many of the AQ channels request privileged access to the mobile device system’s camera and location services, or to browser cookies, suggesting that data is being gathered, arguably a form of payment, which raises potential general data protection regulation (GDPR) issues. It is important to consider how narratives of fear and “empowerment” are operationalized across AQ channels to establish a market of concerned individuals that will purchase personal sensors, masks, or air filters (Crespin and Ferron, 2016). The consequences

of marketing AQ channels as “open-access” or “empowering” services, and the role of this driving channel uptake warrants further investigation.

Patterns of uptake expressed across the AirTEXT dataset reinforce that uptake of AQ channels is unlikely to be uniform across the population of London (Figure 9). Additionally, it is likely individuals are adopting ERBs or practices at different rates. The lack of socio-demographically linked data precludes observation of such detailed patterns, and whether they might mirror patterns observed across the controlled experiments presented in the literature review. Furthermore, the availability of commercial products designed to mitigate exposure introduce another layer of inequity regarding patterns of air pollution exposure across a population (Sun et al., 2017). Greater transparency surrounding the profit motivation of certain AQ channel ventures and the inequities such systems perpetuate, in addition to their reliance on government data to deliver commercial products, can help reduce exploitation of environmental and health risk for financial gains. Involving residents throughout state managed environmental data production processes can facilitate the development of more equitable evidence bases for policy development and air quality governance, while helping combat against data-exploitative enterprises.

5.4 *Barriers to AQ Channel Uptake*

5.4.1 Messaging barriers

This section discusses how AQ channel messaging results and mechanisms for information delivery might contribute to “where” and “when” AQ channels are accessed across London. The U.S. EPA has cited concerns over disparate reporting of AQ conditions, which they emphasize is a function of the instrumentation used to estimate air pollution at the location in question (Woodall et al., 2017). The study results reinforce that AQ “readings” are either tied to the specific location of a monitor or sensor or, in the case of nowcast derived pollution

estimates, associated with a broad or variable geographic area. If individuals are seeking AQ information associated with their exact physical location, most AQ channels are incapable of providing it. Only portable AQ sensors, with questionable accuracy, held by individual users can indicate personal exposure. Furthermore, typical “hourly” reporting standards point to significant temporal gaps in communicating air pollution concentrations. The technical limitations of pollution estimation aren’t communicated transparently by AQ channels and only in some cases embedded in footnotes or “Terms and conditions”.

ERB messaging across the dataset is largely standardized to AQI rhetoric. Such messaging perpetuates the unidirectional deficit model, whereby a disconnected entity is the privileged knowledge authority as opposed to the situated, affected individual (Haraway, 1988). This raises questions about whether AQ channels augment or stifle intrinsic knowledge from sensations and “lived experience” of pollution that already exists in the body. It aligns with discussions surrounding the relationship between technology and the human body, and whether such data-driven interactions render phenomena like air pollution more “real” (Whatmore, 2006). While the theory of diffusion of innovations describes communication and knowledge building as a “two-way process convergence”, it fails to interrogate the role of sensory cues and the phenomenological dimension of “sensemaking” emerging throughout encounters with innovations (Rogers, 1995). The results reinforce the potential for future AQ channel iterations to test participatory, sensory-experimental approaches to knowledge building and exchange, as opposed to unidirectional information exchanges.

All but one of the 54 channels presented “readings” alongside AQI messaging which contain embedded ERBs, while many channels included additional messaging targeting specific groups. This messaging is predominantly geared towards groups labelled as “sensitive” or “at-risk,” with specific mention of adults and children with respiratory or cardiovascular

conditions, older adults, pregnant women, and babies. While some channels present targeted, actionable messages for these groups according to the registered pollution estimate, the majority don't specify what constitutes a "sensitive" or "at-risk" group or individual. This presents a potential barrier for uptake of AQ channels and ERBs, further exacerbated when English language knowledge is limited. It is also worth noting that none of the channels included messaging ERBs associated with specific indoor based activities that might contribute to exposures. This signals an opportunity to establish design features or messaging that supports self-identifying as "at-risk" in multiple languages, thus responding to evidence from the literature that common risk messaging omits certain sociodemographic groups known to be at risk. From a behavior adoption standpoint, it is also important to consider how adopting 'emissions reducing' ERBs, such as switching from petrol to electric vehicles or paying extra for lower emitting delivery or transport options, may be associated with different personal motivations and capacities to choose such options (Whitmarsh, 2009). An approach to messaging that establishes opportunities for individuals to self-identify risk and capacity could operationalize the findings that greater "concern" and "response efficacy/outcome expectancy" are associated with increased ERB uptake, while taking care to supply widely actionable recommendations that can help reduce pollution exposures.

Messaging across the AQ channels reviewed consistently presented numerical air pollution estimates or "readings." Numerical, sterile representations of environmental phenomena can have a "depoliticizing" or dissociative effect by emphasizing highly scientific, reductionist understandings of air pollution (Barry, 2002). Additionally, pathologizing AQ shrouds the fundamental human experience of breathing in fear, while scientific and medicalized language may have the effect of alienating non-specialists (Crespin and Ferroud, 2016). This demands scrutiny of the motives of channel providers and raises critical questions whether goals to

“empower” individuals to breathe clean air align with the subconscious creation of a pathological problem for which a commercial solution is then conveniently supplied.

5.4.2 Structural barriers to AQ Channel access

While information and mechanisms for delivery often self-describe as being inclusive by virtue of being “open-access”, they are still subject to the effects of digital and informational inequality. Certain social and demographic groups are more likely to engage with and potentially benefit from this genre of information (Shaw & Hargittai, 2018). Access patterns vary by AQ channel mode of information delivery, as demonstrated by the three case examples. Results from AirTEXT demonstrate that patterns of access are driven by pre-existing health conditions, while the linear model reinforced the significant effect of population density on subscriptions. The Pearson correlation plot showed a positive correlation between number of AirTEXT subscribers and mean annual NO₂ concentrations at the outer postcode level (Figure 11). Even after removing outlier postcodes with numbers of subscribers greater than two standard deviations above the mean ($25.63 + 61.92$), the correlation was still positive. The postcode outliers were examined in greater detail and pertained to areas of Islington, Camden, Whitechapel, the South Bank, Battersea, Putney, Tooting, Wandsworth, Fulham, and north Croydon. Further research is warranted as to what is driving greater uptake of AirTEXT in these outer postcode areas.

The linear regression model also estimated a modest correlation between annual NO₂ concentrations and AirTEXT subscriptions at the borough level. Considering this alongside the absence of any significant association with IMD seems to hint away from an environmental inequality perspective. However, this may be a consequence of the coarser geographic scale at which the model is estimated. Additional research is warranted to examine what factors drive

AQ channel uptake at finer geographic scales, in addition to whether patterns of uptake observed with respect to AirTEXT are expressed across other AQ channels.

Digital trace data from the two case examples showing temporal access trends, London Air and Breathe London, point to common time windows during which these AQ channels are accessed. Access to London Air increases at 9:00AM and Breathe London at 8:00AM, for which it can be assumed individuals check these AQ channels before their morning commute. Access levels remain high for both channels through 16:00 align with individuals checking the channel before their return commute. Both channels also show a peak around 14:00, which may indicate parents checking before collecting children at school or during lunch breaks (Figures 11 & 12). These findings suggest that AQ channel innovation stimulates an awareness that may drive ERB uptake. Days when access spiked for London Air and Breathe London don't appear to correlate with high pollution events. However, on one of the days demonstrating high access across both Breathe London and London Air (October 21st 2020), the Guardian released two articles about air pollution. No direct links to either AQ channel were provided in the articles suggesting that individuals took it upon themselves to seek out AQ information.

It is also worth noting that the timeframe during which user analytics data were analyzed included the UK national COVID-19 lockdown between November 5th and December 2nd 2022. Access to both AQ channels remained consistent throughout this period, which raises questions around what might be motivating this engagement. A more detailed examination of the dates when access spiked across these and other AQ channels, particularly over the course of the COVID-19 pandemic, could reveal additional information about drivers and patterns of access to AQ information. In addition, a systematic search for other press or social media mentions,

could support greater understandings of the effects of journalism, media, and messaging on uptake of AQ channels, alongside which groups are most likely to engage with this genre of information.

The trend towards decentralized, locally generated knowledge, along with AQ data production and exchange through AQ channels contrasts with the impetus of the original UK Clean Air Act and its respective, centralized monitoring and “evidencing” protocols that still dominate AQ governance today. Key questions raised by the diffusion of AQ channels include: *who* in a population is most likely to engage with these AQ channel information sources and which individuals have the psychosocial or economic capacity to shift behaviors and lifestyle? It is therefore essential to ask where AQ channels fall within the broader scope of AQ governance, whether the onus is being placed on individuals to safeguard against the health impacts of air pollution, how AQ channel uptake may be socio-demographically stratifying knowledge production surrounding AQ and patterns of exposure reduction, and how co-creative methods can help mitigate such challenges.

6. Conclusion

This study systematically identified and characterised channels delivering an emerging genre of information about localized AQ in real-time across London, UK. By establishing clear criteria for inclusion according to features identified across the literature, a list of 54 AQ channels was generated. Upon examination, the channels demonstrated clear overlap in air pollution estimates and models used to present a “reading.” The marketing of personal sensors and other pollution-abating commercial products was apparent across multiple channels, while simultaneously emphasizing messages of personal responsibility and self-identification of risk surrounding exposure reduction, narratives of “empowerment” and that the provision of such

services align with the UN Sustainable Development Goals (Breezometer, 2022 and AirVisual, 2022). These varied and occasionally contradictory framings across AQ channels warrant critical attention from groups who are developing the channels, as well as those who are consulting them, signalling an opportunity for participatory and co-design methods to approach such discrepancies. Furthermore, critiques of whether AQ channels can be truly “free” – whether it be a function of internet access, device costs, digital skills, or giving up personal data – must be extended and amplified.

A lack of critical engagement from both users and the academic community surrounding AQ channels and the information they proliferate, in addition to a lack of transparency on the part of channel developers, maintains conditions that neglect fundamental insights surrounding what constitutes sustainable, democratic AQ knowledge production. This includes the continued employment of the information deficit model, the narrow focus of messaging around pathologizing of the subject of AQ, opaque framings of risk, and reporting of inaccurate or imprecise AQ conditions, often associated with disparate geographic resolution of pollution estimates or failure to adjust for meteorological conditions.

The diffusion of innovations theory established a useful research design framework for tracing patterns of uptake using user analytics and metadata yet fell short when confronted with results indicating that the AQ channel innovation evolves continuously as opposed to a step-by-step process. The theory also struggled to address how AQ channels and their data become enmeshed throughout social life. Future AQ channel developments should exercise participatory methods that actively involve individuals in producing knowledge, as opposed to the passive logging of data. This can be accomplished by employing co-design methods when developing sensing and data management infrastructures, or interactive, iterative user

interfaces. Channels will therefore not only engage individuals more effectively, but also consciously identify as “living” projects that incorporate many diverse and important experiences of air pollution that exist across a population.

Advancing knowledge of what drives increased access to AQ channels, including further investigation of the effects of news media on channel uptake, can also illuminate whether different drivers are more likely to influence certain groups in a population. Specifically, the question of whether uptake of ERBs exacerbate existing exposure inequalities if such behaviors are not uniform across the population will require user analytics data that is demographically linked. Ideally such data would be anonymized by AQ channel providers and shared for non-commercial, academic research purposes with the goal of developing more equitable channels for AQ information communication. Rigorous empirical research can support future understandings of the association between AQ channel uptake, varieties of ERBs, the contexts underpinning their adoption, how they might modify exposure patterns and health outcomes ranging from individual to the population level, along with potential trade-offs or unintended consequences of the innovation. There is also more to be learned around whether AQ channels and ERBs had any effect on early COVID-19 case rates, particularly in urban areas. Air pollution is a pervasive challenge that is deeply interconnected with the social, institutional, and commercial facets of everyday life. The potential for AQ channel development to shift towards a trajectory that critically approaches disproportionate patterns of exposure in a co-creative capacity remains to be seen.

CHAPTER THREE:

Variation in representations of air pollution at six hospitals across London, UK

Abstract:

Advances in sensor-based monitoring and internet-connected technologies have facilitated a deluge of digitally available, real or near real-time information about local air pollution conditions via mobile and web-based applications. Empirical evidence reinforces that this information can serve as a “digital health intervention” by encouraging “vulnerable groups” to adopt exposure reducing behaviors (ERBs). ERB recommendations are often linked to an air quality index (AQI), a numeric tool used to indicate health risk associated with air pollution threshold levels. Concerns have been raised throughout literature regarding inconsistency in the information provided across these proliferating informational “AQ channels.” This inconsistency has yet to be observed systematically. To respond to this research gap, this pilot study examines variation in representation of air pollution across a sample of “openly accessible” AQ channels obtained from a prior systematic technology review presented in Chapter II. Pollution estimates derived from a series of application programming interfaces (APIs), in addition to screenshot images, were analyzed to examine variability in air pollution information reported for the same geographic locations. The results demonstrate significant variation in estimated particulate matter (PM_{2.5} & PM₁₀), NO₂ and AQI for a specific latitude/longitude location. Findings suggest that different AQ channels report varying air pollution estimates for the same geographic location, which may affect ERB patterns and associated health outcomes at the population level.

1. Introduction

As air quality or “AQ channels” are being developed in different locations around the world, implications surrounding the quality and consistency of this information, and how it can affect patterns of pollution exposure reducing behavior across populations, remain unclear (Noonan, 2011; Hubbell et al., 2018; McCarron et al., 2022; Riley et al., 2021; Schulte, 2022; Woodall et al., 2017). Empirical evidence points to great variability in AQ information systems or “AQ channels”, from the way air pollution “readings” are generated, to the format and behavioral messaging displayed across channels (McCarron et al., 2022; Schulte, 2022; Woodall et al., 2017a). This heterogeneity across the AQ information landscape, and what drives variation, have yet to be examined systematically.

In response to this gap in the research, and how this can affect health-protective, exposure reducing behavior patterns at the individual, this pilot study examines variation in air pollution estimates derived from a series of application programming interfaces (APIs)⁷ supplying data to a sample of 54 AQ channels. The sample was obtained from a prior systematic technology review, which identified a mixture of 13 public and private APIs as common sources of air pollution readings delivered across 31 AQ channels (Schulte, 2022). In this study, 7 of the 13 APIs are employed to examine variation in modes for estimating pollution concentrations, which inform the readings delivered across 18 channels (Figure 14). Screenshots of each channel are obtained to examine variation across user interfaces. It is worth noting that while units for reporting air pollution estimates may be consistent, modes for derived estimates vary across the 7 APIs. In addition, while a common set of models supply air pollution estimates across multiple AQ channels, the averaging time, AQI formula used, and geospatial resolution of reported readings can vary from channel to channel (Schulte, 2022).

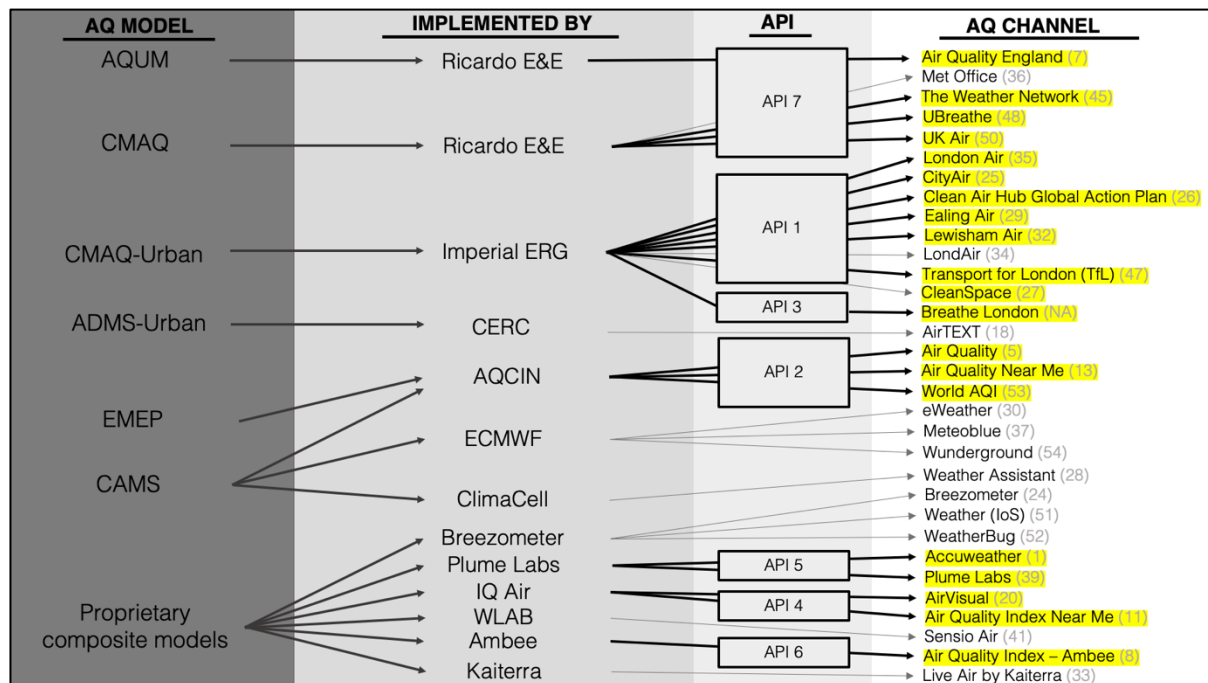


Figure 14. Adapted figure from Chapter II showing the 7 common APIs servicing 18 unique AQ channels.

⁷ Application programming interfaces (APIs) are a set of digital instructions that allow one or more computers or software to communicate and exchange data with one another (Reddy, 2011).

This pilot study responds to the overarching research question: *Does the proliferation of AQ channels imply increasing variability in air pollution information for the same locations?* To accomplish this, it systematically explores variation in air pollution “representations”, that is any numbers, visual or textual indication of air quality, presented across a sample of the AQ channels emerging from a previous systematic technology review of channels that are “freely” available to individuals across London, UK. To examine the variability in air pollution information reported across AQ channels, the “front” and “back” end components for a sample of channels served by openly accessible APIs were analyzed. Scripts were written in Python to query the APIs supplying air pollution estimates at the back end for common geographic point locations throughout London, UK over a weeklong period. The resulting dataset was analyzed alongside screenshots of the front end, user interface displays for a sample of AQ channels sourced by the selected APIs. The paper concludes with a discussion of the implications of variability in air pollution information with respect to reliability, heterogeneous messaging and how this can affect the adoption of pollution exposure reducing behaviors.

2. Background

2.1 Measuring air quality & relaying estimates

Air pollution estimates or measurements presented across AQ channels are commonly derived from government monitors, lower-cost sensors or through modelling techniques (Simpson et al., 2012; Snyder et al., 2013). Measurements generated using government monitoring equipment, such as the Automatic, Urban Rural Network (AURN) or London Air Quality Network (LAQN) stations across London and the UK more broadly, pertain to a specific geographic point, are subject to rigorous management and data quality standards, and cost hundreds of thousands of pounds to maintain (Morawska et al., 2018). There are approximately 100 government monitors delivering hourly measurement data across the whole of London

(Greater London Authority, 2022). While models can supply hourly London-wide air pollution estimates resolutions ranging from 5m² to 20m², concerns have been raised around the sparse distribution of a network of instruments to supply reliable air pollution measurements.

Rapidly emerging, lower cost stationary and portable air pollution sensors are being layered into air quality monitoring networks. These sensors deliver measurements of variable quality, time averaging, and correspond to a specific geographic point (Woodall et al., 2017). Alternatively, estimates generated via modelling rely on mathematical equations and a variety of datasets including pollution emissions inventories, weather data, land use data and roadway traffic patterns, to forecast or “nowcast” air pollution concentrations (Zhang et al., 2012). Outputs from the models are then projected onto a gridded map at different geographic and temporal resolutions. Both instrument and modelling based methods are commonly applied to generate insight into air pollution conditions. This insight commonly takes the form of air pollution data, which can then be piped into the “back end” of apps, websites and other digital channels using API technology (Schulte, 2022). The mechanisms through which this is accomplished are described in the following paragraph.

The employment of APIs as mechanism to relay air pollution information has facilitated the proliferation of AQ channels over the past ten years (Schulte, 2022). Third parties and developers can access air pollution estimates generated by government, commercial organizations, or others who have implemented APIs, often doing so for their own internal purposes to support efficient transfer of data across computers or devices. A growing number of air pollution estimate providers have publicly accessible APIs, enabling third parties to set up a “query” and obtain specific data from a server, which is then returned in json file format (Reddy, 2011). Air pollution APIs are either “free” or require a paid subscription to access their

estimates or measurements databases. Findings from Chapter II demonstrated that multiple AQ channels display air pollution estimates and ERB messaging associated with a common set of API-derived data (Figure 14). This Chapter also demonstrated that certain AQ channels collect personal data as an alternative form of payment for their services.

Questions surrounding whether the employment of APIs and proliferation of AQ channels has facilitated variation in reported air pollution estimates and associated ERB messaging have yet to be explored systematically. The aim of this study is to shed light on this topic and whether such variation presents when examining API-derived pollution estimates displayed across different AQ channels for common geographic locations. It is important to reinforce however that APIs are different from the front-end, user-facing platforms displayed by AQ channels. The following section reviews the literature focusing on the qualities of the user-facing displays presented to individuals accessing AQ channels.

2.2 Representing air quality

In terms of reported pollution values, AQ channels typically report a common set of pollutants, which mirror the species and units of measure implemented throughout regulatory contexts (COMEAP, 2010; Garnett, 2016). These “criteria” pollutants include particulate matter at 10 and 2.5 micrograms (PM₁₀ and PM_{2.5}), sulphur dioxide (SO₂), carbon monoxide (CO), nitric oxides (NO), nitrogen dioxide (NO₂) and ozone (O₃), along with regional temperature, humidity, and weather data (Defra, 2022). Featuring these pollutants across AQ channels reinforces notions of air quality being synonymous with specific “pollutants, monitoring methods and acceptable concentration thresholds”, with anything falling outside of this space susceptible to dismissal or excessive critique for not being a “good enough” measure of air pollution (Gabrys et al., 2016; Schulte, 2022). In line with traditional modes of measuring air

pollution, the WHO recently published stricter pollution concentration guidelines, lowering the 24-hour mean for certain criteria pollutants by 5 or more $\mu\text{g}/\text{m}^3$ (Figure 15). These guidelines, which are not legally binding nor do they consider policy trade-offs, were updated according to systematic reviews synthesizing evidence that identifies health harms at low pollution exposures (Fuller et al., 2022; Murray et al., 2020; Chen & Hoek, 2020; Orellano et al., 2020). This further complicates the AQ information landscape and may establish additional barriers for interpretation amongst an already convoluted informational space.

Pollutant	Averaging Time	2005 AQGs	2021 AQGs
PM _{2.5} , $\mu\text{g}/\text{m}^3$	Annual	10	5
	24-hour ^a	25	15
PM ₁₀ , $\mu\text{g}/\text{m}^3$	Annual	20	15
	24-hour ^a	50	45
O ₃ , $\mu\text{g}/\text{m}^3$	Peak season ^b	-	60
	8-hour ^a	100	100
NO ₂ , $\mu\text{g}/\text{m}^3$	Annual	40	10
	24-hour ^a	-	25
SO ₂ , $\mu\text{g}/\text{m}^3$	24-hour ^a	20	40
CO, mg/m^3	24-hour ^a	-	4

μg = microgram

^a 99th percentile (i.e. 3–4 exceedance days per year).

^b Average of daily maximum 8-hour mean O₃ concentration in the six consecutive months with the highest six-month running- average O₃ concentration.

Note: Annual and peak season is long-term exposure, while 24 hour and 8 hour is short-term exposure.

Figure 15. WHO recommended 2021 air quality guideline (AQG) levels compared to 2005 AQGs (WHO, 2022)

The establishment the thresholds listed in the table consider the large body of empirical evidence demonstrating causal links between exposure to specific pollutants in the short and long term, and specific adverse health outcomes, including but not limited to respiratory conditions, cardiovascular conditions, cancer, and death (Fuller et al., 2022; Kelly and Fussell, 2012). Nevertheless, the WHO, medical professionals, and population health scientists continually reinforce that there is no safe level of air pollution exposure (WHO, 2022). With this in mind, air quality indexes (AQIs) are designed to communicate air pollution conditions to “the public”, in an attempt to mitigate short-term risks (McCarron et al., 2022).

The aim of an AQI is to supply information about air quality conditions and in certain cases, deliver health and behavioral advice for reducing exposures (Kelly et al., 2012; Monteiro et al., 2017; Ramírez et al., 2019). AQIs identify vulnerable groups and supply specific, conservative messaging to those groups. However, this identification only extends to physiological characteristics and fails to account for social or demographic characteristics (Fairburn et al., 2019; Koman et al., 2018; Schulte, 2022). Throughout their research, Pritchard and Gabrys emphasize the multiplicity of “the public” as an audience to which air pollution information is conveyed. They expand on the notion of “publics” as *emergent*, being a function of their relations with air pollution (Pritchard and Gabrys, 2016). The implications of approaching publics as emergent or co-constituted via their engagements with and interpretations of information presented across AQ channels, has yet to be considered throughout the literature.

Further adding to the convolution of interpreting the AQI are its methods for calculation, and their variability from region to region. Previous research demonstrated a rise in the volume of “freely” available AQ channels in London UK since 1995, that is channels that do not require additional payment to gain access, beyond owning an internet-connected device (Schulte, 2022). In an increasingly digital and global society, it is possible that individuals in London, UK to be consulting an AQ channel that has been crafted in another country, amidst that country’s unique regulatory, cultural, environmental and inequality contexts. An example of this was presented in Chapter two (Figure 1), which illustrated differences in the numerical thresholds and messaging communicated by the government disseminated US AQI and UK DAQI. This reinforces the importance of interrogating the universality of AQ channels and

how this can affect comprehensibility and resonance amongst the regional population interacting with the London AQ information landscape.

A mixture of numerical and visual strategies are employed to communicate information across AQ channels. The AQI itself blends these strategies as it smooths information about the concentration of a configuration of the six criteria pollutants into a single numeric, verbal, and pictorial representation of air pollution conditions (McCarron et al., 2022). The mobilization of information is addressed throughout the concept of circulating reference, which describes in detail the theoretical process of communicating an “observation of nature” (Latour, 1999). From the collection of data in the field, to publishing a journal article, some form of information passes through a series of transitions in which something is kept constant so that it can be communicated. In the context of the environmental knowledge production Latour observed, this transpired through the collection of geologic samples, employment of diagrammatic or symbolic references, geographic mapping, and identification of color using a Munsell chart (Latour, 1999). The mechanics of these fragmented data and information are such that they are “more socially transportable” and readily subsumed within machines, while knowledge and wisdom are “heavy” and laden with the values of its producers (Jasanoff, 2004). The “pyramid of knowledge” reinforces a process of distillation with data the bottom, followed by information, then knowledge and finally wisdom at the top, with successive step adding “organization, value and meaning by revealing relationships and truths about the world” (Kitchin, 2014). In this sense, knowledge is “de-politicized” by shedding some of its situatedness to be communicated more freely in the form of information. This raises questions about what kinds of visual and numerical formats are adopted to retain some “constant” meaning about air quality conditions, and how this helps characterize variation throughout the London AQ informational landscape.

The presentation of a “unitless” AQI number or threshold dilutes the complexity of scientific air pollution measurements, facilitating the unencumbering of air quality knowledge so it can “move” more freely throughout society in the form of simplified data or information. Recent critiques reinforce the inadequacy of AQIs as a “top-down”, uni-directional mechanism for conveying information in a manner that follows the information “deficit model” (Hubbell et al., 2018; McCarron et al., 2022). The deficit model is predicated on the assumption that more information or “scientific facts” will deliver a desired outcome. This model has been critiqued for its failure to consider the complexity of knowledge production and individual-level behavior and psychology (Hart & Nisbet, 2012; Schulte, 2022).

Researchers have identified participatory methods as one approach to the production of research and knowledge about air quality by involving adversely affected groups. This approach has been shown to enhance the relevance and applicability of emerging research and knowledge products for improving governance of environmental challenges including air pollution, climate change and flood risk mitigation (Haraway, 1988; Hubbell et al., 2018; McCarron et al., 2022; Whatmore & Landström, 2011). Participatory methods collapse knowledge hierarchies that can unconsciously privilege scientific epistemologies or numerical data as the only types of viable “evidence”. They can also help establish research protocols that are better positioned to systematically acknowledge local knowledge and “lived experiences” (i.e. health episodes, neighbourhood dynamics, psychosocial factors including concern, fear, trust) (Barry, 2002; Gabrys et al., 2016). Involving impacted groups directly in the definition of information delivery parameters via participatory methods could result in more effective, individual-level air pollution exposure mitigation.

3. Data and Methods

3.1 Summary

The literature revealed two components or layers where variability can manifest across AQ channels. The first is through the front-end, AQ channel user interface where information is presented to the public audience. The second is at the back end and is determined by which API is being queried for an air pollution estimate. To examine each of these layers, specific datasets were acquired. For the back end, computational methods were applied to generate a dataset of air pollution estimates from 7 APIs pertaining to six specific hospital locations across London. For the front end, screenshots were obtained for the 18 AQ channels deriving their pollution estimates from the 7 APIs.

It is important to consider that while several AQ channels may be querying the same API at the back end, a channel's unique front-end may be transforming or presenting the queried pollution estimate data in a unique way. An additional, second layer of potential variation arises as multiple APIs queried for the same geographic location may not return the same air pollution estimate, as they commonly employ varying methods for deriving said estimate. To identify the presence of variation, the analysis of the front and back end datasets were focused around five categories established throughout the literature. The categories include reported pollutants, numerical values, AQI calculation method, ERB messaging content and general visual features across the AQ channel.

3.2 Data

3.2.1 Scheduled API queries

To examine numerical variation across the AQ channels, a novel dataset containing air pollution estimates was generated by querying a sample of 7 of the 13 APIs supplying “freely”

available air pollution information to the 18 AQ channels identified in the Chapter II study. These 7 APIs, and the resulting 18 channels were selected for the analysis based on their accessibility and cooperation with the providers. For the purposes of this analysis, the APIs are not named. The 7 APIs were queried simultaneously at the six hospital locations across London over a weeklong period from May 16th – May 23rd 2022, during peak commute hours (7:00 – 11:00 and 14:00 – 19:00). The decision to focus on commute hours stems from evidence throughout the literature that identifies the commute as a significant contributor to individual daily pollution exposure (Özkaynak et al., 2013; Park & Kwan, 2017). Each of the APIs were queried using Python version 3.10.2 language and saved as csv files using the *pandas* 1.4.1, *requests* 2.27.1 and *schedule* 1.1.0 packages. Comma-separated value (csv) files were analyzed in R version 3.6.2 using the *dplyr* 1.0.9, *ggplot2* 3.3.5, *sf* 1.0-3, *geosphere* 1.5-14, *leaflet* 2.1.1 and *stargazer* 5.2.3 packages. As described in the background section, 18 AQ channels derive the air pollution estimates they present across their interfaces from one of the 7 APIs. These 7 APIs, and the resulting 18 channels were selected for the analysis based on their accessibility and cooperation with the providers. The 7 APIs were queried simultaneously at the six hospital locations across London over a weeklong period from May 16th – May 23rd 2022, during peak commute hours (7:00 – 11:00 and 14:00 – 19:00).

3.2.2 Sampling location selection criteria

API-derived air pollution estimates were gathered over a weeklong period at six hospitals across London, UK. The six locations were selected according to the volume of government managed air quality monitors in the area, the demographic composition of the area, and for their sociocultural status as hospitals. Presence of nearby regulatory AURN/LAQN monitors and government-private partnership *Breathe London* to increase the density of London's air pollution sensing network, and rough geographic spread of hospitals across London was also considered when selecting locations for this analysis (Figure 16 & Table 6).

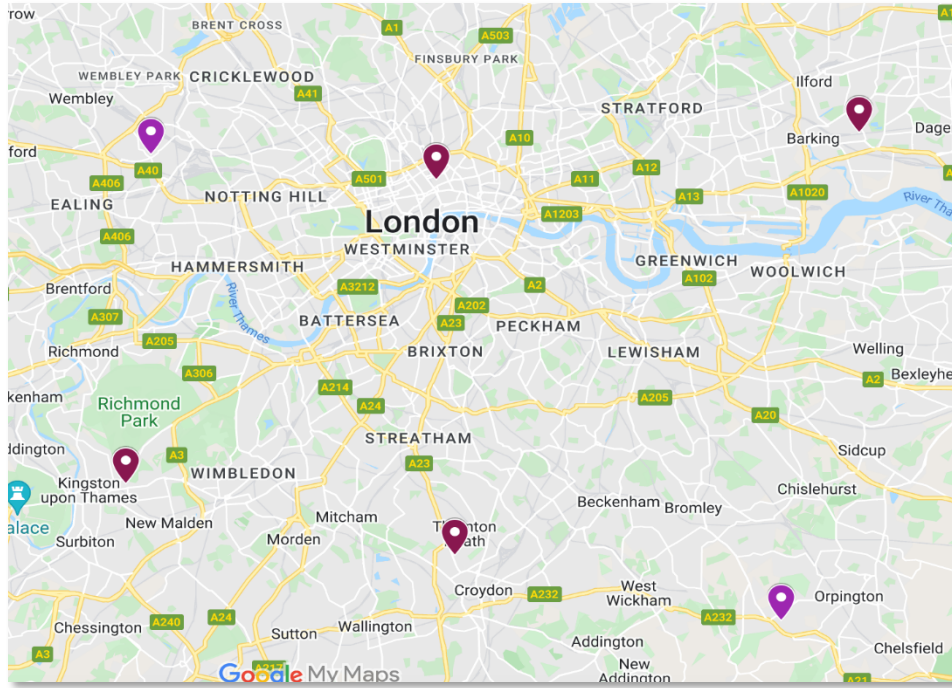


Figure 16. Location of 6 hospitals in London included in the analysis

3.2.3 Visual data extraction

Screenshots of the main “landing” pages from each of the 18 AQ channels was obtained manually by using a screenshot application. Screenshots are organized according to which API the AQ channel derives its air pollution estimates from. 14 of the 18 AQ channels identified in the literature review are featured in the main text, showcasing a sample of the visual interfaces generated from each API. As 7 visual interfaces were generated using API 2, the three most downloaded interfaces were retained in the main body of the text, while the remaining four were relegated to Appendix 2 to help streamline the presentation of the results. The evaluation and comparison of the visual features displayed across AQ channels that share a common API as the source of pollution estimates is conducted while acknowledging that timing of the screenshots does not correspond to the API querying schedule or six hospital locations described below.

3.3 Methods

3.3.1 Statistical and graphical methods

Each of the APIs were queried using the Python programming language and saved as csv files using the *pandas*, *requests* and *json* packages. The csv files were then analyzed in R version 3.6.2 using the *dplyr*, *ggplot2*, *sf*, *geosphere*, and *leaflet* packages. Time series graphs and summary statistics, including coefficients of variation, were generated to examine variation in reported pollutants and concentrations across each of the APIs, along with the geographic and temporal resolutions returned when air quality information is requested at a specific geographic location. The decision was made not to include a baseline or “correct” air pollution estimate from a government managed instrument to evaluate each estimate’s “accuracy”. This choice is in line with discussions throughout the literature regarding the politics around air pollution measurement and reporting, and how individuals accessing AQ channels may not be discerning of the method through which a particular channel derives its air pollution estimates (Bickerstaff & Walker, 2003; Hubbell et al., 2018; McCarron et al., 2022; Pritchard et al., 2018; Snyder et al., 2013). Instead, details pertaining to the method by which air pollution was estimated, and whether the group responsible for generating the estimate is a government, commercial, or academic entity, or a hybrid of these categories, were reported.

To help contextualize the estimates and support the analysis of the data, AQI thresholds, UK hourly regulatory limits and WHO hourly limits are presented alongside the resulting dataset. Indication of the threshold values are shown on the y-axes of the timeseries graphs presenting PM_{2.5}, PM₁₀ and NO₂ estimates in the results section. In addition, indication of how many times an API estimated a value exceeding these thresholds at each of the six locations during the two time windows is reported in Table 6. These results will support the analysis of heterogeneity

in reported air pollution estimates and accompanying ERB recommendations across AQ channels available to individuals in London, UK.

3.3.2 Visual analysis methods

Semiology, or the deconstruction of an image to “trace how it works in relation to broader systems of meaning” offers a methodological basis for extrapolating key features across the AQ channel visual interfaces, exploring heterogeneity in the reporting of air pollution estimates and associated ERB recommendations, and discussing their implications throughout the air pollution information landscape (Rose, 2016:106; Williamson, 1978). Focal elements of semiological analysis include general composition, colors, shapes, and signs that can be analyzed for symbolic social and cultural significances (Rose, 2016). For example, research examining the association between color scheme and psychological functioning correlates the use of reds and yellows to stimulate “forceful action” or “arousal”, while blue and green insightful relaxation or calm (Elliot & Maier, 2013).

With respect to signs, Rose draws upon Peirce’s sign typology to differentiate between different forms, that is, the *icon*, *index*, or *symbol*. Icons demonstrate a likeness to a particular image or concept, such as a photograph or graphic of a baby. Diagrams are also considered as icons according to Peirce’s typology, as they “show relations between the parts of their object” (Rose, 2016). An index reinforces “an inherent relationship” among the sign and what is being signified, such as employing the image of a pacifier to denote a baby-changing facility. Symbols demonstrate an “arbitrary relation between signifier and signified”, such as the use of the image of a baby to denote future generations. While acknowledging that signs may contain certain social or cultural nuances that can affect their interpretation, this typology is adopted as

a tool for deconstructing the visual content relating to AQI calculation method, ERB messaging content and general visual features across each of the AQ channel.

Table 5. Six hospital locations in London, UK.

Location Code	Hospital location name	Borough	LSOA IMD* (1 – 10)	Distance from LAQN monitor (kilometers)	Distance from BL node (kilometers)	Postcode	Latitude	Longitude
locA	Barking Hospital	Barking and Dagenham	1	3.59	1.07	IG11 9LX	51.53871	0.09866
locB	Princess Royal University Hospital	Bromley	9	5.17	0	BR6 8ND	51.36609	0.05815
locC	Croydon University Hospital	Croydon	1	2.57	1.06	CR7 7YE	51.38919	-0.1113
locD	Kingston Hospital	Kingston upon Thames	7	1.03	0	KT2 7QB	51.41482	-0.2824
locE	Central Middlesex Hospital	Brent	2	0.945	1.47	NW10 7NS	51.53094	-0.26907
locF	Great Ormond Street Hospital	Camden	3	0.36	0	WC1N 3JH	51.52186	-0.12074

*Index of multiple deprivation (IMD) scaled 1 – 10 from most to least deprived.

4. Results

4.1 Summary

As stated in the methods section, data associated front and back-end components of AQ channels were extracted and analyzed in response to the research question surrounding whether the proliferation of AQ channels implies increased variability in air pollution information for the same locations. Variability or heterogeneity in air pollution representation was approached as a function of reported pollutants, numerical values, AQI calculation method, ERB messaging content and visual features across the AQ channel.

For the back end, APIs were queried at six hospitals across London over a weeklong period during two-time windows (May 16th – May 23rd 2022, 7:00 – 11:00 and 14:00 – 19:00). The features of each API and the resulting pollution estimates are reported in Table 6 to support the analysis of numerical, spatial, and temporal (averaging) variation across the 7 APIs at each hospital location. Alongside Table 6, a series of graphs (Figures 17a – c and 18) are employed to visualize the variation in AQI thresholds reported at each location. After sub-setting the dataset to focus on specific time windows (i.e. morning and afternoon/evening) and specific pollutants, not all of the APIs sampled were represented in the dataset. These results, contained in Tables 6 and 7, are described in detail throughout section 3.1. Specifically, Table 6 indicates which APIs delivered estimates for each pollutant, at which hospital locations, alongside the specifications of the pollution estimation method.

For the front end, screenshots of the user interfaces for 14 of the 18 AQ channels are presented and analyzed. Visual methods were employed to examine varying features across the sample and respond to the overarching research question regarding whether AQ channel proliferation

has resulted in variability in the air pollution information reported at the six common hospital locations.

4.2 Numerical representations of air pollution

Each API delivered estimates for a different selection of pollutants. The most reported pollutant was PM_{2.5}, delivered by all APIs apart from API 4. APIs 1, 5, 7 and 8 delivered PM₁₀ estimates for a subset of the six locations (all apart from Croydon University, Kingston, and Princess Royal University Hospitals), while APIs 1, 4, 7, and 8 delivered NO₂ estimates for all locations. APIs 2, 4, 5, and 6 reported AQIs (Figures. 17a – c). API 5 did not supply an AQI for the locations of Croydon University, Kingston, and Princess Royal University Hospitals (Table 6). Reported AQIs are shown across Figures 17a, 17b and 17c and are shown on separate graphs according to the method that is used to calculate the AQI. Three of these four APIs reported AQIs in the “moderate” range or above during the sampling time frame. API 4 reported 39 instances, API 2 reported 28 and API 5 reported 25 instances of the AQI being in the moderate range or above. These figures are reported in Table 5 as percentage of total hours sampled where the AQI was declared to be in the moderate range by each API at the six locations. Figure 18 looks across the four APIs that relayed AQI threshold readings using different AQI calculation methods. It shows how the proportion of AQI threshold readings by each API in the moderate or higher range varies within a particular hospital location. This demonstrates that different APIs are relaying different AQI threshold levels for the same location.

PM_{2.5}, PM₁₀ and NO₂ readings supplied by each API are “raw” estimates pertaining to the physical location of the monitor, sensor, or in the case of modelled estimates, a specific geographic area. To examine these estimates in greater detail, summary statistics for PM_{2.5} and NO₂ estimates from the morning and evening commute windows are presented below (Table

5). These results revealed that not all APIs sampled for the primary dataset were represented. The reason for this was computational in nature, where certain APIs failed to return estimates for the specified time windows. During this morning commute timeframe (7:00 – 12:00), mean PM_{2.5} and NO₂ estimates ranged from 7.64 – 17.25 µg/m³ and 11.80 – 22.78 µg/m³ respectively among the six hospital locations. In the evening (14:00 to 19:00), means ranged from 6.47– 13.12 µg/m³ and 8.31 – 25.44 µg/m³ for PM_{2.5} and NO₂ respectively. Coefficients of variation ranged from 48.74 to 106.70 across all 6 sampling locations. In each instance, the coefficient of variation was higher in the morning than in the evening for both pollutants, apart from NO₂ at location E (Central Middlesex Hospital). Coefficients of variation tended to be higher for PM_{2.5} in comparison with NO₂, at each of the locations, apart from location B (Princess Royal Hospital) and location E. Acknowledging that what is driving this variation is beyond the remit of this study, the coefficient of variation serves as an indicator of one or more mechanisms driving the scale of variations. These may include, but are not limited to, pollution measurement mechanisms, data management infrastructure, or range of possible pollution sources or behaviours such as commuter patterns. The coefficient of variation is interpreted plainly as an indicator of the presence of variation. That is, the lower coefficients of variation indicate there was less variation in mean pollution concentrations registered across the APIs at a specific hospital location for a particular pollutant, while the higher coefficients signify greater variation observed at a specific hospital and for a particular pollutant.

Timeseries graphs (Appendix 2) showing PM_{2.5}, PM₁₀ and NO₂ estimates from each API across all six hospital locations illustrates some of the variation captured by the summary statistics in Table 6. In the case of PM_{2.5}, estimates from most of the APIs demonstrate agreement apart from API2. In the case of NO₂, API 5 appears to deviate from estimates supplied by APIs 5 and 6. Although API derived estimates are the focus of these figures, a subset of the 18 AQ

channels also display raw pollutant estimates. However, as the screenshots were not obtained at the same time and for the same location, they are not directly comparable. The screenshots are intended to support the analysis of visual features.

Table 6. 7 APIs queried at 6 geographic locations (Hospitals in London, UK)

API #	Commercial, government or hybrid?	Model, Monitor or Sensor?	Number of Queries	Locations queried	Pollutants measured	AQI Calculation method	Averaging time	% AQI readings “moderate” or above	Distance from locA	Distance from locB	Distance from locC	Distance from locD	Distance from locE	Distance from locF
API1	Government	Model	614	locA, locB, locC, locD, locE, locF	PM2.5, PM10, NO2, O3	N/A	hourly	NA	0	0	0	0	0	0
API2	N/A	Monitor	589	locA, locB, locC, locD, locE, locF	AQI, PM2.5, O3	CAQI	hourly	4.75	0	0	2.63	0	0	0
API3	Hybrid	Sensor	936	locA, locB, locC, locD, locE, locF	PM2.5, NO2	N/A	hourly	NA	0	0	1.06	0	0	0
API4	Commercial	Monitor/Model	430	locA, locB, locC, locD, locE	AQI	US AQI	hourly	9.11	3.52	0	0	0	0	0
API5	Commercial	Model	606	locA, locB, locC, locD, locE, locF	AQI, PM2.5, PM10, NO2, O3	Plume AQI	30 min	4.12	0	0	0	0	0	0
API6	Commercial	Model	420	locA, locB, locC, locD, locE, locF	AQI, PM2.5, PM10, NO2, O3	US AQI	hourly	0	0	0	0	0	0	0
API7	Government	Monitor	142	locD, locF	PM2.5, NO2	N/A	hourly	NA	N/A	N/A	N/A	N/A	1.36	0.36

*Distance is measured as kilometers between two latitude/longitude coordinate points

Figure 17.a. *AQI estimates in US EPA format from an API sampled at 6 locations over one week*

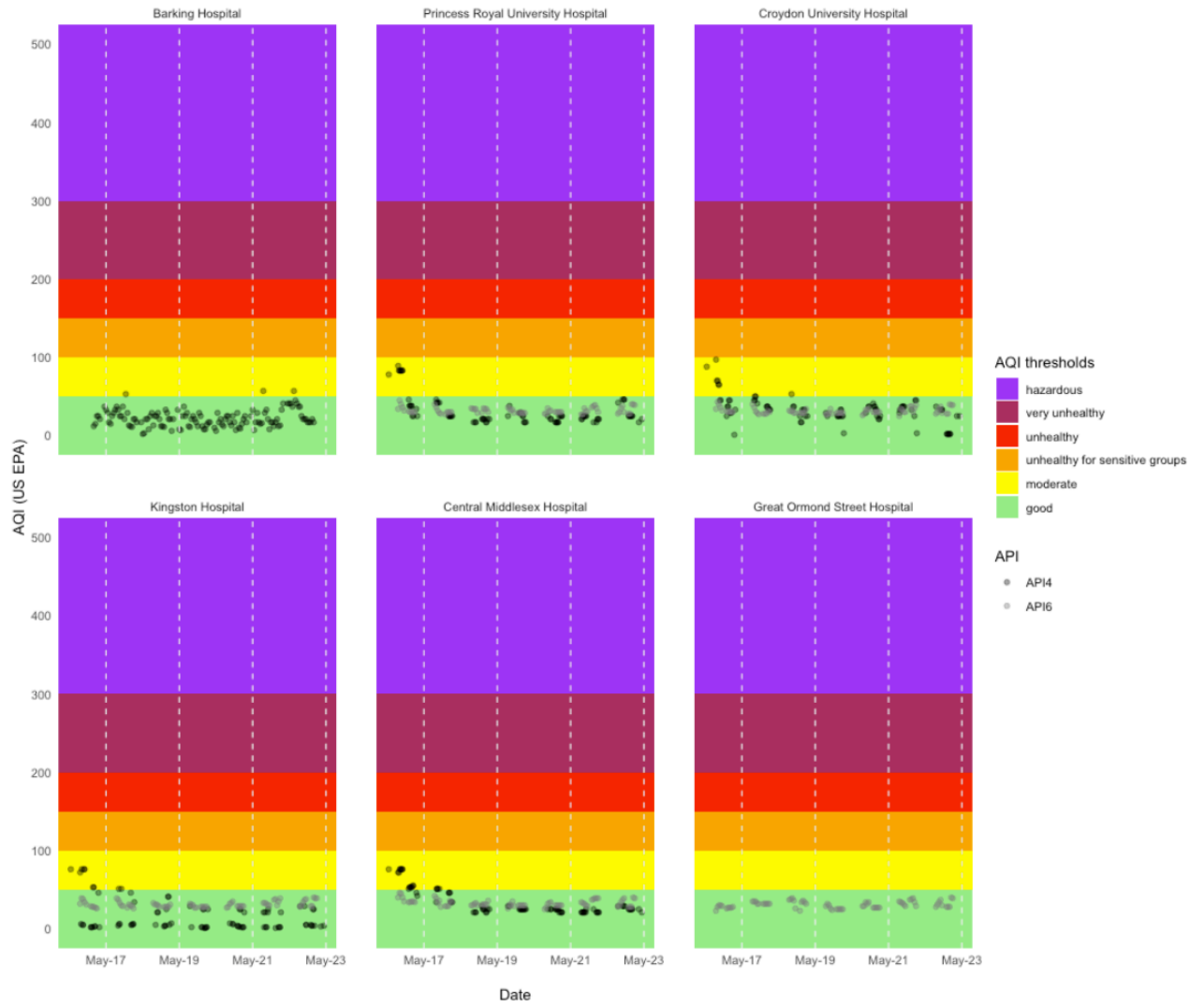


Figure 17.b. CAQI estimates in EU format from an API sampled at 6 locations over one week

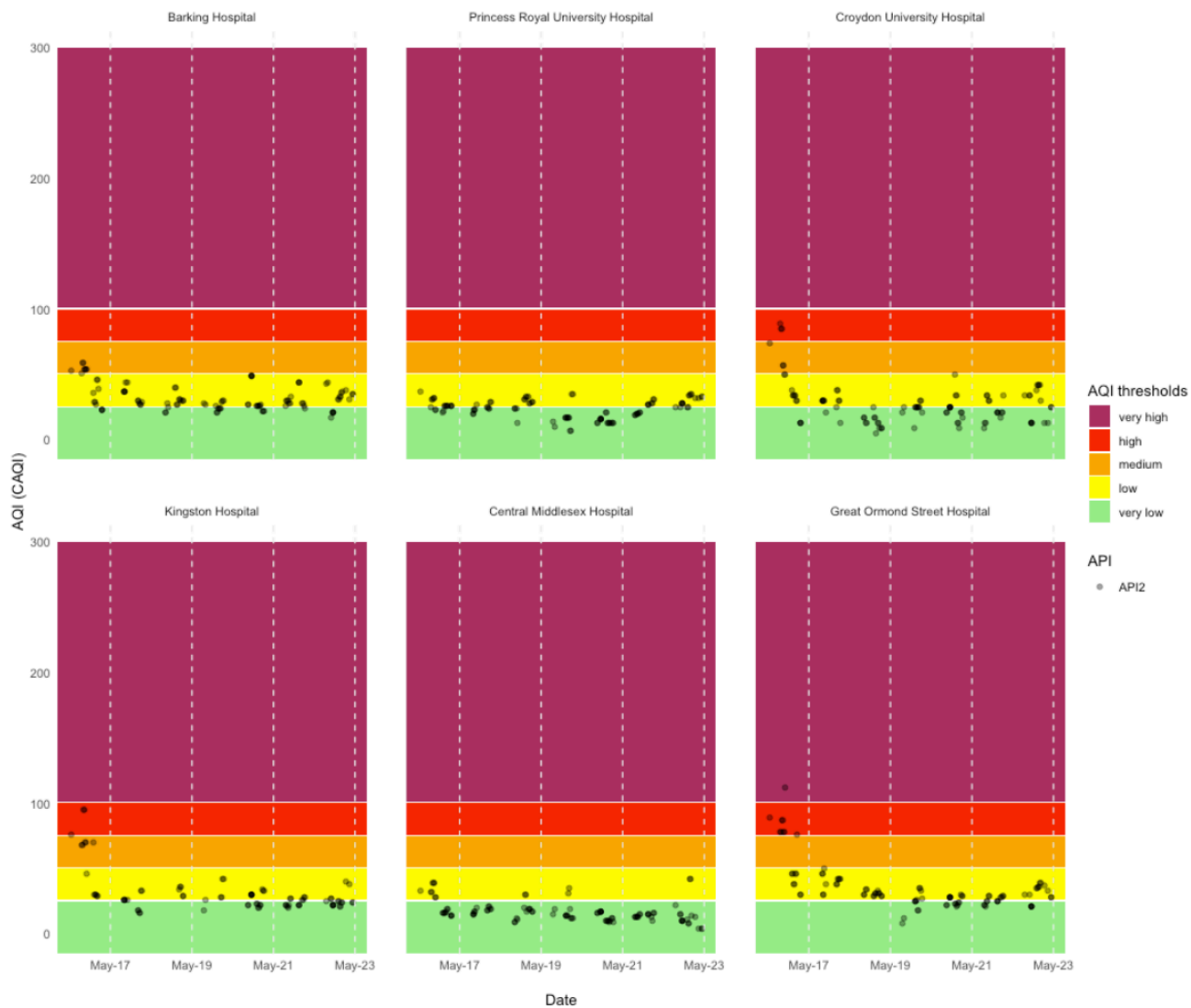


Figure 17c. Plume AQI estimates from an API sampled at 3 locations over one week

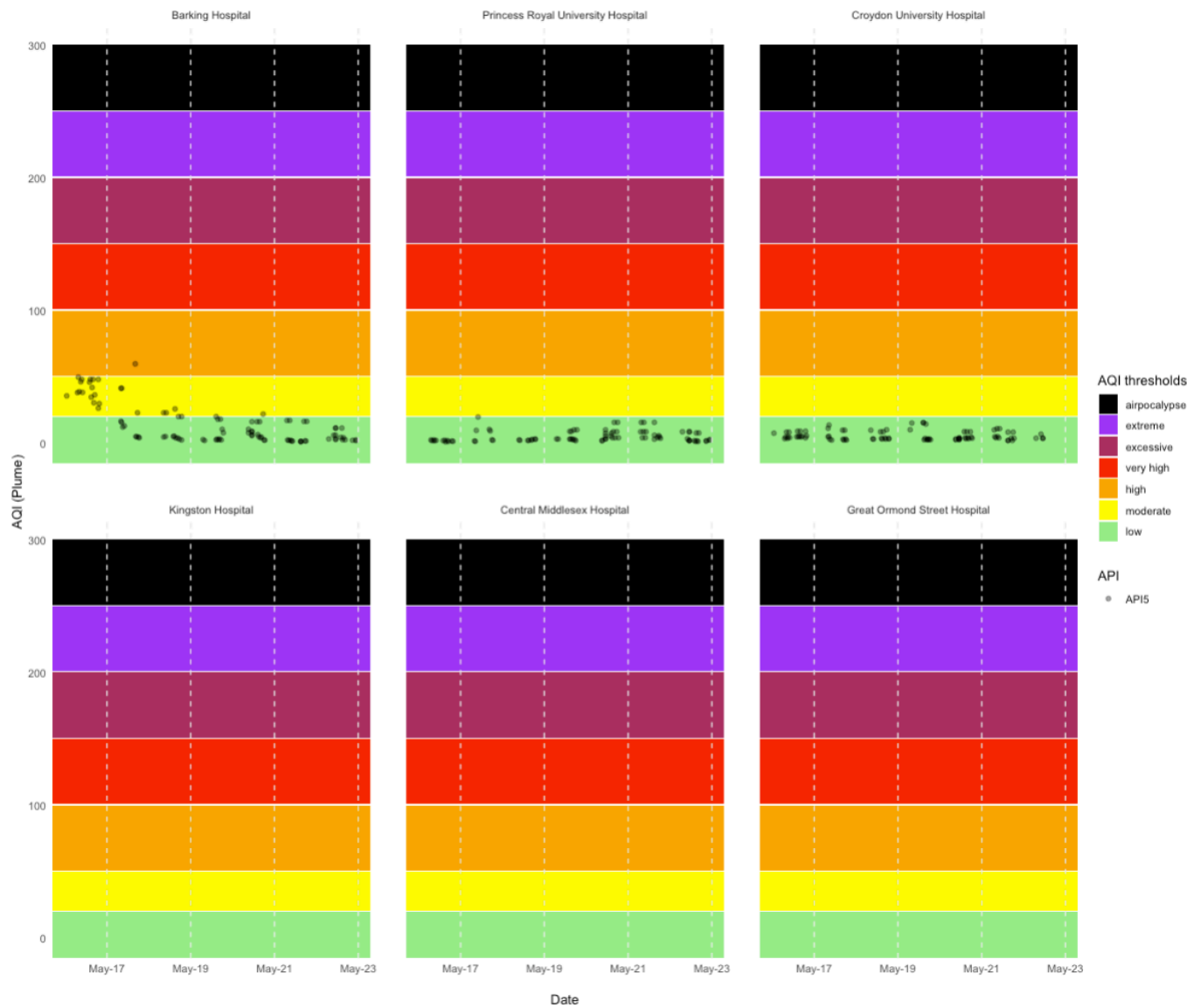
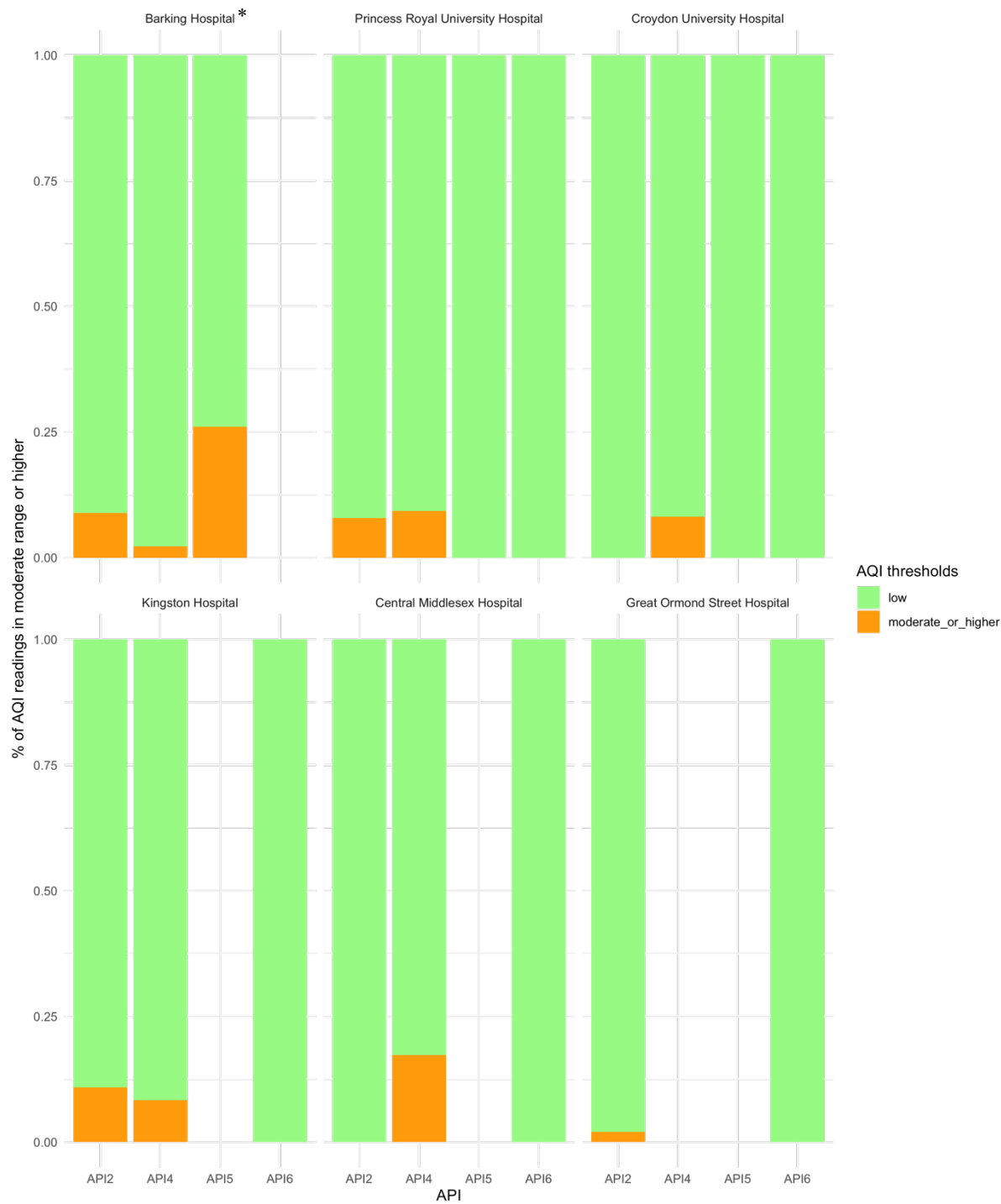


Figure 18. Proportion of AQI estimates in moderate range or higher reported by each API at the 6 hospital locations



* AQI from API 4 for location A (Barking Hospital) was derived from a sensor, while estimates for the other locations are derived from the API 4 model. See Limitations (5.2) for further clarification.

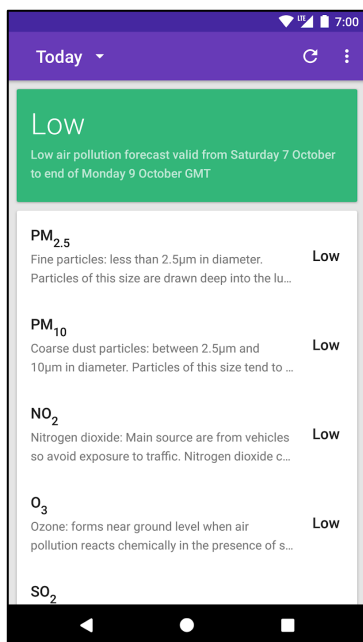
Table 7. Descriptive statistics for PM2.5 and NO2 pollution estimates across multiple APIs at each hospital location during weekday commute

	Morning (7:00 - 12:00, weekdays)		Evening (14:00 - 19:00, weekdays)		
	PM2.5	NO2	PM2.5	NO2	
Mean	17.25	22.78	13.12	25.44	Barking Hospital
SD	15.50	15.99	9.34	13.01	
Max, Min	59.00, 3.48	52.20, 3.01	46.00, 3.55	53.42, 2.63	
Coef. of Variation	95.71	70.20	73.28	51.15	
# of observations	102	77	148	107	
Mean	7.64	11.80	5.63	8.31	Princess Royal University Hospital
SD	5.00	8.3	1.93	5.44	
Max, Min	26.64, 0.14	30.12, 2.75	9.08, 0.24	21.03, -0.51	
Coef. of Variation	65.43	70.33	34.37	65.47	
# of observations	76	76	107	107	
Mean	15.40	16.40	11.33	13.91	Croydon University Hospital
SD	16.72	10.89	9.64	6.84	
Max, Min	89.00, 1.59	38.46, 2.70	50.00, 1.69	28.77, 2.35	
Coef. of Variation	108.56	66.41	85.11	49.15	
# of observations	76	76	107	107	
Mean	14.81	14.88	8.91	12.04	Kingston Hospital
SD	18.14	9.35	8.08	6.66	
Max, Min	95.00, 0.89	34.77, 2.67	70.00, 0.99	26.99, 1.94	
Coef. of Variation	122.47	62.80	90.64	55.36	
# of observations	103	76	141	107	
Mean	8.36	16.24	6.47	16.39	Central Middlesex Hospital
SD	5.17	11.01	2.34	11.40	
Max, Min	27.93, 1.43	38.16, 2.89	12.89, 1.53	46.69, 2.15	
Coef. of Variation	61.83	67.80	36.20	69.54	
# of observations	76	76	107	107	
Mean	16.46	20.92	12.79	23.07	Great Ormond Street Hospital
SD	19.14	12.66	11.69	13.39	
Max, Min	112.00, 3.68	45.16, 3.23	76.00, 3.36	53.80, 1.30	
Coef. of Variation	116.26	60.51	91.38	58.12	
# of observations	138	76	188	107	
APIs Sampled	1,2,5,6,7	1,5,6	1,2,5,6,7	1,5,6	

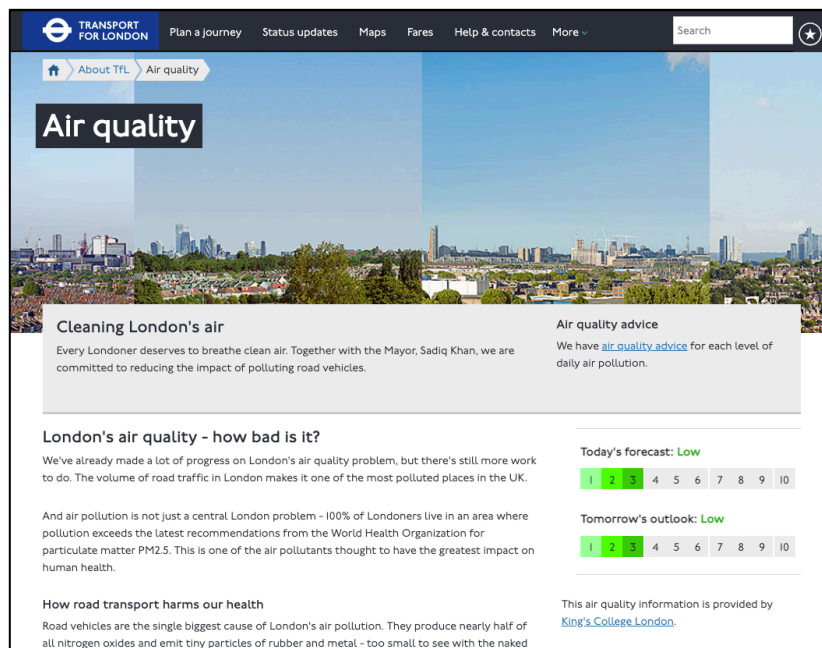
4.3 Visual representations of air pollution

The following section delivers a general description of the visual features, reported pollutants, AQI calculation method, and ERB messaging content expressed across screenshots of the main “landing page”, that is the portion of the page immediately visible to visitors, for the sample of AQ channels. The sample of AQ channels each derive their displayed air pollution estimates from one of the 7 APIs identified throughout the literature review and a prior systematic technology review. The screenshots are presented in across five different groups, which show how they each transform API-obtained air pollution data into different metrics, show different pollutants, employ different AQI thresholds and supply varying ERB messaging.

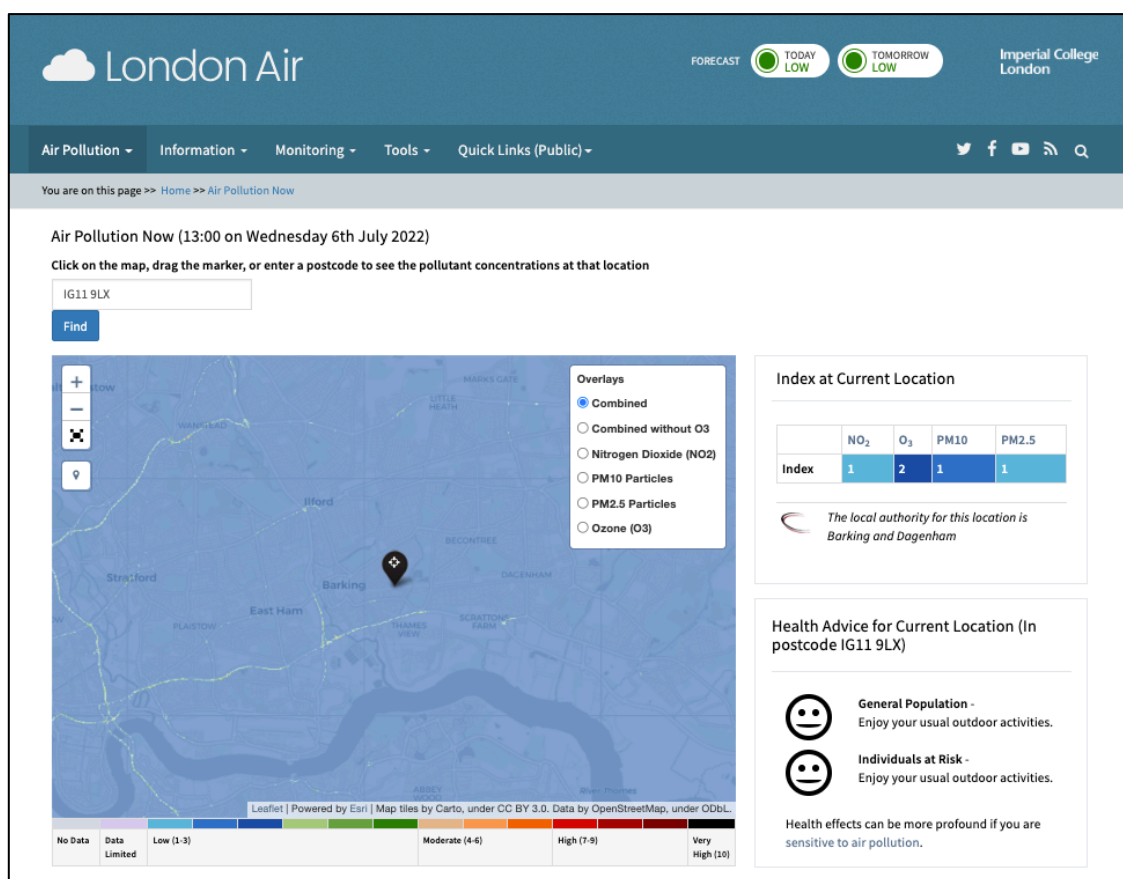
The first series of screenshots were obtained from a mixture of website and mobile app based AQ channels that derive air pollution estimates using API 1. Channels 19.i and 19.iii present readings for multiple pollutants, while 18.ii displays only an AQI threshold. AQ channels 19.i and 19.ii display the color green to indicate low air pollution estimates, and 19.iii uses blue for the lowest AQI thresholds. 19.ii and 19.iii display numerical values, while 19.i uses language only. All three channels supply a general indication of daily air quality derived using the UK’s DAQI equation, presented either in the form of a AQI numeric threshold (19.ii and 19.iii), or in the case of 19.i, verbally in an enlarged font size with a colorized background featured at the top of the landing page. 19.ii is the only channel that presents a future air pollution estimate labelled: “Tomorrow’s outlook”. 19.iii is the only AQ channel containing ERB messaging displayed directly on the landing page.



(19.i)



(19.ii)

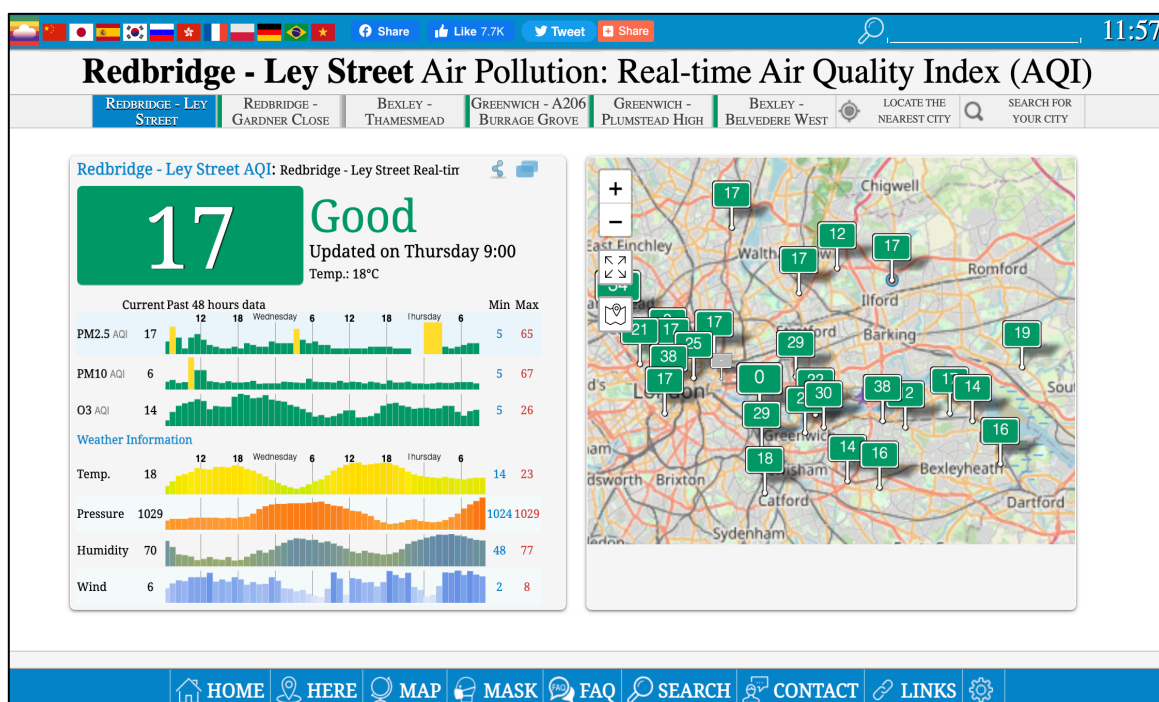


(19.iii)

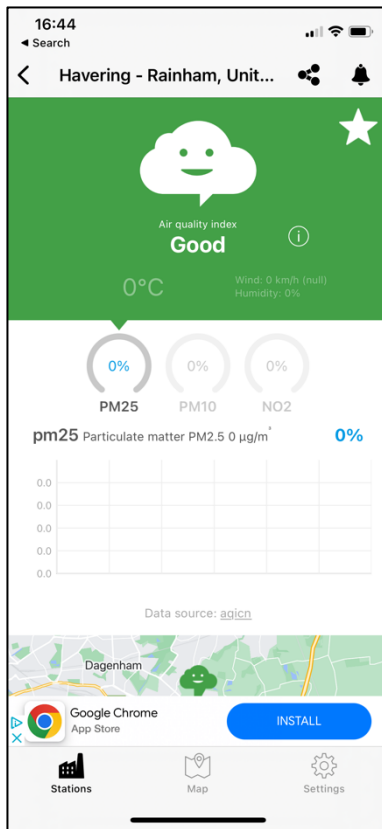
Figure 19. AQ channels (i) Londair (mobile), (ii) Transport for London (web), (iii) London Air (web) each derive air pollution estimates from API1

The second set of screenshots pertain to a sample of AQ channels that derive air pollution estimates using API 2. Channels 20.i, 20.ii and 20.iii supply readings for multiple pollutants

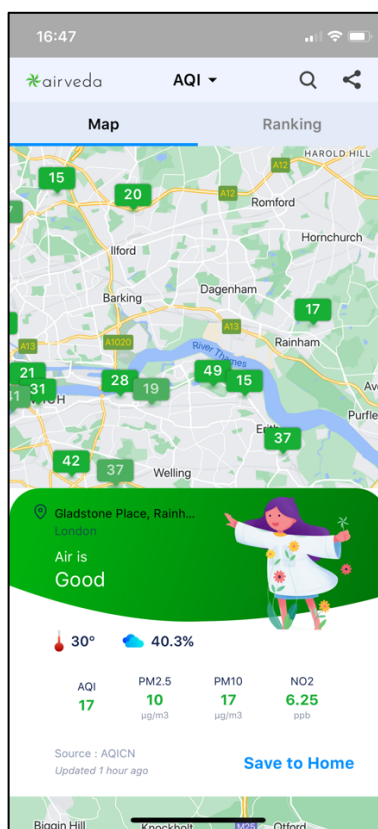
and feature a verbal or numerical indication of pollution in general derived using the European CAQI equation, presented on the landing page in an enlarged font size with a colorized background. Channels 20.i, 20.ii also feature pictorial icons of a smoke cloud with a happy face and a youthful person respectively. 20.iv displays “number of cigarettes smoked” per day as a fraction calculated according to pollution estimates derived via API 2. None of the AQ channels present ERB display directly on the landing page.



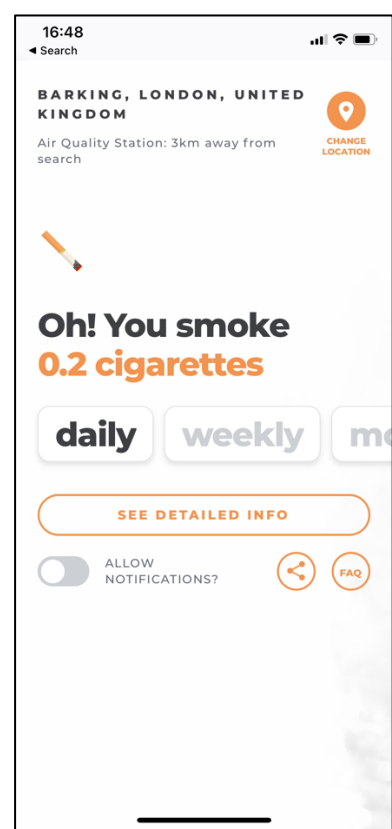
(20.i)



(20.ii)



(20.iii)



(20.iv)

Figure 20. AQ channels (i) World AQI (web), (ii) Air Quality Around Me (mobile), (iii) Airveda (mobile), and (iv) Sh*t I smoke each derive air pollution estimates from API 2

Figure 21 presents a screenshot of the hybrid government commercial AQ channel associated with the Breathe London project. This channel displays PM_{2.5} and NO₂ estimates converted into DAQI format derived via API 3. It displays a map of London overlaid with circles pertaining to specific stationary sensors or “nodes”. The circles are colored according to DAQI thresholds, beginning with light green, through orange, red and lastly black to indicate the highest threshold levels. This channel does not display ERB messaging directly on the landing page.

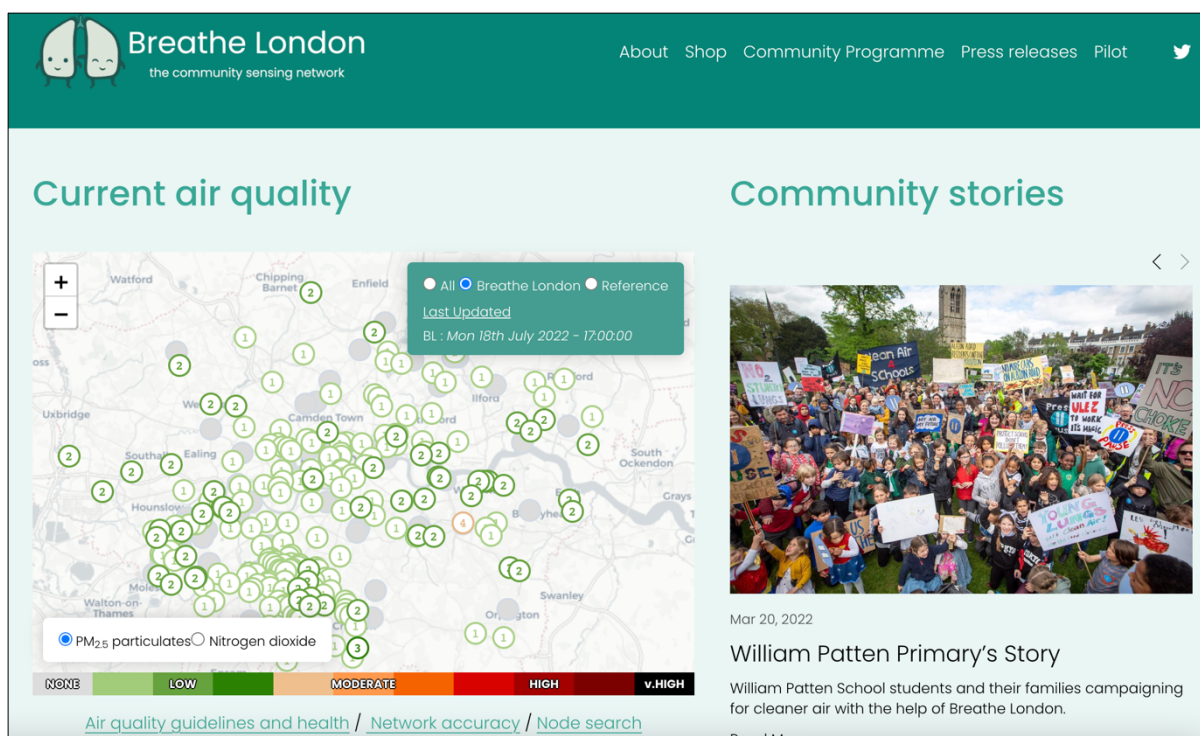


Figure 21. Hybrid commercial-government AQ channel, Breathe London (API3)

Figure 22 presents three AQ channels derived using commercial APIs (APIs 4 – 6). All three channels present a numerical AQI value at the top of the landing page, 22 .i and 22 .iii were calculated according to the U.S. Environmental Protection Agency’s (EPA) AQI equation, while 22 .ii was calculated according to a custom AQI equation. 22 .i and 22 .ii display readings for multiple pollutants on the main landing page. 22 .i and 22 .ii both display the AQI value in a “speedometer” style partially broken circle, colored in a gradient from green/turquoise to red/purple. The AQI in 22 .iii is displayed over a green rectangular backdrop at the top of the page and is accompanied by a pictorial symbol of a human face with a slight smile. Only 22 .ii displays ERBs as pictorial symbols under the text heading “Tips by category” directly in the landing page view. Additionally, all three AQ channels supply information about current weather conditions including temperature, cloud cover, precipitation and in the case of 22 .ii and 22 .iii, wind direction.

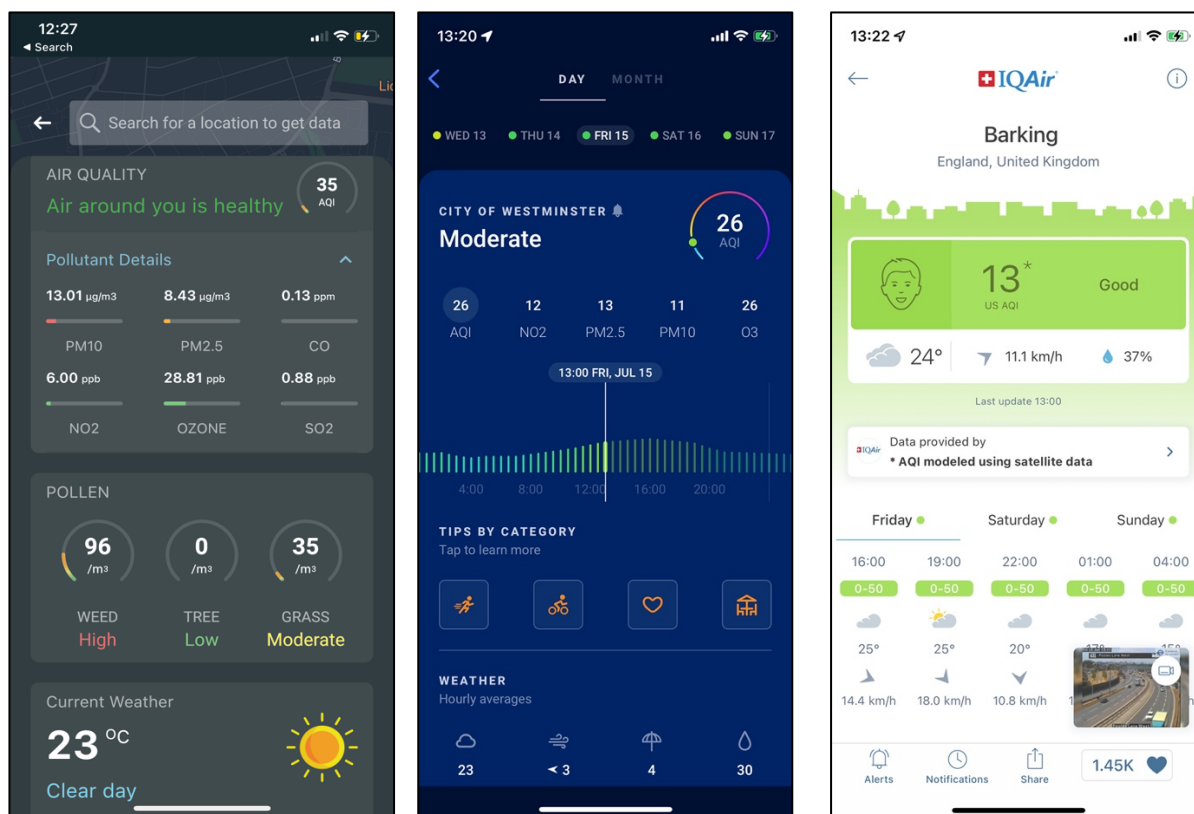
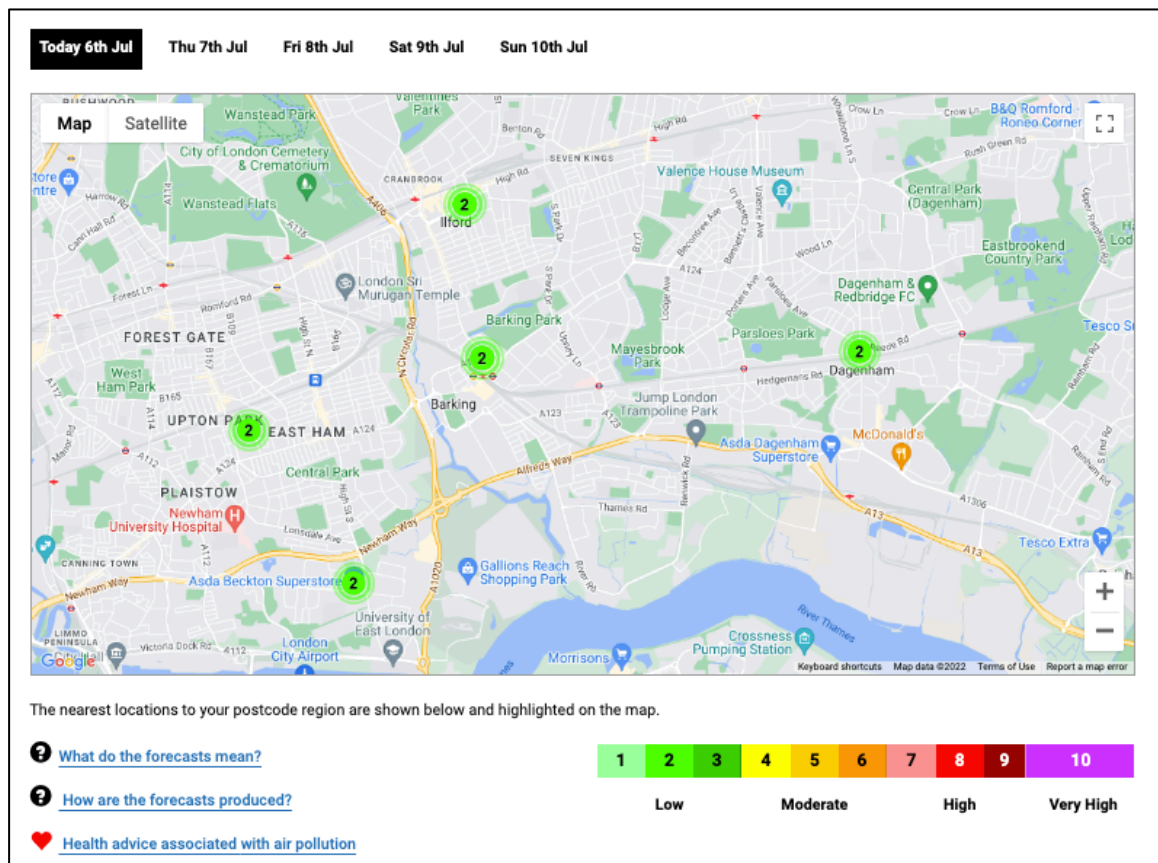
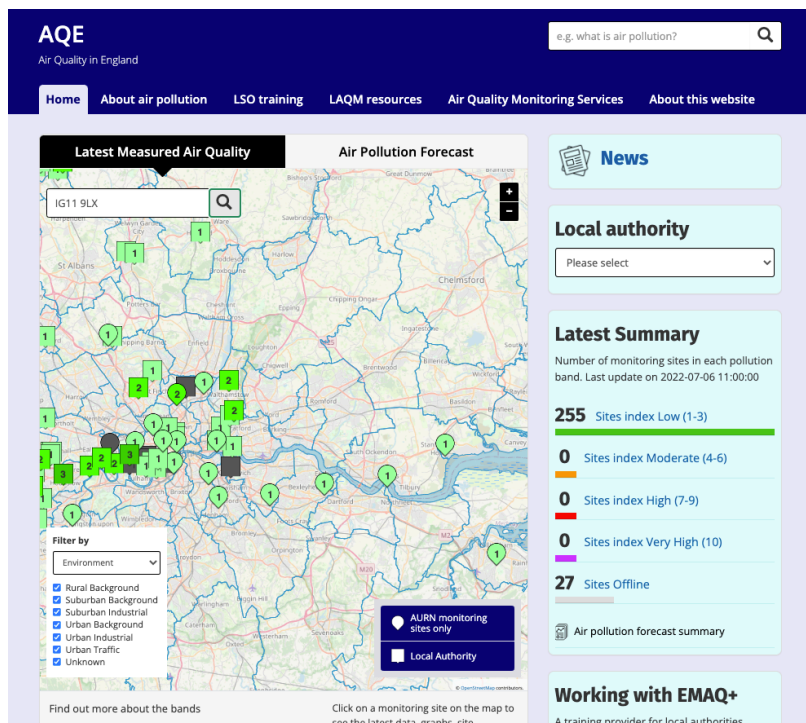


Figure 22. Commercial AQ channels (i) Ambee (mobile), (ii) Plume (mobile) and (iii) AirVisual by IQAir

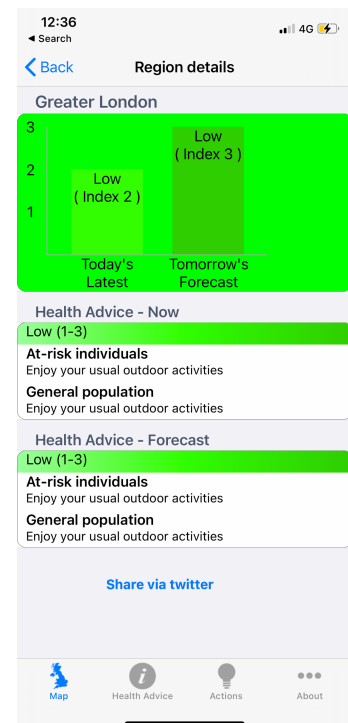
The final series of AQ channel screenshots present air pollution estimates using API 7. All three AQ channels supply numerical readings for the AQI only in DAQI format on their landing pages. Readings are displayed over a color backdrop, ranging from bright green at the lower thresholds to purple at the highest threshold. 23.ii and 23.ii present AQI readings in circles overlaid onto a map of London. The circles correspond to AURN monitoring stations. 23.iii presents a combination of numerical and text indication of the AQI threshold over bright colored rectangular panels. 23.iii is the only channel that presents ERB display directly on the landing page.



(23.i)



(23.ii)



(23.iii)

Figure 23. AQ channels (i) UK Air (web), (ii) Air Quality England (web), (iii) UBreathe (mobile) each derive air pollution estimates from API 7

5. Discussion

5.1 Summary

Following the analysis of the front and back-end layers of the AQ channels sampled in this study, the results demonstrate substantial variability in the visual features, reported pollutants, numerical values, AQI calculation method, and ERB messaging content. Visual strategies for communicating and representing air pollution vary greatly across the channels reviewed. However, several common symbols and themes are repeatedly leveraged across multiple channels. In terms of numeric variation, the APIs supplying air pollution estimates to 18 of the AQ channels demonstrate significant variation in estimated particulate matter (PM_{2.5} & PM₁₀), NO₂, O₃ and AQI at the six hospital locations examined in this study. The implications of such variation when representing air pollution for communicating health and behavioral recommendations are discussed below.

5.2 Limitations

This study delivers an analysis of a sample of “freely” accessible AQ channels in London, UK, that is without additional payment beyond ownership of a WIFI-enabled device. As such, the findings are not necessarily generalizable to all AQ channels globally. Further research is warranted to examine whether the patterns and characteristics observed in this study are replicated across AQ channels in other parts of the world, particularly in areas where channel use is prominent and air pollution conditions are hazardous.

Due to both time and financial constraints, the APIs were only queried for a short period of time (one week). This resulted in a smaller dataset and diminished opportunity to evaluate variation in pollution estimates at each location over time. Following the scheduled querying

exercise, several of the APIs failed to return values for certain specified pollutants. API 1 failed to return AQI estimates and API 5 failed to return AQI estimates for the locations of Kingston hospital, Central Middlesex hospital and Great Ormond Street hospital. This reveals the limitations of computational data retrieval and the potential for missing data. In addition, after sub-setting the dataset to focus on specific time windows (i.e. morning and afternoon/evening) and specific pollutants, not all of the APIs sampled were represented in the dataset. Additional efforts are required to address these gaps in the data, including investigation into the nature of the failure of the API to return data for specific pollutants, and the conducting of manual calculations of AQIs using the respective formulas. A range of issues could have contributed to the failure of the API to return data for specific pollutants. Examples include malfunctioning of the sensor measuring pollution concentrations, power outages, WIFI disruption, or database integration failures. APIs consist of a series of computationally invoked calls and responses. If one link in this series is disrupted it can result in a failure at the query end.

Due to a coding error, the estimates returned for API 4 at location A (Barking Hospital) were unusable. The API providers were unable to supply modeled data retrospectively, and so data from their nearest sensor, was adopted as API 4's air pollution estimate for location A. The sensor is located 3.53 kilometers from location A. The remaining estimates from API 4 are still derived from the provider's model. This fact is considered as the variation in AQI estimates across the APIs at location A is reviewed in the proceeding sections.

Considering the pilot nature of this study, these conditions do not detract from the findings presented here. However, future studies might consider analyzing a larger sample of AQ channels to be able to analyze variation in estimates for specific pollutants at precise geographic locations.

5.3 Variability in numerical features, AQI, and pollutants reported

This section reviews the numerical variability observed across the sample of AQ channels and their associated APIs, while discussing the sources of this variability. The APIs employing models to deliver pollution estimates (APIs 4, 5, 6) allowed for the querying of precise latitude/longitude coordinate points. The query responses from these APIs deliver a single pollution estimate corresponding to the inputted coordinate. This is a fallacy because modelled air pollution estimates are calculated over a geographic area range, typically 5 – 20m² but can be as large as 1km² (Schulte, 2022). As such, the query responses rather pertain to an average of what has been estimated across a 5 – 20m² area. It is important to note how this might contribute to false interpretations of pollution estimates and to consider the implications of obscure reporting of distance from the location or geographic point of interest. Although information about the geographic resolution at which a particular model estimates air pollution is available in documentation generated by the estimate provider, in the case of all AQ channels, individuals would have to leave the main AQ channel platform interface and navigate to this information elsewhere on the providers official website. For those AQ channels deriving air pollution estimates from APIs relaying monitoring station or sensor data, the name and location of the instrument are frequently displayed. Nevertheless, there is no clear statement on any of the sampled AQ channel in this category highlighting that the location of the estimate provided is different from the device geolocation used to determine the nearest instrument-based estimate to report. It is possible that this lack of clarity or transparency about the geographic resolution to which an air pollution estimate pertains can have implications broader implications for policy development, ERBs recommendations, and understandings and governance of air pollution in general.

The results also demonstrated that by focusing on specific pollutants, the number of consultable APIs was reduced. O₃, SO₂, CO and NO and were less commonly reported across the 7 APIs, if they were even reported at all. This finding raises questions around the choice to report certain pollutants over others. By examining the list of pollutants reported by each API (Table 6), one can infer that the audience or “end users” of this technology is a technical one and are aware of the criteria pollutants and their threshold values. If this is not the case or aim of API and AQ channel providers, then pollutants estimated and reported across APIs should be transformed to better respond to the needs of their key audiences. A possible alternative exclusively framing AQ channels as sources of information about “air pollution” would be to shift towards framing them as information sources on “air quality.” As a concept, air quality is less reductionist and establishes more space to account for situated knowledges and experiences with respect to poor air quality exposures (Barry, 2002; Haraway, 1988). This approach to information framing is arguably more aligned with the types of data and information presented across AQ channels, as many present additional data, such as weather data, pollen counts, and ERB messaging, designed inform to interpretations of air quality as opposed to just pollution.

Lastly, as the APIs reviewed in this study have been shown to report different pollution estimates for the same geographic location, it is important to consider how this might affect the delivery of ERB recommendations. Figure 18 demonstrated that different APIs are relaying different AQI threshold levels for the same location by showing how the proportion of AQI threshold readings in the moderate or higher range varies within a particular hospital location. In theory, the proportions should be uniform across the APIs for a unique location. However, varying method of AQI calculation shown in Figures 17a-c, methods of pollution estimation, and the geospatial area to which an estimate pertains (Table 6) appear to be back-end drivers

of variation observed across the AQ channels reviewed in this study. One caveat to note is that the AQI reading from API 4 for location A (Barking Hospital) was derived from a sensor, while estimates for the other locations are derived from the API 4 model. See Limitations (5.2) for further clarification on this point. Nevertheless, the findings from the other APIs and locations signal important questions about how this may affect ERB uptake patterns and associated health outcomes at the population level. Of the 31 AQ channels relying on API derived pollution estimates to deliver messaging, all supplied some form of associated ERB recommendations. ERB recommendations are tied to specific pollution threshold values. The results from this study indicate that it is possible for two individuals standing in the same place, while each consulting an AQ channel that draws on estimates from separate APIs, could receive varying health or exposure reducing behavioral advice.

It is important to note that like visual features, numerical readings are also representations of the phenomenon of air pollution. Both categories of representations are implicated throughout the co-production of understanding and knowledge around what constitutes “air quality”. This extends to how it should be mitigated at the individual level and societal scale. The following section discusses variability in ERB messaging, often bound to visual and numerical representations such as in the case of AQIs, and what the implications of this might be for the adoption of behavioral transformations.

5.4 Temporal and spatial variability

This section describes the temporal and spatial variation expressed across the seven APIs at the backend of the 18 AQ channels analyzed in this study. All APIs apart from one (API 5) reported pollution estimates averaged over a one-hour period. API 5 delivered estimates

averaged over 30-minute periods. The data here are consistent with dominant air pollution data and information delivery trends.

There were multiple instances where the estimate returned was for a location other than the latitude/longitude location of the hospital specified in the Python querying protocol (Table 6). For Croydon hospital, APIs 2 and 3 each returned estimates for a location that were 2.63 and 1.06 kilometers away from the hospital, respectively. API7 returned estimates that were 1.36 kilometers away from Central Middlesex Hospital and 0.36 kilometers away from Great Ormond Street Hospital. In the case of API4, the estimate returned off by 3.5 kilometers away from Barking Hospital due to a coding error.

5.5 Variability in visual features

In this study, screenshots of the main landing pages of 18 AQ channel platform interfaces were gathered and examined for key visual features, including general composition, colors, and signs. The focus on these features links to discussions throughout the literature regarding the comprehensibility of representations of air pollution and environmental phenomena in general prompted by Latour, Gabrys, Pritchard, and Rose. Several aspects relating to general composition were uniform across the AQ channels, such as text descriptions and the employment of a color scheme to denote air pollution thresholds (apart from 18.iv).

The employment of color schemes across all but one of the channels signals reinforces an association with the AQI as a tool for communicating about air quality, where green is “good” and red or progressively darker colors, such as purple or black, are “bad”. While the use of color can be a compelling approach for delivering alerts, it nevertheless relies on personal, intrinsic interpretations of risk. The provision of a color without context can result in a case

where individuals accessing the information may disengage due to a lack of clarity (McCarron et al., 2022a). Alternatively, to make sense of the information an AQ channel is delivering, they may rely heavily on their own situated experiences of pollution and potentially over or underestimate risk (Pritchard et al., 2018). One of channels (17.iii) uses blue to indicate the lowest threshold of pollution, also considered to be a pacifying, calming color according to psychological research by Elliot and Maier. This channel also included color-based indicators (grey and mauve) to indicate a lack of data. This is unique across the AQ channel sample and introduces an additional layer of context that the presentation of a particular color is reliant on data of a specific quality and quantity. When considering the full sample of channels reviewed, differences in color schemes may contribute to convolution across the broader AQ information landscape if a channel lacks context around why a particular color is being presented.

A selection of the AQ channels featured specific signs designed to represent facets of air pollution exposure. Specifically, four of the AQ channels presented anthropomorphized icons that depict human emotional expression, namely a smoke cloud with a slight smile (18.ii), and a cartoon human face (20.iii). These icons appear to associate certain air pollution thresholds with an emotional state such as happiness or sadness. This employment of visuals alongside visceral experiences can contribute to collective understandings and culture surrounding air pollution, for better or for worse. One of the channels employed the symbol of a cigarette to convey exposure and associated connotations (18.iv). The reliance on signs to co-produce understandings of air pollution plays into notions of “publics as emergent”. That is, signs have the potential to simulate knowledge production and self-identification as high or low risk with respect to air pollution by presenting social and cultural cues. This process reinforces the great responsibility of AQ channel producers to consider how the representations of air pollution

they put forward are contributing to individual-level, as well as broader social conceptions of air quality.

7 of the 18 channels displayed maps on their main landing pages. The employment of maps is an orthodox approach to situating information amidst geographic context that has expanded alongside the advent of “big data” (Rose, 2016). As form of big data, without spatial, temporal or measurement unit context, air pollution data can be nebulous and incomprehensible. While only 7 channels displayed maps on their main landing pages, 10 of the 18 feature maps somewhere on their platform. This commonality suggests that maps are likely to be an effective visual mechanism for representing air pollution and further research is warranted around how maps can be employed to contextualize air quality conditions even more effectively.

Many features varied from channel to channel, including which pollutants were reported, the decision to use numbers over text to indicate pollution levels, specific color choices and the employment of unique signs. Variation or diversity across AQ channels is not inherently problematic, it is rather the interpretability and comprehensibility of the information displayed across each channel. McCarron et al propose further personalization of messaging, which will inevitably increase the variability of information displayed across AQ channels (McCarron et al., 2022). Increased personalization will inevitably contribute to greater variation in content displayed across AQ channels, but most crucially it should deliver personalized context to enhance the interpretability of air pollution information. Context can take the form of additional, tailored information, or the establishment of spaces where individuals accessing the channel can actively contribute to supplying context. The latter approach lends itself to participatory co-design. This may run counter to profit seeking aims of commercial AQ channels, which rely on users of their AQ channel as a market of possible consumers of

pollution abating commercial products. It is therefore important to consider what the underlying motivations are for delivering AQ information, why a particular AQ channel has entered the AQ information landscape and fundamentally, where they derive the underlying source of pollution estimates.

5.6 Variability in ERB messaging

While a more in-depth analysis demonstrated that the majority of AQ channels supplied some form of ERB messaging, only two of AQ channels reviewed contain ERB messaging directly on the main landing page. One possible reason for this is to simplify the amount of information delivered in a limited amount of space. Such design choices are aligned with critiques of the information deficit model, reinforcing a transition away from more to better, personalized information about air quality conditions (Hart & Nisbet, 2012; McCarron et al., 2022).

Although individuals may be able to input personal details into a channel platform, such demographic, health or geolocation information, the process for generating the ERB recommendation delivered by an AQ channel is not fundamentally participatory (Schulte, 2022). The reasons for this are centered around the level of transparency and equitable collaboration required to satisfy the conditions of a properly participatory endeavor. Furthermore, the ERB messaging delivered across the sample of AQ channels still does not move beyond limited conceptions of what constitutes a “vulnerable” individual. The absence of a participatory approach to AQ information and ERB messaging delivery sustains this. This is because persistent social-digital divides and infrastructures limit more widespread engagement with AQ channels so more diverse individuals are unable to “self-define” their vulnerabilities and the contexts that underpin them (Dimaggio & Hargittai, 2001; Schulte, 2022). Again, shifting the descriptive focus of AQ channels from air “pollution” to air “quality” information delivery could support the transition of channels to include new fields where

participants can contribute contextualizing insights to build understandings of air quality in a particular area.

McCarron calls for the increasing “personalization” of AQ information. As discussed in the preceding sections, variation, and diversity in AQ information is not incorrect or bad, it is the comprehensibility of those data and information delivered across channels that warrants greater attention. Specifically, acknowledging that comprehensibility and understanding is in a co-productive endeavor. For individuals to develop deeply rooted, lasting comprehension of a subject, their meaningful involvement is required alongside ample opportunity or spaces for iterative exchanges (Whatmore & Landström, 2011). Great care must be taken throughout such participatory, co-design ventures to avoid exploiting time, labor, and personal data to develop a tool or product.

6. Conclusion

This study responded to the key research question surrounding whether a proliferation of AQ channels implies increasing variability in air pollution information for the same locations. It accomplished this by examining numeric and visual air pollution representations across a sample of AQ channels for six specific hospital locations were examined for variability. The results revealed notable differences in air pollution estimates reported across the channels for common geographic locations. This took the form of both numerical and visual features at the front and back end of the AQ channel, predominantly driven by the employment of different pollution estimation methods and AQI calculation methods.

Numeric variation across APIs is associated with geographic location of the monitor or sensor device, or in the case where a model is employed to generate the estimate, the spatial resolution

and possible smoothing of that model. This emphasized the importance of increasing transparency around what geographic and temporal scale AQ channels deliver information about air quality conditions. Here, the choice of AQ channel, alongside a clear understanding of the source of the air pollution estimate could be the difference between interacting with health protective, ERB messaging that has the potential to improve health outcomes. Considering the finding that each of APIs relayed different AQI threshold readings for common locations, it is possible that two individuals standing in the same place, each consulting an AQ channel that draws on a different API to deliver its air pollution reading, could receive varying health or ERB advice.

This finding also reinforces that a key driver of the visual representations across the AQ channels reviewed are its API-derived, back-end source of pollution estimates. Coupling this with the diversity in visual features employed across channels front ends contributes to even greater heterogeneity. While many of the visual features presented across the AQ channels reviewed varied from one another, the use of signs, maps, and the employment of a color scheme to depict air quality conditions were common across most channels. Use of colors to represent air pollution thresholds can be a “loud” abstraction that is also exclusionary in the case of blind or color-blind individuals and other vulnerable or disabled groups who may require additional interpretative support. This signals the importance of reconsidering the universal signifying potential of a color scheme and its abstract, context-less nature. AQ channels should consider providing additional context underpinning the selection of a particular color scheme.

As discussed in section 5.5 on variability in visual features, ERB messaging advice was delivered alongside certain symbols indicating specific categories of exposure mitigating

activity or to target vulnerable population sub-groups. Considering that it is the information underpinning which colors and associated ERB messaging are computationally rendered across the AQ channels, that is of interpretive importance, it is worth considering whether there are alternative approaches to developing intuitive, data-driven representations of air pollution. The focus of this study on analyzing representational disparities across AQ channels, and their lack of linkages to knowledge production, psychology and behavior change theory, helps to illuminate a critical point of communication breakdown amidst the air pollution information landscape.

Beyond contributing to the literature on environmental and health information variability, and associated health outcomes, as well as data typologies employed across AQ channels, this study contributes to the literature on computational methods for generating datasets derived from internet-based platforms. It also empirically demonstrates the potential pitfalls of both numerical and visual representations of the phenomenon of air pollution, specifically in the vicinity of hospitals where more physiologically vulnerable individuals are present. It is necessary to note however that these findings may not be generalizable to other hospital settings across the UK, as variation in pollution microenvironments may be more pronounced in London due to density of transportation networks and other infrastructures. A shift from representing air in terms of *quality*, as opposed to exclusively focusing on pollution, is one possible approach for reframing AQ channels as spaces for collective, participatory, and representative knowledge building, and ultimately policy and messaging, about environmental conditions. Findings from this study have helped to illuminate areas for improvement across air pollution information landscape, while encouraging accountability among AQ channel providers to transparently communicate the geographic and temporal resolutions at which they report air pollution information.

CHAPTER FOUR

Examining psychosocial, health status, and demographic predictors of air pollution exposure reducing behaviors across the UK

Abstract

This study presents a novel, empirical contribution towards understanding sociodemographic and psychosocial predictors of air pollution perceptions and ERB adoption at the population level. It explores whether patterns from controlled, app-based experiments are mirrored at the population level by leveraging survey response subsamples from the “Clean Air Public Insight Tracker” dataset (CAPIT), collected at two waves ($n = 4,002$ and $n = 4,011$), a nationally representative survey commissioned by UK charity, Global Action Plan. Results from ordinary least squares and ordered logistic regression models estimating awareness about the health impacts of air pollution showed greater awareness among women, higher educated individuals, older individuals up until retirement age, and individuals who have or care for others with certain health conditions. Models estimating concern for the long-term health impacts of air pollution was found to be greatest among individuals who have or care for others with certain health conditions. The study also confirms findings that increased awareness, concern for long-term health, as well as the psychosocial concept of “outcome expectancy,” or belief that one’s actions can positively affect the air they breathe, are all associated with greater adoption of ERBs at the UK population level. Such findings can help inform the design of air pollution informational campaigns to address disproportionate air pollution exposures, while taking care not to place the burden solely on individuals to evade pollution.

1. Introduction

Air pollution is one of the greatest global environmental and public health challenges of our time, with 99% of the world’s population being exposed to dangerous levels (Dockery, Pope, Xu, et al., 1993; Kelly & Fussell, 2015). Exposure varies across populations and is a function of diverse factors, including but not limited to geographic location, proximity to point and mobile sources of air pollution, ventilation, occupation, and commuter behavior (Tonne et al., 2018). Air pollution exposure can be mitigated in a variety of ways. At the macro level, this includes regulation and reduction of major air pollution sources, such as factories, farming, and transportation (Kelly & Fussell, 2015). At the micro level, individuals may adopt certain exposure reducing behaviors (ERBs) (Janke, 2014; Neidell & Kinney, 2010; Rappold et al.,

2014). Examples of ERBs include choosing low-emission travel alternatives, managing domestic emissions, and keeping spaces well-ventilated (Ban et al., 2017; Janke, 2014).

The role of the perception of risk around air pollution and how this affects ERB adoption is sparsely documented in the literature. Studies have highlighted that air pollution risk is not necessarily cited as a top concern by those who are most vulnerable in the UK from a demographic standpoint (BMG, 2018 and Brody et al, 2004). It is also worth noting that air pollution alert systems, such as the UK's daily Air Quality Index (DAQI), defines "sensitive" or "at risk" individuals as adults and children with heart or lung problems (Defra, 2020). In addition, the DAQI was originally designed to be a short-term intervention (COMEAP, 2011). The current scope for classifying risk or vulnerability to the effects of air pollution across the alert system is limited to health risk and does not incorporate evidence from literature regarding associations between socio-demographic deprivation and greater exposure risk (Koman et al., 2018).

Outside of specific smaller-scale studies or interventions, little is known about population-level adoption of air pollution related ERBs and how these are patterned. Existing empirical research has focused largely on the effectiveness of messaging strategies delivered through controlled experiments using mobile apps (see D'Antoni et al. 2019, Rappold et al., 2019, and Johnston et al., 2018). These studies relied on small, non-representative samples, which in the case of D'Antoni's study were biased toward individuals with higher educational attainment, and towards individuals with pre-existing health conditions in the case of the three studies cited above. This study involved a short period of data collection (approximately one month) and did not include follow up engagement with study participants. A comprehensive evaluation of patterns of ERB uptake requires follow up investigation to determine how behavioral

transformations are sustained or change over time. Exploring such patterns of ERB uptake, and their associations with psychosocial and sociodemographic factors at the population level can support more informed, comprehensive air pollution exposure mitigation efforts.

To examine whether these psychosocial, demographic or health factors predict ERB adoption patterns at the population level, this study leverages a cross-sectional, nationally representative survey of the UK population commissioned by the Global Action Plan charity. The study presented in this Chapter establishes the foundation of the sociodemographic analysis of AQ channel and ERB uptake contained in this thesis. It serves to unite and contextualize the research presented in Chapters Two and Three against the backdrop of the broader sociological and population health inequalities literature. It responds to the following research questions:

RQ1. Do certain sociodemographic or health-status groups demonstrate greater a.) awareness, and b.) concern with respect to air pollution?

RQ2. Which psychosocial characteristics are the strongest predictors of exposure reducing behaviors?

2. Background and Theory

2.1 Exposure reducing behaviors (ERBs)

There are numerous examples of ERBs, some of which are socio-culturally specific. In the UK, ERBs can be categorized based on whether they are practiced indoors or outdoors. For example, recommendations on how to mitigate exposures inside the home include managing domestic emissions such as not smoking, using the extractor fan when cooking, purchasing low-emission furniture and cleaning products, and keeping spaces well-ventilated and keeping one's boiler maintained (Ban et al., 2017; Janke, 2014). Examples of outdoor focused ERBs include limiting barbeques or burning of solid fuel outdoors, keeping vehicles maintained and adopting low emission travel alternatives. There is a degree of overlap among outdoor focused

ERBs and what is referred to as “pro-environmental” behavior, such as reduced energy consumption, active travel, public transport or electric personal vehicles or electric taxis (Rüttenauer, 2021; Whitmarsh, 2009).

The sizable literature focused on “pro-environmental” behavior helps to illuminate key predictors of such behavior. While individuals maintain opinions or attitudes that favour environmental and health protection, survey-based research reinforces that “saving money” or “convenience” are often the dominant motivators for the adoption of certain pro-environmental behaviors like turning off the lights or adopting public transport (Whitmarsh, 2009). An “attitude-behavior” gap has also been identified with respect to ethical or pro-environmental consumer behavior (i.e. purchasing low emissions or “eco-friendly” products) (Wai et al., 2018). While attitudes can be a significant motivator for both ERB and pro-environmental behavior, they are also considered to be “in flux” and mediated by other psychosocial factors including social norms, guilt, attribution, and values (Bamberg & Möser, 2007).

2.2 ERB adoption and health context

Critical social and human geography research reinforces that perception of risk and behavior with respect to air pollution are a function of local, situated knowledge, including everyday experience and social-cultural factors (Brody et al, 2004 and Bickerstaff and Walker, 2001, Zeidner & Shechter, 1988). An example is living with or caring for someone with a health condition. One study examining uptake of the U.S. AQI found that individuals were more likely to engage with this information if they had illnesses or considered themselves to be the target audience of the messaging (Johnson, 2012). Such findings reinforce the need to focus on analysing how micro-level factors and social circumstances can motivate patterns of ERB adoption.

The COM-B theoretical framework provides a basis for probing what underpins perceptions of, and behavioral responses to, air pollution. It highlights the interplay of three core components, that is “capability”, “opportunity” and motivation” to adhere to a certain behavior (D’Antoni et al., 2019; Michie et al., 2011). The model illustrates interplay of individual and group level intrinsic factors (red and green inner bands) and extrinsic factors (outer grey band) that affect behavior (Delmas & Kohli, 2019). This study aims to identify which components are most strongly associated with adoption of ERBs, while considering concurrent psychosocial and sociodemographic predictors.

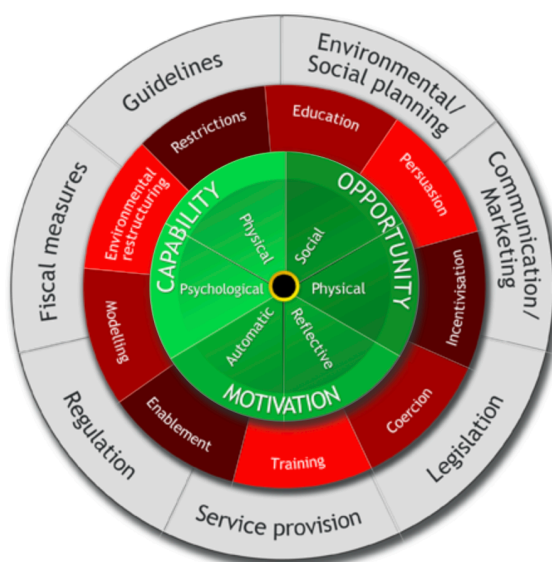


Figure 24. Capability, Motivation and Opportunity Behavior model (Michie et al, 2011)

Falling within the COM-B category of “motivation”, perceptions of health risk have been cited as major catalysts for engagement with the topic of air pollution (Gabrys and Pritchard, 2016; Kaufman et al, 2017). Both short and long-term health effects, including asthma, diabetes, cardiovascular and cardiopulmonary disease, have been causally linked with air pollution exposures (Brunekreef & Holgate, 2002). Physiological mechanisms include but are not limited to vascular deterioration, inflammatory responses, and pulmonary obstructions, which

affect different demographic groups such as older individuals, those who are pregnant, and children, disproportionately (Hoek et al., 2013; Koman et al., 2018).

Results from the U.S. EPA's SmokeSense mobile app study demonstrated while initial interactions with air quality information may have been prompted by perception of health risk, continued engagement, and adoption of ERBs were driven by the presence of physical symptoms (Rappold et al., 2019). Engagement was also supported by the "citizen science" nature of the study design, whereby participants could take on a more involved role in generating study outcomes. Such an approach can translate into more equitable research and policy outcomes, that have been transparently co-produced alongside members of the community (Barnes et al, 2020). The participatory design of this specific study amplified the "opportunity" for individuals to adopt ERBs, however it is still unclear whether perceptions of health risk or experiencing sensory-based cues associated having a health condition "motivate" greater adoption of ERBs at the UK population level.

2.3 ERB adoption and sociodemographic factors

Results from the literature are mixed when it comes to identifying relationships between ERB adoption and sociodemographic factors (i.e. age, gender, education, whether an individual has children), with some studies finding clear linkages while others do not (D'Antoni et al., 2017; Hano, Prince, et al., 2020; Johnston et al., 2018). When looking to the body of literature that examines the relationship between socioeconomic status and health disparities, difficulties in disentangling the mechanisms that drive poor health outcomes are apparent (Pampel et al., 2010; Phelan et al., 2010). The resources, or "opportunity" enabled by financial, educational,

and employment-related conditions, each contribute to whether an individual adopts health protective behaviors.

Having children, specifically those who have asthma, has been shown to influence ERB adoption following the issuing of an air pollution alert (Hano, 2019, Wei, et al., 2020; Janke, 2014; Neidell & Kinney, 2010). It is necessary to examine whether the same patterns of health risk perception ('concern') and ERB adoption (those with pre-existing health conditions and those with children, particularly children who have asthma) are observed where there has been no air pollution messaging alert treatment. This leads to the following hypotheses:

H1a: Individuals who have primary school children aged children (under 11) have greater awareness around air pollution.

H1b: Individuals who have primary school children aged children (under 11) have greater concern around air pollution.

H1c: Individuals who have health conditions themselves, have children with, or care for others with health conditions, have greater concern around air pollution.

2.4 ERB adoption and psychosocial factors

Results from digital intervention studies demonstrated that certain psychosocial factors (i.e. attitudes, awareness, concern, response efficacy/outcome expectancy, personal experience, etc.) are associated with the adoption of ERBs (D'Antoni et al., 2017; B. Hubbell et al., 2018; Riley et al., 2021a). Specifically, D'Antoni examined the effect a series of perception-rooted, psychosocial variables on likelihood of considering permanent exposure reducing behavior changes. Cognitive "capability" related factors like dissonance, confirmation bias, information overload and abstraction have been identified across the health and environmental literature as barriers to uptake of pro-health or pro-environmental behaviors. Perception of "not having

enough time” was also found to have a significant indirect effect on considering adopting permanent behavior changes (D’Antoni et al., 2017). The variables “worry,” “severity,” “response efficacy/outcome expectancy”, and “response efficacy” were also found to have statistically significant effects on actual behavior change measured after four weeks of engaging with the experimental mobile app (D’Antoni et al., 2019). Outcome expectancy, or the belief that something can be done to improve certain circumstances, was also found to significantly predict adherence to health advice received through air quality information channels (D’Antoni et al., 2017). This leads to the hypotheses that:

H2a: Individuals with greater awareness around air pollution exposure adopt more ERBs.

H2b: Individuals who are more concerned about the long-term health effects of air pollution exposure adopt more ERBs.

H2c: Individuals who believe their actions can positively affect air quality in their immediate surroundings adopt more ERBs.

By leveraging the “Clean Air Public Insight Tracker” (CAPIT) dataset, this study is uniquely positioned to examine the relationship between psychosocial factors and demographic contextual factors, including the effects of health-status and parenthood on ERB adoption at the UK population level. In addition, these results can be compared with patterns observed across mobile app-based informational intervention experiments to examine the generalizability of those findings to wider population samples. To our knowledge, this study is the first nationally representative analysis of its kind.

3. Data and Methods

3.1 Data and Samples

Anonymized data associated with perceptions of air pollution linked with socio-demographic characteristics at the individual level were obtained via a nationally representative, pre-weighted cross-sectional survey of the UK population conducted by the charity, Global Action Plan through Opinium. Survey respondents were recruited via Opinium's panel consisting of approximately 40,000 individuals, and from a partner panel that leverages a mixture of their own panels and other internet-based sampling methods (i.e. river sampling, where panel providers recruit participants through websites). The sample is not restrictive (i.e. it is nationally representative and doesn't screen out any demographics or attitudes), and is sent out to a nationally representative sample, resulting in a response rate of 95%. The web-based survey is administered to the representative sample who mostly qualify for the survey; the only individuals excluded were those who either completed the survey in an incoherent manner, speed through the survey, or input identical responses throughout. To ensure national representativeness, responses are weighted to match current UK demographic and socioeconomic conditions (Appendix 3.1.2).

Eight waves of data collection took place between January 2019 and December 2020, and a new group of individuals were sampled each time so that the data are in the form of a repeated cross-section. Each survey wave contained between 166 and 229 questions, including demographic characteristics. Survey questions were administered as batteries of questions that were not burdensome for the respondents, and a subset of the questions was not repeated in each wave. Two samples (Sample A & B) were extracted from the CAPIT dataset to support this analysis. Sample A included survey responses related to past voting behavior, ethnicity, and education, which were only posed during the September and December 2020 sampling waves ($n = 4,002$) (see Table 8). Sample B included responses about presence of health conditions, which were only posed during the June 2019 and April 2020 sampling waves ($n = 4,011$) (see Table 9). Both Samples A & B included the outcome variables selected for analysis in this study.

3.2 Measurement of Variables

3.2.1 Outcome variables

The outcome variables examined in this study include “awareness”, “concern” and number of ERBs adopted. Each of these variables were self-reported and are present across both Samples A & B. This section begins by describing the two psychosocial outcome variables examined in the first set of hypotheses (awareness and concern), and then moves on to discuss the ERB outcome variable examined throughout the second set of hypotheses (see Table 11 for visual aid).

As addressed in the literature, “awareness” about air pollution can take many forms. The decision was made to construct a composite measure of awareness about health issues associated with air pollution exposure including responses to the questions “which of the following, if any, do you think are health issues associated with a) indoor air pollution, and b)

outdoor air pollution. Survey responses were coded as an ordinal binary response to indicate whether the individual was aware of specific health outcomes associated with air pollution exposure. A “score” or count was derived and assigned to each respondent in the sample, which involved taking the sum of the coded responses where a higher number is indicative of greater awareness around air pollution. The resulting measure was assessed for internal consistency using Cronbach’s alpha test, where the standardized alpha ≥ 0.70 at 0.93 for Sample A and 0.94 for Sample B (Tavakol & Dennick, 2011). For the complete list of survey questions contained within each variable measure, see Appendix 3.1.

For the “concern” variable, responses to the survey question asking respondents “how concerned are you about the long-term health impacts of pollution exposure” were treated as ordered factors, ranging from “no concern”, “minor concern”, “moderate concern” to “major concern” in the ordered logit regression models.

A composite ERB measure was generated to respond to the second research question and hypotheses examining whether different sociodemographic and psychosocial factors were associated with a greater volume of ERB adoption. Survey responses were coded as an ordinal binary response to indicate whether the individual had adopted a specific ERB. A count was derived and assigned to each respondent in both Samples, which involved taking the sum of the coded responses where a higher number is indicative of greater ERB adoption with respect to air pollution. Cronbach’s alpha test for internal consistency indicates that ERB scores were reliable measures where the standardized alpha ≥ 0.70 at 0.77 in Sample A and alpha ≥ 0.70 at 0.79 in Sample B. For the complete list of survey questions contained within this measure, see Appendix 3.1.

Outcome variables were examined for suitability in both Sample A and B. Awareness scores were skewed slightly right. Concern an belief in effect of personal actions on air pollution (response efficacy and outcome expectancy variable) were normally distributed. ERB scores were skewed right for both samples and so the square root was obtained and implemented as the independent variable (Appendix 3.2).

3.2.2 Predictor variables

Predictor variables included in the analysis fall into three categories: demographic, health status and psychosocial. The demographic predictor variables for “Having Children” in different age groups were present across both samples. Respondents were asked whether they were pregnant or had children in specific age groups. A dummy variable was constructed to indicate whether the individual had a child below 11 – 13 (primary school age)⁸. Individuals that were childless or did not have a child within this age group were coded as “0” for the dummy variable.

Health status predictor variables are contained only in Sample B. They include categorical responses of “Yes” or “No” to questions whether an individual has themselves, has a child with, or cares for someone with asthma, high blood pressure, a heart condition, another respiratory condition, or another health condition. An aggregate binary dummy variable indicating whether an individual had “any health condition” was generated using individuals’ responses regarding whether they had specific health conditions.

⁸ Supplementary analyzes examined the effect of having children below 11 or 18. While both were found to be significant demographic predictors across models generated in response to the RQs, having children below 11 was a comparatively stronger predictor.

It is necessary to clarify several aspects of the variable is denoted as “higher education” throughout this study. Tertiary educational attainment (above secondary school) across the CAPIT samples is slightly higher than UK population level higher educational attainment as reported by the Organization for Economic Co-Operation and Development (OECD), which was 50.1% in 2021 for individuals between the ages of 25 – 64 (OECD, 2022). The proportions across the CAPIT sample are higher as they present a wider age range (18 – 84) and it is possible that the survey is biased towards respondents with higher educational attainment.

In response to the second research question and set of hypotheses regarding ERB uptake, “awareness”, “concern” and “self-efficacy/outcome expectancy” were selected as key predictor variables. The variables of “self-efficacy” and “outcome expectancy” were examined in unison due to the nature of how the survey question was posed. Specifically, the question asked: *To what extent do you think your personal actions can make a positive difference to the quality of air that you breathe?* This composite survey response variable was treated as ordered factors, ranging from “no difference”, “minor difference”, “moderate difference” to “extreme difference”. An additional psychosocial predictor variable relating to attitudes about air pollution was included throughout sensitivity analyzes in line with evidence from the literature surrounding environmental attitudes (Bamberg & Möser, 2007; Wai et al., 2018). This included responses to the survey question: *Should air pollution be considered a priority* were treated as ordered factors, ranging from “not a priority”, “minor priority”, “moderate priority” to “major priority”.

Table 8. Sample A: General descriptive statistics

	Total (N=4002)
Gender	
Male	2009 (50.2%)
Female	1993 (49.8%)
Age group	
18-25	242 (6.0%)
26-35	815 (20.4%)
36-45	601 (15.0%)
46-55	593 (14.8%)
56-65	772 (19.3%)
66-75	815 (20.4%)
76-80	120 (3.0%)
Over 80	44 (1.1%)
Has children under age 11	
No	3086 (77.1%)
Yes	916 (22.9%)
Education	
Alevel	593 (14.8%)
GCSE	803 (20.1%)
higher_ed	2358 (58.9%)
noformalqual	248 (6.2%)
White/non-White	
Non-White	322 (8.0%)
White	3680 (92.0%)
Income	
Under £10,000	284 (7.1%)
£10,000-£19,999	639 (16.0%)
£20,000-£29,999	709 (17.7%)
£30,000-£39,999	508 (12.7%)
£40,000-£49,000	386 (9.6%)
£50,000-£59,999	302 (7.5%)
£60,000-£69,999	205 (5.1%)
£70,000-£79,999	201 (5.0%)
£80000+	156 (3.9%)
Don't know	73 (1.8%)
None of these	78 (1.9%)
Prefer not to say	461 (11.5%)
Region	
Yorkshire and Humberside	343 (8.6%)
London	367 (9.2%)
Scotland	289 (7.2%)
Northern Ireland	69 (1.7%)
North East	172 (4.3%)
North West	473 (11.8%)
East Midlands	362 (9.0%)
West Midlands	386 (9.6%)
Wales	146 (3.6%)
East of England	369 (9.2%)
South East	705 (17.6%)
South West	321 (8.0%)

Table 9. Sample B: General descriptive statistics

	Total (N=4011)
Has asthma	
No	3470 (86.5%)
Yes	541 (13.5%)
Has child with asthma	
No	3764 (93.8%)
My child	247 (6.2%)
Cares for someone with asthma	
No	3720 (92.7%)
Other people in my care	291 (7.3%)
Has other respiratory condition	
No	3714 (92.6%)
Yes	297 (7.4%)
Has child with other respiratory condition	
No	3934 (98.1%)
My child	77 (1.9%)
Cares for someone with other respiratory condition	
No	3774 (94.1%)
Other people in my care	237 (5.9%)
Has other heart condition	
No	3679 (91.7%)
Yes	332 (8.3%)
Has child with other heart condition	
No	3953 (98.6%)
My child	58 (1.4%)
Cares for someone with other heart condition	
No	3754 (93.6%)
Other people in my care	257 (6.4%)
Has high blood pressure	
No	3089 (77.0%)
Yes	922 (23.0%)
Cares for someone with high blood pressure	
No	3593 (89.6%)
Other people in my care	418 (10.4%)
Has other health condition	
No	2920 (72.8%)
Yes	1091 (27.2%)
Has child with other health condition	
No	3899 (97.2%)
My child	112 (2.8%)
Cares for someone with other health condition	
No	3480 (86.8%)
Other people in my care	531 (13.2%)
Social grade factor (NC-SEC)	
C1 - Junior managerial position	1148 (28.6%)
A - Higher managerial position	355 (8.9%)
B - Intermediate managerial position	1170 (29.2%)
C2 -Skilled manual worker	520 (13.0%)
D - Semi-skilled manual worker	321 (8.0%)
Student	20 (0.5%)
E - Retired/state pension only	270 (6.7%)
Unemployed/long-term illness	207 (5.2%)

Table 10. Descriptive statistics for outcome variables (Samples A & B)

	Sample A (N=4002)	Sample B (N=4011)	Overall (N=8013)
Awareness Score			
Mean (SD)	6.83 (7.12)	7.50 (7.41)	7.16 (7.28)
Median [Min, Max]	5.00 [0, 32.0]	6.00 [0, 32.0]	5.00 [0, 32.0]
Concern			
No impact	391 (9.8%)	374 (9.3%)	765 (9.5%)
Slight impact	1373 (34.3%)	1455 (36.3%)	2828 (35.3%)
Moderate impact	1730 (43.2%)	1705 (42.5%)	3435 (42.9%)
Major impact	508 (12.7%)	477 (11.9%)	985 (12.3%)
Self-efficacy/outcome expectancy			
No impact	401 (10.0%)	489 (12.2%)	890 (11.1%)
Slight impact	2398 (59.9%)	2468 (61.5%)	4866 (60.7%)
Moderate impact	971 (24.3%)	813 (20.3%)	1784 (22.3%)
Major impact	232 (5.8%)	241 (6.0%)	473 (5.9%)
Number of ERBs adopted			
Mean (SD)	5.37 (4.04)	5.42 (4.06)	5.40 (4.05)
Median [Min, Max]	5.00 [0, 28.0]	5.00 [0, 26.0]	5.00 [0, 28.0]

3.3 Analytical approach

Table 11. Modelling approach

Hypothesis	Outcome Variable	Predictor Variables*	Model	Samples used
H1a	Awareness (continuous)	Having primary school aged children (under 11)	Ordinary least squares (OLS)	A & B
H1b	Concern (discrete)	Having primary school aged children (under 11)	Ordered logistic regression (OLR)	A & B
H1c	Concern (discrete)	Having health conditions themselves, having children with, or caring for others with health conditions	Ordered logistic regression (OLR)	B
H2a	Number of ERBs adopted (continuous)	Awareness	Ordinary least squares (OLS)	A & B
H2b	Number of ERBs adopted (continuous)	Concern	Ordinary least squares (OLS)	A & B
H2c	Number of ERBs adopted (continuous)	Self-efficacy/outcome expectancy	Ordinary least squares (OLS)	A & B

* chart does not list additional demographic controls included in each model

This section describes the modelling approach adopted in this study (see Table 11 for visual aid). To test the first hypothesis (H1a), we estimated an ordinary least-squares (OLS) model using both Samples A and B to examine the association between awareness around air pollution and having primary school aged children. For the second hypothesis (H1b), we estimated an

ordered logistic regression (OLR) model using both Samples A and B to examine association between the ordered categorical concern variable and having primary school aged children. Both sets of models were adjusted for age group and gender of respondent, with the age group 18 – 25 and male gender serving as reference categories.

The association between having a health condition, having a child with a health condition, or caring for someone with a health condition and being concerned about the long-term health effects of air pollution was estimated using data from Sample B to assess the third hypothesis (H1c). OLR models estimated the effects of the respondent themselves having a health condition included covariates for age group and gender with the age group 18 – 25, the male gender as reference categories. An additional set of OLR models estimated the effects of either having child or caring for individuals with a health condition included covariates for age group, gender, and whether the individual has a health condition themselves ('No' as reference) with the same reference categories.

OLS models were estimated using both Samples A and B to respond to the second research question (RQ2) regarding whether certain psychosocial characteristics predict greater ERB adoption. OLS models were estimated to examine the association between psychosocial factors, namely "awareness", "concern" and "self-efficacy/outcome expectancy", and number of ERBs adopted across both samples (H2a – c).

Demographic controls for age, gender, region (Tonne et al., 2001), social grade factor, and having children under the age of 18 were included in throughout the analysis of both samples, while educational attainment (D'Antoni et al., 2017), income, and ethnicity were controlled for in models estimated using Sample A. Age group 18 – 25, male gender, East Midlands, junior

managerial (C1), not having children, and A-level as highest level of education achieved, £10,000 – 19,000, and white British, serve as reference categories.

Social grade factor variables are constructed in alignment with UK National Statistics Socioeconomic classification schema (NC-SEC) and were used as an indicator of socioeconomic status in this analysis, as income data was not collected during each wave unlike social grade (ONS, 2021 and Goldthorpe & McKnight, 2006). Models estimated using Sample B include a control variable to account for whether survey responses were collected before and after the first COVID-19 lockdown in the UK. The two waves that comprise Sample A were both collected after the first COVID-19 lockdown (September and December 2020), while the first wave included in Sample B was collected in June 2019 (pre-COVID), and the second in April 2020 (post-COVID).

In Sample B, the variable to indicate the survey was gathered after the first COVID lockdown was found to be collinear with the variable for “Having a child with a respiratory condition.” The reason for this collinearity is unknown, however it may be a result of differences in how individuals responded to survey questions pertaining to respiratory conditions following the onset of the COVID-19 pandemic. The decision was made to omit the variable for “Having a child with a respiratory condition” from the model as it did not contribute additional information into the model. Following this correction, variance inflation factor (VIF) multicollinearity tests were performed across each of the models using the *car* package, where $VIF < 10$ indicates no multicollinearity issues (Fox & Monette, 1992). Outputs from the complete set of sensitivity analyzes can be found in Appendix 3. Data cleaning (*dplyr* package), OLS regression (*stats* package), ordered logistic regression (*MASS* package) table outputs (*stargazer* and *sandwich* packages) were conducted using R, version 3.2.6.

4. Results

4.1 Summary

This section outlines the results of OLS and OLR models estimated to identify whether certain sociodemographic groups or individuals with health conditions are more likely to have higher levels of awareness, concern, response efficacy/outcome expectancy, and adoption ERBs with respect to air pollution. It also reviews results from models developed to examine whether certain psychosocial factors are associated with greater adoption of ERBs.

4.2 Association between demographic factors and air pollution-related psychosocial factors

This section describes the results from OLS models estimated using Sample A to explore whether demographic and health context are associated with greater awareness and concern about health effects in the long-term. The hypothesis (H1a) that individuals who have primary school age children have greater awareness around air pollution was not supported by the data. Having children aged 11 or younger was associated with having a lower awareness score by -1.83 points, equivalent to 26% of 1 SD (95% CI = -1.95, -1.70) in Sample A and -1.73, or 23 % of 1 SD (95% CI = -2.45, -1.02) in Sample B (Table 12). This was the case even when education and income were controlled for in the model (Appendix 3.3.1). Age group and gender covariates were significant predictors of higher awareness in Sample A, where being a woman and between the ages of 46 and 75 was associated with greater awareness (Table 12). Being between ages 26 to 35 was significantly associated with lower awareness scores, while having A-level or a higher education qualification were incrementally significantly associated with greater awareness (Appendix 3). The hypothesis (H1b) that individuals who have primary school children aged children (under 11) have greater concern about the long-term health effects air pollution was supported by the data, where having children under 11 was associated

with an increase in concern in Sample A by 0.45 units or 6% of 1 SD (95% CI = 0.16 – 0.74), and by 0.23 units or 9% of 1 SD (95% CI = 0.04 – 0.43).

The addition of health status covariates to models generated using Sample B eliminated the significance of gender and age variables as predictors of increased awareness. Supplemental analyzes incorporating interaction effects estimated a significant increase in awareness for those between the ages of 26 – 35 who also care for an individual with another health condition (Appendix 3.3).

Table 12. Estimated associations between awareness and sociodemographic characteristics (H1a)

	Sample A	CI	Sample B	CI	Sample Size
Intercept	-3.53*** (0.93)	(-5.36, -1.71)	-2.67*** (0.91)	(-4.44, -0.90)	
Concern for longterm health	0.96*** (0.15)	(0.68, 1.25)	1.19*** (0.16)	(0.88, 1.49)	
Response efficacy/Outcome expectancy	0.92*** (0.18)	(0.59, 1.24)	1.11*** (0.17)	(0.77, 1.44)	
Should reducing air pollution be a priority?	1.18*** (0.12)	(0.93, 1.43)	1.10*** (0.13)	(0.85, 1.36)	
Gender: Female	0.46** (0.22)	(0.03, 0.88)	0.23 (0.23)	(-0.22, 0.67)	
Aged 26 - 35	-1.26** (0.55)	(-2.28, -0.23)	0.29 (0.66)	(-1.02, 1.59)	
Aged 36 - 45	-0.25 (0.56)	(-1.28, 0.78)	0.20 (0.65)	(-1.08, 1.48)	
Aged 46 - 55	1.11** (0.57)	(0.09, 2.14)	0.61 (0.64)	(-0.64, 1.86)	
Aged 56 - 65	1.46*** (0.55)	(0.46, 2.46)	0.49 (0.64)	(-0.76, 1.73)	
Aged 66 - 75	1.16** (0.55)	(0.16, 2.17)	0.25 (0.65)	(-1.02, 1.52)	
Aged 76 - 80	0.07 (0.73)	(-1.43, 1.57)	-0.57 (0.86)	(-2.26, 1.11)	
Over 80	0.91 (0.99)	(-1.27, 3.08)	0.001 (1.12)	(-2.18, 2.19)	
Has Children Under 11	-1.83*** (0.32)	(-2.47, -1.18)	-1.73*** (0.36)	(-2.45, -1.02)	
Has asthma themselves			0.32 (0.34)	(-0.34, 0.99)	n = 541
Has child with asthma			0.35 (0.47)	(-0.58, 1.28)	n = 247
Cares for someone with asthma			-0.12 (0.45)	(-1.00, 0.76)	n = 291
Has other respiratory condition themselves			0.30 (0.46)	(-0.60, 1.19)	n = 297
Cares for someone with other respiratory condition			-0.19 (0.52)	(-1.21, 0.83)	n = 237
Has other heart condition themselves			-0.40 (0.43)	(-1.25, 0.44)	n = 332
Has child with other heart condition			-1.74* (1.02)	(-3.75, 0.27)	n = 58
Cares for someone with other heart condition			0.38 (0.52)	(-0.65, 1.40)	n = 257
Has high blood pressure themselves			-0.15 (0.29)	(-0.72, 0.41)	n = 922
Has child with high blood pressure			-2.22* (1.15)	(-4.46, 0.03)	n = 47
Cares for someone with high blood pressure			-0.75* (0.41)	(-1.56, 0.05)	n = 418
Has other health condition themselves			1.95*** (0.27)	(1.42, 2.48)	n = 1091
Has child with other health condition			2.01*** (0.71)	(0.62, 3.40)	n = 112
Cares for someone with other health condition			2.24*** (0.38)	(1.50, 2.98)	n = 531
COVID: Post 1st lockdown			0.07 (0.22)	(-0.37, 0.51)	
Observations	4,002		4,011		
R ²	0.13		0.13		
Adjusted R ²	0.12		0.12		
Residual Std. Error	6.66 (df = 3963)		6.96 (df = 3965)		
F Statistic	15.94*** (df = 38; 3963)		12.93*** (df = 45; 3965)		

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from OLS regression models examining awareness and concern (outcome variables) as predicted by demographic characteristics. Robust standard errors and standardized coefficients are shown.

Reference categories: Concern (none), Response efficacy/outcome expectancy (none), Gender (male),

Age (18 - 25), Has children under 11 (none), has or cares for someone with health condition (none).

Table 13. Estimated associations between concern and sociodemographic characteristics (H1b)

	Sample A	CI	Sample B	CI
Intercept: No impact—Slight	0.97*** (0.27)		1.35*** (0.25)	
Intercept: Slight impact—Moderate	3.34*** (0.27)		3.86*** (0.26)	
Intercept: Moderate impact—Major	6.00*** (0.29)		6.62*** (0.27)	
Awareness score	0.03** (0.005)	(1.02, 1.04)	0.03*** (0.004)	(1.03, 1.04)
Response efficacy/Outcome expectancy	1.12 (0.05)	(2.96, 3.15)	1.13*** (0.05)	(2.99, 3.18)
Should reducing air pollution be a priority?	0.51 (0.04)	(1.60, 1.74)	0.46*** (0.04)	(1.51, 1.66)
Gender: Female	−0.26*** (0.06)	(0.65, 0.90)	−0.13** (0.06)	(0.76, 1.00)
Aged 26 - 35	0.15 (0.15)	(0.87, 1.46)	−0.03 (0.19)	(0.60, 1.34)
Aged 36 - 45	0.03** (0.15)	(0.73, 1.33)	−0.30 (0.19)	(0.38, 1.10)
Aged 46 - 55	−0.36*** (0.15)	(0.40, 0.99)	−0.40** (0.18)	(0.32, 1.02)
Aged 56 - 65	−0.35*** (0.15)	(0.41, 0.99)	−0.53*** (0.18)	(0.24, 0.94)
Aged 66 - 75	−0.28*** (0.15)	(0.47, 1.04)	−0.65*** (0.18)	(0.16, 0.88)
Aged 76 - 80	−0.39*** (0.22)	(0.24, 1.11)	−0.48** (0.24)	(0.15, 1.09)
Over 80	−1.09*** (0.31)	(−0.27, 0.94)	−1.00*** (0.31)	(−0.24, 0.98)
Has Children Under 11	0.45 (0.09)	(1.38, 1.75)	0.23** (0.10)	(1.06, 1.46)
Has asthma themselves			0.67*** (0.10)	(1.76, 2.13)
Has child with asthma			0.04 (0.13)	(0.78, 1.30)
Cares for someone with asthma			0.28** (0.13)	(1.07, 1.56)
Has other respiratory condition themselves			0.83*** (0.13)	(2.04, 2.55)
Cares for someone with other respiratory condition			0.04 (0.14)	(0.76, 1.32)
Has other heart condition themselves			0.05 (0.12)	(0.81, 1.29)
Has child with other heart condition			−0.40 (0.29)	(0.11, 1.23)
Cares for someone with other heart condition			0.21 (0.15)	(0.95, 1.52)
Has high blood pressure themselves			0.02 (0.08)	(0.87, 1.18)
Has child with high blood pressure			−0.22 (0.33)	(0.16, 1.44)
Cares for someone with high blood pressure			0.29** (0.11)	(1.12, 1.56)
Has other health condition themselves			0.23*** (0.08)	(1.12, 1.41)
Has child with other health condition			0.26 (0.20)	(0.90, 1.68)
Cares for someone with other health condition			−0.08 (0.11)	(0.71, 1.13)
COVID: Post 1st lockdown			0.14** (0.06)	(1.03, 1.27)
Observations	4,002		4,011	
Residual Deviance:	8568.312		8370.106	
AIC:	8650.312		8466.106	

Note:*p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from OLS regression models examining awareness and concern (outcome variables) as predicted by demographic characteristics. Robust standard errors and standardized coefficients are shown.

Reference categories: Response efficacy/outcome expectancy (none), Gender (male),

Age (18 - 25), Has children under 11 (none), has or cares for someone with health condition (none).

4.3 Association between health status and concern around long term effects of air pollution

This section presents results from OLR models estimated using Sample B to explore whether health status is associated with greater concern about health effects in the long-term. The hypothesis (H1c) that individuals who have health conditions themselves, have children with, or care for others with health conditions, have greater concern around air pollution was supported by the data. Specifically having asthma oneself, another respiratory condition, another health condition, and caring for someone with asthma or high blood pressure were each associated with a higher likelihood being concerned about the long term health effects of air pollution exposure (Table 13).

Age group and gender covariates were significantly associated with lower concern, where women and individuals aged 46 and over were increasingly less concerned about the long-term health effects of air pollution. There was also a significant association between increased concern and the first COVID-19 lockdown (Table 13). The results presented in Table 13 include socio-demographic control variables, however the table only shows only key predictor variables. For a full list of covariates and their estimates see Appendix 3.3.3.

Table 14. Estimated associations between psychosocial factors and ERBs adopted (H2a - c)

	Sample A	CI	Sample B	CI
Intercept	0.11 (0.13)	(-0.13, 0.36)	0.04 (0.11)	(-0.17, 0.26)
Awareness score	0.05*** (0.002)	(0.05, 0.06)	0.05*** (0.002)	(0.05, 0.05)
Concern for longterm health	0.06*** (0.02)	(0.02, 0.09)	0.05** (0.02)	(0.01, 0.08)
Response efficacy/Outcome expectancy	0.17*** (0.02)	(0.13, 0.21)	0.24*** (0.02)	(0.20, 0.28)
Should reducing air pollution be a priority?	0.11*** (0.02)	(0.08, 0.14)	0.13*** (0.02)	(0.09, 0.16)
COVID: Post 1st lockdown			0.12*** (0.03)	(0.06, 0.17)
Observations	4,002		4,011	
Adjusted R ²	0.30		0.31	
Residual Std. Error	3.38 (df = 3955)		3.36 (df = 3964)	
F Statistic	38.46*** (df = 46; 3955)		40.87*** (df = 46; 3964)	height
Note: *p<0.1; **p<0.05; ***p<0.01				
Estimates with 95% confidence intervals from OLS regression models examining psychosocial factors (outcome variables) as predicted by number of ERBs adopted. Robust standard errors and standardized coefficients are shown.				
Reference categories: Concern (none), Response efficacy/outcome expectancy (none), Gender (male),				
Age (18 - 25), Has children under 11 (none)				

4.4 Association between psychosocial characteristics and exposure reducing behavior (ERB) adoption

This section describes the results from models estimated using Samples A and B to explore the second research question regarding which psychosocial characteristics (awareness, concern, response efficacy/outcome expectancy and attitudes) are most strongly associated with ERB adoption. All psychosocial factors were significantly associated with the adoption of a greater number of ERBs. Of the psychosocial factors examined, response efficacy/outcome expectancy was most strongly associated with the adoption of a greater number of ERBs, followed by attitudes (Table 14).

The hypothesis (H2a) that individuals with greater awareness around air pollution exposure adopt more ERBs was supported by the data (Tables 14). Results from the OLS model estimating the relationship between greater awareness and adoption ERBs showed significant, positive associations between awareness and the adoption of indoor and outdoor ERBs, as well ERBs over the past 3 months (Table 14).

The hypothesis (H2b) that individuals who are more concerned about the long-term health effects of air pollution exposure adopt more ERBs was supported by the data (Tables 7 & 10). Models estimated using both Samples A and B demonstrate the strongest association between concern that air pollution will have a “major impact” on long term health and greater adoption of ERBs across each of the categories (Table 14).

The hypothesis (H2c) that individuals who have a greater response efficacy/outcome expectancy adopt more ERBs was supported by the data. Individuals who believe their actions can positively affect air quality in their immediate surroundings adopt more ERBs across all categories (Table 14). Lastly, the hypothesis (H2d) that individuals who believed air pollution should be a priority were more likely to adopt more ERBs was supported by the data (Table 14).

5. Discussion

5.1 Summary

This section reviews the results within the context of the main research questions addressed in this study. First, it reviews the limitations of this study. This is followed by a discussion of the findings in response to this study’s first research question about whether certain sociodemographic groups or groups with specific health conditions demonstrate greater a)

awareness, b) concern, c) “response efficacy/outcome expectancy”. The final section presents a discussion of which psychosocial factors most strongly predict adoption of ERBs and whether this aligns with findings from the literature.

In response to the first set of hypotheses directed towards the first research questions, demographic covariates of gender, age and having primary school aged were associated with greater concern around the long-term health effects of air pollution. Contrary to our hypothesis, having primary school aged children was associated with lower awareness scores. In addition, covariates for educational attainment were associated with higher awareness scores. In addition, the presence of specific health conditions or caring for individuals with certain conditions, as well as controls for residential geography were significantly associated with air pollution awareness, concern, response-efficacy/outcome expectancy and ERB adoption.

In response to the second set of hypotheses crafted to generate insight into the second research question, each of the psychosocial variables examined were significantly associated with greater number of ERBs adopted. Response efficacy/outcome expectancy and attitudes toward civic prioritization of addressing air pollution were found to be most strongly associated with ERB adoption.

4.2 Limitations

Limitations of this research include the absence of key social and demographic variables from certain survey “waves”. This prevented an analysis using the complete dataset (N = 16,024). In addition, as the data was not gathered longitudinally, this study is unable to comprehensively examine how psychosocial factors and patterns of ERB adoption are changing over time. Alternative datasets or proxy measures, such as time use data, speedometer or pedometer data

obtained from smart watches or mobile phones could be leveraged to explore how patterns of ERB adoption may change over time.

It is also necessary to acknowledge that while the language used throughout the survey asking individuals whether they adopted any of the listed behaviors to reduce their exposure to air pollution, the behaviors listed also fall into the parallel categories of ‘pro-environmental’ behavior and ‘low-emission’ behaviors (Whitmarsh, 2009). It is possible that these overlapping classifications may have produced some confusion when responding to the survey questions, therefore impacting the data. However, results from the Cronbach alpha test indicated the summary measure was reliable where $\alpha \geq 0.88$. Another important consideration is that adoption of ERBs was self-reported, which is not necessarily the most accurate indicator of actual behavior.

As with all types of survey data, certain potential biases may be present in the data. Examples of these include selection bias towards different age groups or others who have more time or bandwidth to complete opinion surveys, and the possible influence of question ordering bias, information bias and self-reporting bias on how individuals ultimately respond to survey questions.

Furthermore, the nature of the statistical analysis adopted in this study precludes the interpretation of any causal links between sociodemographic factors, health status, psychosocial facilitators and ERB adoption. It is also necessary to note that these findings may not be generalisable to other UK hospitals, as variation in pollution microenvironments due to density of transportation networks and other infrastructures are more pronounced in London in comparison to other parts of the country.

5.3 Association between demographic context, health status, and psychosocial characteristics

The results generated in response to the first research question found significant associations between certain demographic characteristics and psychosocial factors. Being female and of older age (until retirement) was associated with having higher air pollution awareness scores. This aligns with evidence from the literature highlighting greater awareness among females around health issues during COVID-19 (Perrotta et al., 2021).

Contrary to our hypothesis (H1a), individuals who had children under 11 had significantly lower awareness scores. One possible explanation for this is that parents have decreased “capability” to account for information about air pollution, possibly due to information overload or other parenting related priorities (Gifford & Nilsson, 2014; Rüttenauer, 2021). Another explanation is that individuals with children under the age of 11 are generally younger themselves and may not have come across information about the long-term health effects of air pollution. Additionally, they may not have had direct health-risk related experience, which according to theory can motivate information-seeking behavior.

Hypothesis 1b was confirmed and individuals who had children of primary school age (under 11) were more concerned about the long-term health effects of air pollution. Existing literature has focused largely on the effect and actions associated with having children with health conditions. However, the health literature reinforces that children represent a more vulnerable demographic (Koman et al., 2018). Findings from this study highlight that while individuals with primary school aged children are generally more concerned about the effects of air pollution, they are less aware of sources of air pollution and how to mitigate exposures.

The literature signaled strong associations between pre-existing health conditions, personal experience and concern surrounding the impacts of air pollution. The results from the analysis of the CAPIT datasets reinforced this, as individuals who had asthma, another respiratory condition or another health condition demonstrated greater concern about air pollution. This partially confirms Hypothesis 1c, as having greater concern was not unilateral across all health conditions. Caring for individuals with specific health conditions was also associated with greater concern, as well as “response efficacy/outcome expectancy” or believing one’s actions can positively affect air quality in their immediate surroundings. There are several possible explanations for this. One is that the physical sensations experienced by those with respiratory conditions fundamental to the processing of risk or threat perception in relation to air pollution for these groups, signalling a clear “motivation” within the context of the COM-B model (Rappold et al., 2019). Another explanation is the targeting of dominant air pollution messaging towards individuals with respiratory conditions, suggesting these individuals are likely to be more familiar with how to mitigate their own exposures (Johnson, 2012).

Individuals who had a child with a heart condition were found to be less concerned about the long-term health effects of air pollution. While this finding is not aligned with evidence of the increased vulnerability of children with heart conditions to the effects of air pollution, in line with COM-B parents of children with heart conditions are likely to be under tremendous amounts of pressure and may not have the psychological capacity to be concerned about long-term health effects of air pollution.

5.4 Psychosocial predictors of ERB adoption

Results generated in response to the second research question about which psychosocial characteristics best predict ERB adoption revealed several interesting patterns from the data.

While awareness, concern and response efficacy/outcome expectancy all predicted uptake of the four ERBs, response efficacy/outcome expectancy was the strongest predictor.

By selecting awareness as an indicator of knowledge about the health effects of air pollution exposure, this study was able to test how well awareness predicted ERB uptake. The results highlight that in the context of the CAPIT data, awareness or knowledge about air pollution was linked with greater exposure reducing behavior. When reviewing which sociodemographic characteristics were associated with higher awareness scores, education was consistently a significant predictor. Each level of educational attainment was associated with higher awareness scores. This aligns with evidence from the literature reinforcing the significant link between educational status and health outcomes, and the expanded “opportunity” higher educational status enables (Pampel et al., 2010; Phelan et al., 2010). This reinforces the importance of education throughout collective air pollution knowledge building, and how education inequalities could potentially challenge goals of expanding awareness around air pollution.

Of the psychosocial characteristics, concern and response efficacy/outcome expectancy were found to have significant effects on ERB adoption. Belief that personal actions can improve the quality of the air one breathes, or “response efficacy/outcome expectancy”, as well as concern, demonstrated statistically significant associations with increased ERB adoption for all categories. This finding confirms the third hypothesis and aligns with patterns observed across mobile app based informational intervention experiments. Specifically, the work of D’Antoni et al., which identified statistically significant effects of psychosocial motivators including “worry,” “response” and “response efficacy/outcome expectancy” on behavior change after four weeks (D’Antoni et al., 2019). Within the context of the COM-B model,

“concern” can be considered components of one’s “motivation” to adopt an ERB “response efficacy/outcome expectancy” can be considered as part of one’s “capacity”.

A promising avenue for establishing greater capacity, opportunity and motivation for engagement and behavioral transformations associated with air pollution is by deploying participatory or “co-creative” methods (Barnes, Hayes, De Vito, Williams, 2020 and Pritchard et al., 2018). This includes collaborative approaches to research and program development involving affected members of communities of focus. Such approaches have been effective at bolstering notions of response efficacy/outcome expectancy and establish spaces for generating actionable knowledge around mitigating air pollution exposures, while accounting for the unique socio-demographic qualities present in the community of focus.

6. Conclusion

This study contributes to the growing body of research focused on the relationship among sociodemographic characteristics, psychosocial factors and the adoption of exposure reducing behaviors. It confirms important findings highlighted by previous studies, particularly surrounding the influence of “concern” and “response efficacy/outcome expectancy” when it comes to the adoption of exposure reducing behaviors.

Awareness was a significant predictor of ERB uptake, and awareness was significantly associated with higher educational attainment. This finding adds to the long list benefits associated with bolstering educational infrastructure throughout the UK. Findings also revealed that individuals with primary aged school children (11 or younger) in the UK were less aware of the sources and health effects of air pollution. The bias of targeting air pollution alert messaging towards adults and children with respiratory or heart conditions alone risks

alienating those who don't fall neatly into these categories. This highlights an opportunity to directing messaging towards a variety of vulnerable population subgroups, for example, those who at greater risk to exposures and the associated costs due to geography of residence, place of work, or other behavioral or circumstantial factors.

It is worth exploring how the “sensitive” and “at risk” classifications might be expanded to address additional categories of air pollution risk. This would lend itself to the crafting of messages that point to key times or conditions of increased risk for exposure, such as peak commute hours or high pollution episodes. It is important however that such messages also point to clear, widely adoptable behavioral recommendations, while emphasizing how government and other institutions are working to mitigate air pollution emissions. It is also necessary to acknowledge that there are certain risks or trade-offs associated with ERB recommendations, such as encouraging individuals to stay indoors when pollution is high, while pollution concentrations may in fact be higher indoors due to cooking or other domestic activities. It is important that air pollution messaging clearly acknowledges these dimensions and trade-offs.

The results of this study signaled the importance of reinforcing how individuals can positively affect the quality of the air they breathe by amplifying notions of response efficacy/outcome expectancy and instilling a sense of self-confidence or empowerment. Further research is warranted around what types of messaging most effectively boost response efficacy/outcome expectancy with respect to air pollution, and how this can lead to even greater ERB adoption over time. Until now, the research has been focused on how to maximize behavior change. Results from this study reinforce the importance of shifting air pollution exposure research to examine how to maximize notions “response efficacy/outcome expectancy”, which have been

demonstrated to be clear facilitators of ERB uptake. Exploring this in greater detail will likely require additional, carefully crafted survey questions and ideally the surveying of a demographically representative sample of the UK population on a longitudinal basis.

The public health literature and air pollution governance space has been largely focused on encouraging individuals to shift their behavior to reduce their exposure. While this is an important avenue for reducing pollution exposure and supporting public health, such a narrow focus risks placing an unethical burden on already burdened individuals, while diverting attention and resources away from pollution mitigation activities. Comprehensive approaches to air pollution exposure reduction requires a commitment to widespread mitigation activity, as well as resources for facilitating co-created solutions.

CHAPTER FIVE

Exploring inequalities in air quality information access and uptake of exposure reducing behaviors across the UK

Abstract:

Air pollution is a pervasive global environmental challenge that presents substantial and differential risk across populations. Individual-level air pollution exposure is a function of a variety of factors, including but not limited to geographic location, proximity to point sources, ventilation, and behavioral patterns. Mounting evidence suggests that informational interventions can play a substantial role in mediating air pollution exposures for specific population subgroups and reduce downstream adverse health outcomes. The literature has yet to address whether engagement with air quality (AQ) information sources correlates with increased uptake of exposure reducing behaviors at the population level, and whether certain sociodemographic characteristics correlate with a greater likelihood of adopting exposure reducing behaviors (ERBs). This study represents a first step in answering these questions by analysing responses from the “Clean Air Public Insight Tracker” (CAPIT), a nationally representative survey (n = 1,993) of the UK population administered by UK charity Global Action Plan. Results from logistic and ordinary least squares regression models estimate that 37% of the population have accessed air pollution information. The data demonstrates that the odds of *younger individuals (under 36)*, men, those who have children under 18 and non-white individuals of accessing digitally available AQ information are greater than those who do not fall into these categories. Additionally, the odds of accessing any AQ information for those with a health condition or who caring for some with a health condition are greater than for those who do not. Individuals are also more likely to adopt a greater number of ERBs if they access information daily, from the internet or via a mobile app. These findings contribute to the growing literature surrounding which population groups engage with environmental and health-relevant information channels, and what connects engagement with AQ channels and uptake of exposure reducing behavior. Furthermore, it can inform the flow of resources and targeting of informational campaigns towards sociodemographic groups that are less likely to engage with AQ information.

1. Introduction

Poor air quality is one of the most pressing global challenges of the modern era. According to the World Health Organisation (WHO), one in eight deaths worldwide can be attributed to air pollution, with exposure occurring disproportionately across populations (WHO, 2018; Mohai and Saha, 2015). The burden of air pollution on societies is tremendous, affecting life expectancy, fertility, cognitive ability, educational attainment and impacting the labour force (Brunekreef & Holgate, 2002 and Clifford et al, 2016). Exposure to air pollution throughout

the UK has been shown to have disproportionate effects on the health, livelihood, and life expectancy of different socioeconomic groups (Tonne et al 2017, Milojevic, 2017, Aether, 2017).

Air quality information sources, or “AQ Channels”, deliver air pollution readings alongside accompanying health or exposure reducing behavior (ERB) messaging. In their description of the multistage process for improving air pollution-related health outcomes, McCarron et al identify AQ channels as a “critical bridge between external raw data to reduce exposure” (McCarron et al., 2022:3). Examples of channels include digital sources such as websites, smartphone apps, public digital “billboard” displays, in addition to television, newspapers, and radio (Schulte, 2022). ERBs are conveyed throughout messaging delivered across AQ channels, often in the form of an “Air Quality Index” or AQI. Examples of ERBs delivered across AQ channels are choosing low-emission travel alternatives, managing domestic emissions, and keeping spaces well-ventilated (Ban et al., 2017; Janke, 2014).

Studies have reported that the number of emergency room visits and hospitalizations during high pollution events is reduced when vulnerable individuals adopt ERBs recommended across AQ channels (Rappold et al., 2014; Neidell & Kinney, 2010). Additional evidence from controlled experiments demonstrate that individuals adopt health protective ERBs as a result of engaging with various app-based air quality informational interventions (D’Antoni et al., 2017; Johnston et al., 2018; Rappold et al., 2019). This suggests that AQ channels may play a significant role in mediating air pollution exposures for specific subgroups and reduce downstream adverse health outcomes at the population level.

Previous research contained in this thesis, specifically Chapter two, leverages digital trace user analytics data to build a picture of access to and engagement with AQ channels in London, UK. However, digital trace data is demographically poor and precludes analysis of sociodemographic inequalities permeating patterns of access to this innovation. The final Chapter of this thesis presents a study that fills this gap. By employing a nationally representative survey of the UK population referred to as the “Clean Air Public Insight Tracker” (CAPIT), this Chapter examines whether access with information from AQ channels is sociodemographically stratified, how this correlates with adoption of ERBs, and discusses how this can sustain or even exacerbate pollution exposure inequalities.

2. Background and Theory

2.1 Digital inequality

Real-time or forecasted AQ information is disseminated in a variety of ways, including text message alerts, newspaper articles, and tube and bus stop electronic displays (Schulte, 2022). This study maintains a focus on patterns of uptake of digitally mediated AQ channels, that is, channels available via the internet, social media, or mobile apps. Conceptualizing the population who are accessing digitally available AQ channels warrants a review of the existing literature surrounding *digital inequality*. Digital inequality is characterized by variation in “access to and quality of Internet; digital literacy or skills; and the different manners of engaging with digital technologies, including privacy concerns” that can follow existing patterns of sociodemographic stratification (Bol et al., 2018:184; Dimaggio & Hargittai, 2001; Hargittai, 2010; Scheerder et al., 2017; van Deursen & Helsper, 2015; van Deursen & van Dijk, 2014; van Dijk & Hacker, 2003). It is necessary to differentiate channel *access* from *engagement*. Shaw and Hargittai approach “online participation” as a pipeline, where individuals must first have access to the devices and platforms in question (Shaw & Hargittai,

2018). Once access has been attained, individual may then have the opportunity engage with an AQ channel.

Statistics published by the UK office of national statistics (ONS) indicate that in 2020, 92% of adults were “recent” internet users, that is, used the internet in the past three months (ONS, 2022). Additionally, the proportion of recent internet users above the age of 75 increased from 29% to 54% between 2013 and 2020. Nevertheless, internet use is still stratified by age where working-aged individuals 25 – 55 demonstrate the highest use, and individuals 55 and above indicate incrementally less internet use in the past three months. Internet-connected, digital health interventions implemented across mobile apps or web platforms have become an increasing prevalent approach towards mitigating health conditions that involve behavioral components (Neff & Nafus, 2016).

2.2 Digital health interventions

Digital health interventions are geared towards conditions or “challenges” including weight loss, smoking cessation, asthma management and air pollution exposure reduction (Neff & Nafus, 2016; Zhao et al., 2016). A multi-country survey involving experimental digital health interventions to encourage smoking cessation indicate that 58.8% of users were female with a mean age of 32 (BinDhim et al., 2014). This indicates the presence of potential intrinsic and extrinsic life-stage related motivations guiding to specific health-behavioral interventions (i.e. intervening on smoking behavior at younger ages).

AQ channels are designed to target specific, vulnerable demographic groups (McCarron et al., 2022; Schulte, 2022). Still, across each type of digital health interventions, the user bases generally comprised of individuals in younger age groups. With respect to health outcomes

associated with air pollution exposure, children, older adults, and individuals with pre-existing conditions theoretically have the most to gain from digital health interventions in terms of immediate interventions, while other population subgroups can benefit from such interventions as a form of “preventative care” (Gulliford & Alageel, 2019). Socioeconomic and other forms of inequality can amplify risk additional pressure (Fairburn et al., 2019; Koman et al., 2018)

Considering evidence of the potential for digital interventions to reduce air pollution exposures and improve health outcomes, it is important to examine whether there may be stratification in who is accessing air quality information through internet-enabled channels. Furthermore, who accesses possible health benefits supplied by AQ channel informational interventions? Surveys of internet use in the UK highlights age and socioeconomic factors as key contributors to observed patterns (Hargittai et al., 2019). This study will explore whether such patterns, specifically those relating to age, are associated with variable AQ channel access in CAPIT dataset. Given previous findings, the following hypotheses are anticipated to test which socio-demographic groups in the UK are the most likely to access AQ channels.

H1a: *Younger individuals (under 36) are most likely to access digital AQ channels, compared to individuals above the age of 36*

H1b: *Individuals with health conditions themselves are more likely to access AQ channels, in comparison to those without reported health conditions*

H1c: *Individuals who care for someone with a health condition are more likely to access AQ channels, compared to those who report that they do not care for anyone with a health condition*

2.3 AQ channel access, engagement, and uptake of ERBs

The growing body of literature examining access to and engagement with AQ channels, and associated uptake of ERBs has identified significant intrinsic, individual-level psychosocial factors that affect these information seeking patterns. Findings from Chapter IV aligned with

evidence throughout the literature that “self-efficacy”, “response efficacy” and “outcome expectancy, or factors that describe belief that one’s actions can positively affect air quality in their immediate surroundings, significantly affect uptake of ERBs following exposure to AQ channel messaging (D’Antoni et al., 2019; Rappold et al., 2019; Riley et al., 2021). Awareness of the sources and consequences of exposure to air pollution, and concern about the long-term health effects of air pollution were also strong motivators of ERB adoption, especially when individuals had health conditions themselves, or cared for someone with a health condition. These factors have also been described as “threat appraisal” and “coping appraisal” in Protection Motivation Theory (PMT), which are presented ahead of “action and coping planning” from Health Action Process Approach in McCarron et al.’s multistage schematic of the process linking air pollution data to improved health outcomes (Maddux & Rogers, 1983; McCarron et al., 2022; Schwarzer, 1992). Findings from Chapter IV reinforced that concern was associated with greater ERB adoption.

It is also necessary to consider the effect of extrinsic factors. Examples of extrinsic factors linked to increased access to digital AQ channel specifically include natural disasters, such as wildfire and smog events (Johnston et al., 2018; Rappold et al., 2019), and media influence via publication of articles in popular news outlets.

Having children, specifically those who have asthma, has been shown to influence ERB adoption following the issuing of an air pollution alert (Hano, 2019, Wei, et al., 2020; Janke, 2014; Neidell & Kinney, 2010). It is necessary to examine whether the same patterns of health risk perception (‘concern’) and ERB adoption (those with pre-existing health conditions and those with children, particularly children who have asthma)

Considering this alongside findings from Chapter IV that while women were more aware of the health impacts of air pollution, they were significantly less concerned about them in the long term. This might explain to some degree why the odds of women accessing digital AQ channels were lower.

Empirical evidence demonstrates that accessing AQ information does not directly translate into behavior change, resulting in what McCarron et al refer to as the “motivation-behavior” gap (Noonan, 2011; McCarron et al., 2022). This aligns with science, technology, and society (STS) theories of knowledge production processes, which critique the pervasive “deficit model” whereby the solution to behavior change is merely supplying more, “factual” information (Hart & Nisbet, 2012; Jasanoff, 2004). This evidence also aligns with models of pro-environmental and pollution exposure reducing behavior, which approach behavior rather as the outcome of simultaneous extrinsic and intrinsic factors (Bickerstaff & Walker, 2001; D’Antoni et al., 2019; Elliott et al., 1999).

Until now, the literature has exclusively examined the effect of air pollution informational interventions on ERB uptake through controlled experiments involving app-based AQ channels and meta-analyzes (D’Antoni et al., 2017; Johnston et al., 2018; McCarron et al., 2022; Rappold et al., 2019; Riley et al., 2021). While these studies delivered alerts to participants, they allowed study participants to access the AQ channels on their own accord, however they did not report on specific patterns of engagement. There remains a gap in the literature around patterns of AQ channel uptake the UK population level outside of the controlled study environment, whether such uptake socially stratified, and how it correlates with adoption of ERBs. This study addresses this gap in the literature by presenting an analysis of the March 2022 wave of the “Clean Air Public Insight Tracker” (CAPIT) nationally

representative survey (n = 1993) commissioned by Global Action Plan. The dataset contains survey response data surrounding patterns of AQ channel access and ERB adoption along with information on socio-demographic characteristics of respondents throughout the UK. It aims to respond to whether population-level patterns of AQ channel access correlate with increased adoption of exposure reducing behaviors (ERBs). The following hypotheses are tested:

H2a: *Individuals who access internet based AQ channels adopt more ERBs*

H2b: *Individuals who access AQ channels most frequently are most likely to adopt ERBs*

3. Data and Methods

3.1 Data

Data on patterns of AQ channel access and ERB adoption were obtained through a nationally representative, cross-sectional survey of the UK population conducted on behalf of the charity, Global Action Plan by Opinium. Opinium draws from their own nationally representative panel, for which they have an established recruitment process, to conduct the CAPIT survey. Respondents are recruited from Opinium's panel, which consists of approximately 40,000 individuals, and from a partner panel. The partner panel employs a mixture of their own panels and other internet-based sampling methods such as river sampling, where panel providers recruit participants through websites. The internet-based survey is sent out to the representative sample who mostly qualify for the survey; the only people that are not included are those who removed for completing the survey in an incoherent manner, for speeding through the survey, or for inputting identical responses throughout. The sample is not restrictive (i.e. it is nationally representative and doesn't screen out any demographics or attitudes) and is sent out to a nationally representative sample, resulting in a response rate of 95%. Responses are then weighted across demographic and socioeconomic dimensions to achieve representative figures (Appendix 3.1.2)

Data collection occurred in March 2022 and asked respondents about demographic characteristics, health status, and a set of questions around air pollution information seeking behavior and subsequent ERB adoption (N = 1,993). Descriptive statistics were generated for the sample and distributions for outcome variables of interest were examined (Table 15 & Table 16).

3.2 Measurement of Variables

3.2.1 Outcome variables

The outcome variables examined in this study include whether an individual has accessed AQ information, and how many ERBs they adopt following interactions with AQ information. CAPTI survey responses to specific questions were selected as measures to examine the outcome variables. This section begins by describing the construction of two AQ information access outcome variables to respond to hypotheses H1a - c. The phrases “AQ information access” and “AQ channel access” are used interchangeably as each of the survey options or information sources are considered examples of AQ channels.

The survey question *“Have you ever accessed information about air pollution conditions (forecast or in real-time), and if so, from where?”* asked respondents to indicate whether they had ever accessed AQ information by selecting from a list of sources or AQ channels, which included the options: “The internet generally”, “Social media”, “TV/radio adverts”, “GP surgery”, “National Newspaper”. “Hospital or clinic”. “Local newspapers (and local magazines)”, “Pharmacy”, “Phone app”, “School” and “Other”. Responses were assigned a binary code where “0” indicated non-access and “1” indicated the respondent had accessed that specific AQ information source. A macro-level measure was generated to indicate whether an

individual had ever accessed a digital AQ channel, which included “The internet generally”, “Social media” and “Phone app”. This served as the outcome variable to respond to hypothesis H1a that individuals under the age of 36 are more likely to access digital AQ channels. An additional macro-level measure was generated by assigning a “1” if the respondent had indicated they accessed any of the sources listed above, and “0” if they had not ever accessed any sources. This measure was selected as the outcome variable to test hypotheses H1b and H1c that individuals with health conditions, or who care for someone with a health condition, are more likely to access digital AQ channels.

To measure ERB adoption patterns, responses to the following survey question was considered: *“Have you done any of the following [behaviors] in response to information you received about air pollution conditions (forecasted or real-time)?”* An index variable was generated to serve as the key outcome measure by aggregating responses to the question above, which asked respondents to indicate whether they had adopted certain ERBs following AQ channel access. For context, response options included a list of outdoor behaviors: “Worn a pollution filtering mask outdoors (not a face covering)”, “Avoided spending time outdoors (e.g. walking, exercising)”, “Changed a journey to travel outside of rush hour”, “Cycled or walked instead of driving”, “Driven instead of walked, cycled or taken public transport”, “Switched off the engine of my vehicle when stationary”, “Used public transportation instead of driving”, “Bought and used low polluting car(s) such as an electric vehicle”, “Actively chosen an electric taxi over another vehicle”, “Other”, “None of the above”. And indoor behaviors: “Used an extractor fan in the kitchen and/or the bathroom”, “Not used solid fuel stoves or open fires”, “Worked from home or video conference instead of commuting”, “Had fewer bonfires or barbeques”, “Used an electric lawnmower instead of diesel mowers”, “Burned smokeless fuel/dry, well-seasoned wood on my open fire/stove”, “Kept dust levels low”, Made sure my

boiler is well-maintained (e.g. annual service)", "Avoided smoking in the house", "Used natural/eco air fresheners and/or cleaning products", "Used fragrance free or naturally scented (e.g. without artificial ingredients) personal care products", "Used low emission (labelled low volatile organic compound or VOC) paints, varnishes and glues (e.g. when decorating, crafting)", "Chosen low emission carpets and/or furniture", "Had a boiler service", "Chosen an eco-delivery slot for online shopping", "Switched to a green energy tariff", "Other" and "None of the above".

The outcome variable was constructed by generating a sum "score" for each respondent representing the number of ERBs they had adopted. A Cronbach's alpha test was performed to test the internal consistency of the index variable and indicated the summary measure was reliable where $\alpha \geq 0.88$ (Tavakol & Dennick, 2011). This outcome variable was right-skewed and so the square root of the measure was adopted throughout the models (see Appendix 4).

3.2.3 Predictor variables

The predictor variables examined in this study fall into two categories: demographic characteristics and AQ information seeking behavior. For the first set of hypotheses, demographic variables for age, presence of a health condition and whether the respondent cared for an individual with a specific health condition, were chosen as predictors of AQ information access.

To respond to hypothesis H1a, a binary age variable was generated to indicate whether an individual was younger than 36, or 36 or older (Table 15). The health status predictor variables include categorical responses of "Yes" or "No" regarding whether an individual had a health

condition themselves, has a child with, or cares for someone with a health condition, as well as variables indicating whether the individual has or cares for someone with a specific health condition (H1b & H1c). The health conditions included “asthma”, “high blood pressure”, “another heart condition”, “another respiratory condition” or “another health condition”. An additional, aggregate dummy variable indicating whether an individual had “any health condition” was generated using responses to the health condition questions above.

To examine what types of AQ channels individuals accessed (H2a), responses to “*Have you ever accessed information about air pollution conditions (forecast or in real-time), and if so, from where?*” were used to generate a categorical variable. All AQ channel or information source options were included in the model as binary categorical variables. The options were: “The internet generally”, “Social media”, “TV/radio adverts”, “GP surgery”, “National Newspaper”, “Hospital or clinic”, “Local newspapers (and local magazines)”, “Pharmacy”, “Phone app”, “School” and “Other”. To measure frequency of AQ channel access (H2b), response to the following question were considered, “*How often have you done the following? Accessed information about air pollution conditions (forecasted or real-time)?*”, which presented the options “Daily”, “Several times a week”, “Once a week”, “Once a fortnight”, “Once a month”, “Once every 2-3 months”, “Never”, “Don’t know/ can’t remember”, all of which are retained as categories for analysis.

3.2.3 Control variables

Sociodemographic factors as ethnicity, income, and region or ward of residence, have been shown as important confounders with respect to pollution exposures and ERB (Fairburn et al., 2019; Koman et al., 2018; Tonne, 2018). As such, demographic controls on self-reported age, gender, educational attainment (D’Antoni et al., 2017), ethnicity, social grade factor, and

region of residence (Tonne et al., 2008) were incorporated into the analysis. Respondents were asked whether they were pregnant or had children in specific age categories. An additional dummy variable was generated to indicate whether the individual had a primary school aged child (below 11 – 13). For these variables, individuals with children outside of these age categories and without any children were treated as “0”. These variables were included as controls throughout the models in line with findings from Chapter IV and evidence from the literature that individuals with children, particularly those who have a health condition, adopt a greater number of ERBs (Hano, 2019, Wei, et al., 2020; Janke, 2014; Neidell & Kinney, 2010).

Social grade factor variables are consistent with UK National Statistics Socioeconomic classification schema (NC-SEC) (Goldthorpe & McKnight, 2006). The CAPIT survey allowed individuals to select “other” if they did not identify with the male or female genders. Four individuals selected into this category. These individuals were removed from the portion of the analysis examining the effect of gender on AQ channel access but were included throughout the rest of the analysis which did not correct for gender. Responses to Likert-scale style questions allowed us to include measures of “response efficacy/outcome expectancy” and “concern” for long term health impacts throughout the sensitivity analysis.

In line with findings from D’Antoni et al and McCarron et al and results from Chapter IV, “Response efficacy” and “outcome expectancy” were included as covariates throughout the models examining ERB adoption. These factors were examined in unison due to the nature of how the survey question was posed, which asked: *To what extent do you think your personal actions can make a positive difference to the quality of air that you breathe.* Likert-scale ordered factor responses ranged from “no difference”, “minor difference”, “moderate difference

to “extreme difference”. In line with the literature, a variable indicating attitudes towards air pollution was included throughout the sensitivity analysis. This included responses to the survey question: *Should air pollution be considered a priority* were treated as ordered factors, ranging from “not a priority”, “minor priority”, “moderate priority” to “major priority”.

Table 15. Descriptive Statistics for demographic & outcome variables

	Overall (N=1993)		Overall (N=1993)
Gender		Number of ERBs adopted	
Female	1085 (54.4%)	Mean (SD)	1.36 (2.95)
Male	908 (45.6%)	Median [Min, Max]	0 [0, 25.0]
Age Groups		Ever accessed AQ information	
18-25	202 (10.1%)	No	1437 (72.1%)
26-35	258 (12.9%)	Yes	556 (27.9%)
36-45	314 (15.8%)	Ever accessed digital AQ information	
46-55	371 (18.6%)	No	1605 (80.5%)
56-65	355 (17.8%)	Yes	388 (19.5%)
66-75	378 (19.0%)	Accesses AQ information - Daily	
76-80	73 (3.7%)	No	1954 (98.0%)
Over 80	42 (2.1%)	Yes	39 (2.0%)
Under or over age 36		Accesses AQ information - Several times weekly	
Under 36	1533 (76.9%)	No	1917 (96.2%)
36 or older	460 (23.1%)	Yes	76 (3.8%)
Educational attainment		Accesses AQ information - Weekly	
No formal qualification	349 (17.5%)	No	1872 (93.9%)
A levels	439 (22.0%)	Yes	121 (6.1%)
GCSE	1110 (55.7%)	Accesses AQ information - Fortnightly	
Higher education	95 (4.8%)	No	1894 (95.0%)
Ethnicity		Yes	99 (5.0%)
White	1786 (89.6%)	Accesses AQ information - Monthly	
Non-White	207 (10.4%)	No	1919 (96.3%)
Has children under 18		Yes	74 (3.7%)
No	1455 (73.0%)	Accesses AQ information - Every 2-3 months	
Yes	538 (27.0%)	No	1831 (91.9%)
Social Grade Factor		Yes	162 (8.1%)
C1 - Junior managerial position	122 (6.1%)		
A - Higher managerial position	192 (9.6%)		
B - Intermediate managerial position	528 (26.5%)		
C2 - Skilled manual worker	201 (10.1%)		
D - Semi-skilled manual worker	260 (13.0%)		
Student	22 (1.1%)		
E - Retired/state pension only	549 (27.5%)		
Unemployed/long-term illness	119 (6.0%)		

3.2.4 Analytical approach

Table 16. Modelling approach

Hypothesis	Outcome Variable	Predictor Variables*	Model
H1a	Accessed AQ info (categorical binary)	Age group	Binary logistic regression
H1b	Accessed AQ info (categorical binary)	Presence of health condition	Binary logistic regression
H1c	Accessed AQ info (categorical binary)	Cares for someone with health condition	Binary logistic regression
H2a	Number of ERBs adopted (continuous)	AQ channel type	Ordinary least squares (OLS)

H2b	Number of ERBs adopted (continuous)	AQ channel access frequency	Ordinary least squares (OLS)
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* *chart does not list additional demographic controls included in each model*

Binary logistic regression models were estimated to test the first set of hypotheses regarding which socio-demographic groups engage the most with AQ channels in the UK. For the first hypothesis (H1a), a model was estimated to examine whether younger individuals (under 34) are more likely to access digital AQ channels, as compared to individuals above the age of 36. For the second and third hypotheses, the models examine whether individuals with health conditions themselves, or who care for someone with a health condition are more likely to access AQ channels, compared to those who do not have health conditions themselves or care for those who do. Demographic and psychosocial covariates were included as controls throughout the models.

A second set of models were estimated to respond to the second research question about whether more frequent access to AQ channels is associated with greater ERB adoption. An ordinary least squares (OLS) regression was estimated to examine the association between access to specific AQ channel types and adoption of a greater number of ERBs (H2a). A second OLS model was estimated to examine whether accessing AQ information at different frequencies was associated with ERB adoption (H2b). Sociodemographic covariates were included in the models, where the male gender, ages between “18 to 25”, “A level” educational qualification and white ethnic background were selected as reference categories.

Data cleaning (*dplyr* package), OLS regression (*stats* package), binary logistic regression (*MASS* package), graphing (*ggplot2*), table outputs (*stargazer* and *sandwich* packages) were conducted using R, version 3.2.6.

4. Results

This section describes the results from the binary logistic and OLS regression models generated to examine whether AQ channel access is socio-demographically stratified, and whether engagement with AQ channels correlates with increased uptake of ERBs at the UK population level. Before launching into the results, a summary of patterns of UK population level AQ channel patterns of access are presented.

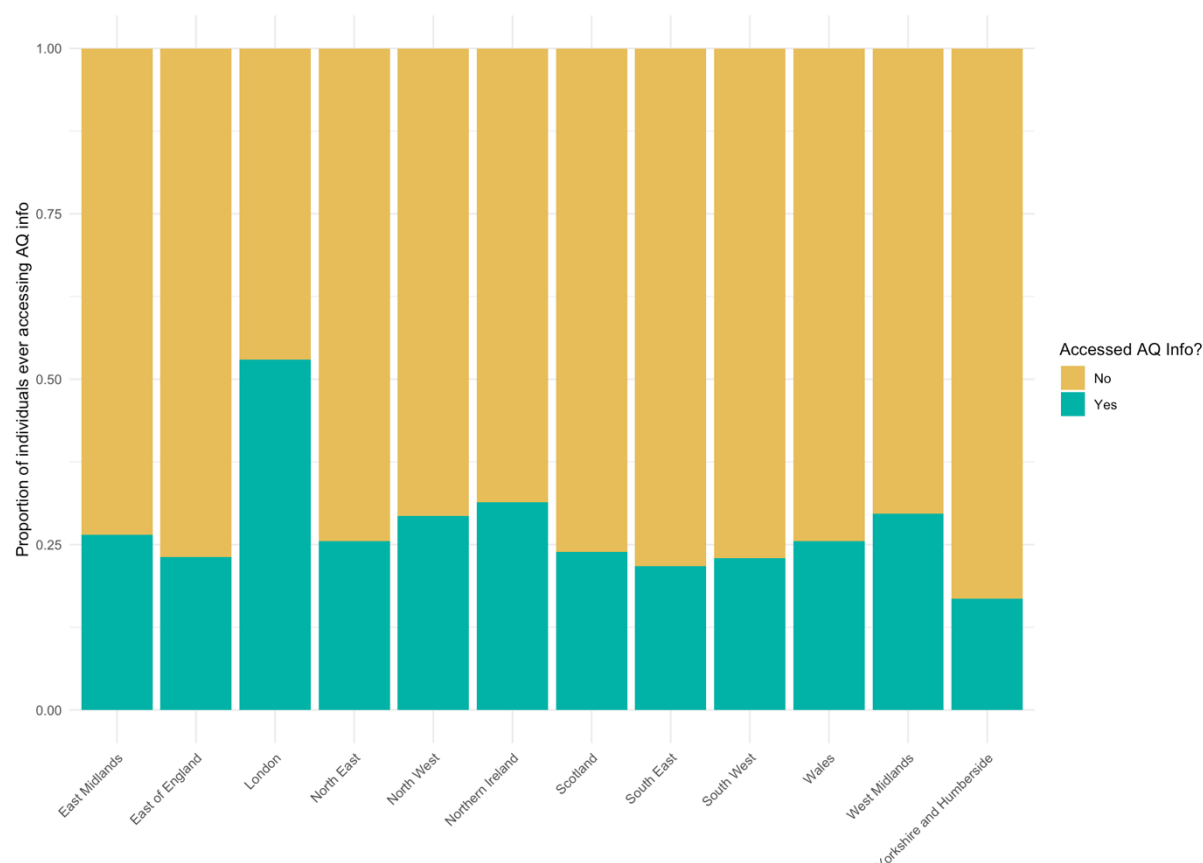
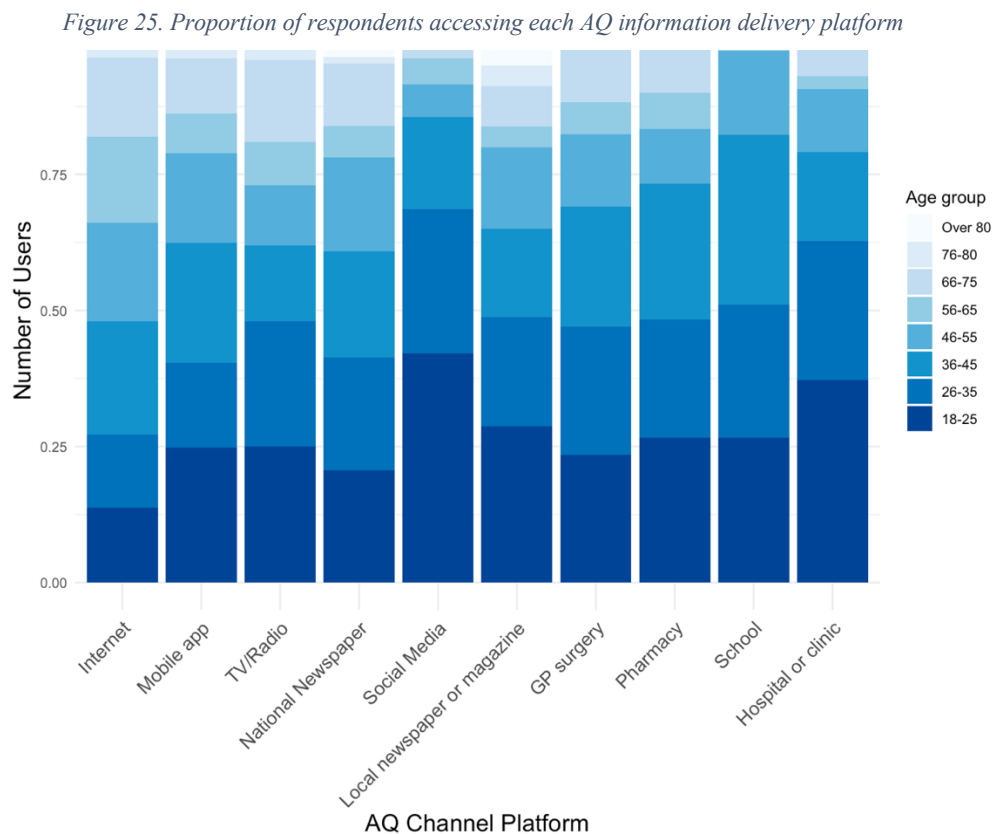


Figure 24. Proportion of respondents by UK region who have ever accessed AQ information

4.1 UK population level general patterns of AQ channel access

This section summarizes population level patterns of AQ information access prior to reviewing the results generated in response to the two research questions and the associated hypotheses. According to the CAPIT dataset, a minority of individuals in the UK engage with AQ information. 37% of respondents indicated they had accessed information about air pollution conditions (forecast or in real-time) (Figure 24). The most common channel for accessing AQ information is the internet by a significant margin (41%) (Figure 25). Of those aged 18-36, the internet was the most common channel to access information on air quality (29%), followed by social media (25%). Younger people reported acquiring information on air quality from a greater variety of sources. “Hospital or clinic” was the least common channel for acquiring air quality information (9%) (Figure 25). Manual workers, retired individuals or those who live on state pensions only, those who are unemployed or have a long-term illness, and non-white individuals were all significantly less likely to access AQ channels (Table 17).



4.1.1 Hypothesis 1A: Younger individuals (18 - 36) are more likely to access digital AQ channels, as compared to individuals above the age of 36

The hypothesis (H1a) that younger individuals (under 36) are more likely to access digital AQ channels, as compared to individuals above the age of 36 was supported by the data. After adjusting for gender, social grade factor, educational attainment and having children under the age of 18, the odds that individuals aged 18 - 36 accessed digital AQ channels were 1.90 (95% CI: 1.82 – 1.98) than for individuals 36 and older (Table 17). Gender and ethnicity covariates were also significant, with the odds of men access digital AQ channels were 1.45 (95% CI: 1.34 - 1.56) greater compared with women, and those of non-white individuals were 1.45 (95% CI: 1.41 – 1.49) greater compared with white individuals. Finally, the odds that individuals who had children under 18 accessed digital AQ channels were 1.69 (95% CI: 1.64 – 1.74) greater than those who did not have children under 18 or any children.

Table 17. Odds ratios from logistic model predicting access to digital AQ channels

<i>Dependent variable: accessed digital AQ info?</i>	
Intercept	0.18*** (−0.45, 0.80)
Gender: Male	1.45*** (1.34, 1.56)
Age: under 36	1.90*** (1.82, 1.98)
Has Children Under 18	1.69*** (1.64, 1.74)
A - Higher managerial position	1.04 (0.99, 1.08)
B - Intermediate managerial position	0.70 (0.61, 0.78)
C2 -Skilled manual worker	0.89 (0.86, 0.92)
D - Semi-skilled manual worker	0.79 (0.71, 0.87)
Student	0.70 (−1.29, 2.69)
E - Retired/state pension only	0.65** (0.11, 1.19)
Unemployed/long-term illness	0.83 (0.54, 1.11)
Education: Higher ed	0.79 (0.67, 0.91)
Education: A-level	1.00 (0.94, 1.06)
Education: GCSE	0.61 (0.53, 0.70)
Ethnicity: non-white	1.45** (1.41, 1.49)
Observations	1,993
Log Likelihood	−933.10
Akaike Inf. Crit.	1,896.00

Note: *p<0.1; **p<0.05; ***p<0.01
N = 1993

Estimates with 95% confidence intervals from binary logistic regression models examining access to AQ channels (outcome variable) as predicted by demographic characteristics.

Odds ratio and CI reported

Reference categories: Gender (female), Age (over 36), Has children under 18 (none), Social grade (C1 - semi-skilled manual worker, ethnicity (white).

4.1.2 Hypothesis 1B: Individuals with health conditions themselves are more likely to access AQ channels

The hypothesis (H1b) that individuals who had health conditions are more likely access AQ information was supported by the data. The odds of accessing AQ information increased by 1.32 (95% CI: 1.03, 1.61) if the respondent had a health condition, while controlling for age (Table 15). When controlling for specific health conditions, the odds of accessing AQ information increased by 1.52 (95% CI: 1.09, 1.94) if the respondent had asthma, by 1.67 (95% CI: 1.04, 2.29) if the respondent had another respiratory condition, by 1.42 (95% CI: 1.01, 1.83) if the respondent had another heart condition, by 1.26 (95% CI: 0.77, 1.74) if the they had high blood pressure, and was lower by 0.76 (95% CI: 0.57, 0.94) if the respondent had another health condition (Table 18).

Table 18. Odds from logistic regression models predicting AQ channel access by health status

	(has any health condition)	(has specific health condition)
Intercept	1.48*** (1.04, 1.93)	1.45*** (1.03, 1.88)
Aged 26 - 35	0.43*** (0.27, 0.59)	0.44*** (0.27, 0.61)
Aged 36 - 45	0.30*** (0.19, 0.41)	0.31*** (0.20, 0.43)
Aged 46 - 55	0.18*** (0.11, 0.24)	0.19*** (0.12, 0.26)
Aged 56 - 65	0.10*** (0.06, 0.15)	0.11*** (0.06, 0.16)
Aged 66 - 75	0.11*** (0.06, 0.15)	0.11*** (0.06, 0.15)
Aged 76 - 80	0.06** (0.01, 0.11)	0.06** (0.01, 0.11)
Over 80	0.14** (0.03, 0.26)	0.15** (0.03, 0.27)
Has a health condition themselves	1.32*** (1.03, 1.61)	
Has asthma themselves		1.52*** (1.09, 1.94)
Has other respiratory condition themselves		1.67*** (1.04, 2.29)
Has other heart condition themselves		1.42*** (1.01, 1.83)
Has high blood pressure themselves		1.26*** (0.77, 1.74)
Has other health condition themselves		0.76*** (0.57, 0.94)
Observations	1,993	1,993
Log Likelihood	-1,071.68	-1,056.73
Akaike Inf. Crit.	2,161.36	2,139.47

Note: *p<0.1; **p<0.05; ***p<0.01

N = 1993

Estimates with 95% confidence intervals from binary logistic regression models examining access to AQ channels (outcome variable) as predicted by presence of health condition with age group covariates. Odds ratio and CI are shown.

Reference categories: Age (18 - 25), Has specific health condition (no)

4.1.3 Hypothesis 1C: Individuals who care for someone with a health condition are more likely to access AQ channels

The hypothesis (H1c) that individuals who care for someone with a health condition are more likely to access AQ channels was supported by the data. The odds of accessing AQ information

increased by 0.61 (95% CI: 0.39, 0.83) if the respondent cared for someone with a health condition, while controlling for age (Table 19). When controlling for specific health conditions, the odds of accessing AQ information increased by 0.58 (95% CI: 0.15, 1.02) if the respondent had a child with asthma, by 0.52 (95% CI: 0.005, 1.04) if they cared for someone else with another respiratory condition and by 2.06 (95% CI: 0.53, 3.59) if they had a child with high blood pressure (Table 19).

Table 19. Odds ratios from logistic model predicting AQ channel access by carer status for someone with a specific health condition

	(carer for any health condition)	(carer for specific health condition)
Intercept	1.31*** (0.92, 1.70)	1.28*** (0.89, 1.68)
Aged 26 - 35	0.46*** (0.29, 0.64)	0.43*** (0.26, 0.60)
Aged 36 - 45	0.32*** (0.20, 0.44)	0.32*** (0.20, 0.44)
Aged 46 - 55	0.19*** (0.12, 0.26)	0.19*** (0.12, 0.26)
Aged 56 - 65	0.12*** (0.07, 0.16)	0.12*** (0.07, 0.17)
Aged 66 - 75	0.12*** (0.07, 0.17)	0.13*** (0.07, 0.18)
Aged 76 - 80	0.06** (0.01, 0.12)	0.07** (0.01, 0.13)
Over 80	0.17** (0.03, 0.30)	0.18** (0.04, 0.33)
Cares for someone with health condition	1.84*** (1.43, 2.24)	
Has a health condition themselves		1.10*** (0.85, 1.36)
Has child with asthma		1.79*** (0.97, 2.61)
Cares for someone with asthma		1.45*** (0.76, 2.13)
Has child with other respiratory condition		1.99** (0.23, 3.75)
Cares for someone with other respiratory condition		1.69*** (0.84, 2.54)
Has child with other heart condition		2.24* (-0.33, 4.81)
Cares for someone with other heart condition		1.01*** (0.53, 1.50)
Has child with high blood pressure		7.85 (-4.49, 20.19)
Cares for someone with high blood pressure		1.01*** (0.60, 1.42)
Has child with other health condition		0.93*** (0.45, 1.42)
Cares for someone with other health condition		1.11*** (0.73, 1.49)
Observations	1,993	1,993
Log Likelihood	-1,060.46	-1,043.51
Akaike Inf. Crit.	2,138.91	2,125.03

Note: *p<0.1; **p<0.05; ***p<0.01

N = 1993

Estimates with 95% confidence intervals from binary logistic regression models examining access to AQ channels (outcome variable) as predicted by carer status for individual with a health condition and age group covariates. Odds ratio and CIs are shown.

Reference categories: Age (18 - 25), Has child with or cares for someone with specific health condition (no)

4.2 UK population level general patterns of ERB adoption following AQ channel access

This section reports the results found in response to the first research question about whether certain patterns of AQ channel access correlate with increased adoption of exposure reducing behaviors.

4.2.1 Hypothesis 2A: Individuals who access internet based AQ channels adopt more ERBs

The hypothesis (H2a) that individuals who access internet based AQ channels, including the “Internet (generally)”, “Social Media” and “Mobile app” channels, are more likely to have accessed AQ information was supported by the data. Accessing internet based AQ channels predicted the highest number of ERBs adopted, where accessing information from the “Internet (generally)” increased number of ERBs adopted by 1.23 standard deviations (95% CI: 3.13, 4.10) and in the case of “Mobile apps” by 1.20 standard deviations (95% CI: 2.75, 4.35) from the mean number of ERBs (mean: 1.36, SD: 2.95). Accessing AQ info via “Social media” increased number of ERBs adopted by 0.59 of 1 SD (95% CI: 1.04, 2.42), however this effect was lower than that of accessing information from “Hospitals or clinics”, the “Pharmacy” “National Newspapers” or “Local Newspapers or magazines” (Table 20).

4.2.2 Hypothesis 2B: Individuals who access AQ information most frequently are most likely to adopt ERBs

The hypothesis (H2b) that individuals who access AQ information most frequently are most likely to have adopted ERBs was supported by the data. Accessing an AQ channel “Daily” was the strongest predictor of adopting ERBs with the highest number of ERBs adopted, or 0.97 standard deviations (95% CI: 0.92, 1.02). This was followed by accessing channels “Once a week” and then “Once a month” (Table 21).

Table 20. Coefficients from OLS model predicting adoption of ERBs by demographics and AQ channel type

Intercept	0.21*** (0.14, 0.28)
Aged 26 - 35	-0.06* (-0.12, 0.01)
Aged 36 - 45	-0.12*** (-0.19, -0.06)
Aged 46 - 55	-0.13*** (-0.20, -0.05)
Aged 56 - 65	-0.17*** (-0.24, -0.10)
Aged 66 - 75	-0.15*** (-0.22, -0.08)
Aged 76 - 80	-0.19*** (-0.28, -0.11)
Over 80	-0.18*** (-0.25, -0.10)
Internet	0.60*** (0.55, 0.65)
TV/Radio	0.27*** (0.17, 0.37)
Social Media	0.29*** (0.18, 0.41)
GP surgery	0.18*** (0.05, 0.30)
National Newspaper	0.26*** (0.16, 0.36)
Local newspaper or magazine	0.25*** (0.14, 0.37)
Pharmacy	0.20*** (0.06, 0.33)
Hospital or clinic	0.20** (0.02, 0.37)
Mobile app	0.48*** (0.39, 0.57)
School	0.35*** (0.19, 0.50)
Observations	1,993
R ²	0.64
Adjusted R ²	0.64
Residual Std. Error	0.26 (df = 1975)
F Statistic	209.54*** (df = 17; 1975)

Note: *p<0.1; **p<0.05; ***p<0.01
N = 1993

Estimates with 95% confidence intervals from OLS regression models
examining whether or not individuals have adopted ERBs

Robust standard errors are shown.

Reference categories: Age (18 - 25), AQ channel (none).

Table 21. Coefficients from OLS model predicting adoption of ERBs by frequency of AQ information access

Has adopted one or more ERBs	
Intercept	0.00
Daily	5.82*** (4.58, 7.07)
Don't know / can't remember	-0.00 (0.00, 0.00)
Once a fortnight	3.97*** (3.35, 4.59)
Once a month	4.35*** (3.59, 5.11)
Once a week	4.26*** (3.69, 4.82)
Once every 2-3 months	5.06*** (4.43, 5.69)
Several times a week	5.63*** (4.59, 6.68)
Observations	1,993
R ²	0.54
Adjusted R ²	0.54
Residual Std. Error	2.00 (df = 1985)
F Statistic	333.29*** (df = 7; 1985)

Note: *p<0.1; **p<0.05; ***p<0.01
N = 1993

Estimates with 95% confidence intervals from OLS regression models
examining whether or not individuals have adopted ERBs

Reference categories: Age (18 - 25), AQ channel (none).

5. Discussion

5.1 Overview

This section describes the results of the analysis conducted in response to research questions surrounding which socio-demographic groups in the UK are most likely to access AQ channels, and whether certain patterns of access correlate with increased uptake of AQ channels. Results from this analysis demonstrate that younger individuals are more likely to access digital AQ channels such as websites and mobile apps. In addition, both hypotheses regarding whether greater access to AQ channels was correlated with greater ERB adoption were confirmed by the data. Over the course of this section, the implications of these findings for understanding the “motivation-behavior” gap around AQ channel uptake and ERB adoption are discussed, while illuminating avenues for further investigation.

5.2 Limitations

Due to the nature of the modelling approach adopted throughout this study, no causal inferences can be made with respect to the effect of AQ channel access on ERB adoption. It is also necessary to consider that there may be varying interpretations of what constitutes an AQ channel. While the survey question specified air quality information to mean “real-time or forecasted” air pollution, it is possible that individuals responded to the question as though it encompassed any form of information about air pollution. Although a small subset of the CAPIT survey is administered by telephone or written survey, the survey is predominately administered online. It is possible that this may bias results towards respondents who are more ‘digitally literate’, have greater access to the internet or are more comfortable with web-based applications, which is not entirely representative of the UK population. For future investigations such as this, it is worthwhile to consider other survey administration modes. Furthermore, this study is limited to the patterns associated with AQ channel access and ERB adoption in the UK. Additional research is warranted surrounding patterns of AQ information

access and ERB adoption around the world, particularly in regions where poor air quality contributes to a greater proportion of adverse health outcomes and mortality throughout the population.

5.3 Uptake of AQ Channel according to socio-demographic characteristics

Despite a minority proportion, or 37% of the sample indicating that they had ever accessed AQ information (Figure 24), the results demonstrated that younger individuals (under 36) have greater odds of accessing digital AQ channels. This finding aligns with statistics on internet use throughout the UK. Importantly, it highlights which demographic group in the UK has the greatest odds of interacting with AQ information landscape. Conversely, it suggests that older individuals might be missing out on opportunities to access AQ information. The results revealed a gender and ethnicity disparity associated with digital AQ channel access. This raises important questions about why men access AQ channels more readily, and what is driving non-white individuals to access digital AQ channels more commonly. It is worth noting the covariate for individuals who have children under 18 was statistically significant, and the odds of these individuals accessed digital AQ channels was greater than for those who did not have children under 18 or any children. This aligns with discussions in the literature that individuals with children, particularly those with health conditions, are motivated to engage with AQ information for its potential to mitigate exposures and protect health (Hano, 2019, Wei, et al., 2020; Janke, 2014; Neidell & Kinney, 2010).

Having a health condition oneself was associated with greater access to AQ channels, however, the state of caring for an individual with a health condition showed up as having a stronger

association with AQ channel access. The influence and motivation of care has been shown throughout the literature to play a significant role in engagement with AQ information and ERB practices (Bickerstaff & Walker, 2003; Noonan, 2011; McCarron et al., 2022) . The results from this study suggest that individuals accessing AQ channels may be doing so more often in support or protection of another.

Air pollution affects every member of the population. While evidence clearly indicates that certain groups are more vulnerable to health outcomes associated with exposure, the literature also emphasizes that certain groups are more vulnerable to higher exposures (Keivabu et al., 2022; Fairburn et al., 2019). This could be due to a host of factors, including but not limited to geographic location of residence or work, commute pattern, and occupation. The findings from this study help identify areas and socio-demographic groups in need of greater attention and resources with respect to AQ information communication.

5.4 Relationship between AQ Channel access and ERB adoption patterns

A closer look at the data revealed that the most accessed AQ channel platform was the internet, followed by mobile apps. This is likely associated with the digital nature of the platform, that is, its ease of physical accessibility, opportunity for customization, and relative coherence of the information presented. Considering this alongside the finding that individuals under age 36 have greater odds of accessing digital AQ channels compared to those above 36, an age disparity in access to AQ information and associated ERB recommendations reveals itself. It is possible that due to the digital nature of these channels, a technological-structural barrier is preventing older individuals from accessing relevant, health protective information.

Future CAPIT survey iterations should consider including an internet access or internet use variable. This would allow for clearer testing of whether the younger age groups are accessing AQ channels because they are more digitally connected. As older individuals were revealed to be a portion of the population that was less engaged with AQ channels, while considering their increased vulnerability to the health impacts of poor air quality exposures, it is important to consider how this population group can be presented with opportunities to engage with AQ channels and associated ERB recommendations.

The results confirm that more frequent access to AQ channels, specifically digital channels, is correlated with the adoption of more ERBs. We can infer that the AQ channel intervention contributes to behavioral transformations survey question explicitly asked whether individuals were adopting certain behaviors following engagement with an AQ channel. This highlights an opportunity to leverage the greater penetration rate of digitally enabled AQ channels throughout the population. When doing this, it is crucial to consider which groups in the population are slipping through the cracks and how channels can be made both physically and intellectually more accessible.

6. Conclusion

This study was aimed at filling a gap in the research literature about the relationship between AQ channel access and ERB adoption. To disentangle this relationship and the factors that link information access with behavior change, research questions were posed surrounding which socio-demographic groups in the UK are most likely to access AQ channels, and what patterns of access correlate with greater adoption of ERBs. To examine this dynamic, this study presented an analysis of the novel “CAPIT” dataset generated by the Global Action Plan Charity.

A key finding from this study was that a minority proportion of the UK population has accessed information about air pollution via AQ channels as of March 2022. Additionally, younger individuals are more likely to access AQ channels, while manual workers, retired individuals or those who live on state pensions only, those who are unemployed or have a long-term illness, and non-white individuals were less likely. The literature reinforces that while the mechanisms are still not entirely transparent, individuals who access AQ channels having a higher chance of accessing health benefits associated with the exposure reducing behavioral advice.

The ability to process information and training that it is important to gather information is linked to higher levels of education (Pampel et al, 2010). Future research should explore the role of educational attainment and whether this affects AQ Channel access patterns and ERB adoption rate. Another future research direction could involve the introduction of an interaction term to look at frequency of accessing AQ information according to need (i.e. having a children under age 18, having health conditions oneself or caring for someone with health conditions). This could help generate insights around whether those who access AQ information daily are doing for specific reasons, and which reasons are most common.

As additional research and funding is funnelled towards digital health and air pollution exposure interventions, it is crucial that any emerging ventures take care to consider which portions of the population are more likely to miss out on these channels. The question then becomes how we bring these alienated groups and individuals into the development of AQ channels so they can evolve to cater to a majority. This might include crafting channels through existing networks that maintain connections and trust with specific population subgroups. AQ

channel design is a prime space to implement co-design methods and generate more effective, wide-reaching air quality information interventions.

CONCLUSION

“An analysis of air reveals who belongs and who does not, who is deserving and who is not in a constellation of megacity inequality.” (Adey, 2013:294)

1. Summary

Adey’s quote highlights the potential for research examining interactions with the “air” to illuminate who in a population experiences disproportionate burdens relating to pollution exposure. The aim of this doctoral thesis was to examine the patterns of social, informational, environmental and health inequality and how this could support improvements to individual-level pollution exposure in the UK. It responds to the overarching question: *who cares about the air?* through the disciplinary lenses of sociology, demography, and human geography. By virtue of this approach, this thesis characterizes the contemporary air quality (AQ) information landscape, delivers novel findings around sociodemographic patterns of access to AQ information, and highlights associations with the adoption of exposure reducing behaviors (ERBs) among population subgroups across the UK.

The thesis concludes by highlighting key findings emerging from each of the empirical Chapters, proposing avenues for further research and policy recommendations. In broad summary, Chapters II and III focused on mapping the AQ information landscape, identifying “pinch points” where social, demographic, spatial (geographic/neighborhood) or digital inequalities might flourish under the narrow, reductionist framings of air pollution and which groups are at risk, which are maintained across current AQ channels. Results from Chapter II generated by employing user analytics data highlighted the role of news media as an extrinsic factor motivating access to AQ channels. Furthermore, the results from these two Chapters point to substantial variation in reporting and representations of air pollution across freely

accessible AQ channels in London, UK. The implications of this for the delivery of ERB messaging were discussed in detail in Chapter III and are reemphasized below.

Chapters IV and V leveraged a unique dataset that measured public perceptions of air pollution to examine the relationship between patterns of ERB adoption, AQ channel access and different sociodemographic, health status and psychosocial characteristics. Key findings from Chapter IV demonstrate that the psychosocial factors of “awareness”, “concern”, and “self-efficacy/outcome expectancy”, or belief that one’s actions can positively affect the air they breathe, are all associated with greater adoption of ERBs at the UK population level. Sociodemographic and health characteristics including being older (up until retirement age), female, having higher educational attainment were associated with greater levels of awareness, while and having certain health conditions oneself or caring for others with certain health conditions were associated with greater concern. Findings from Chapter V demonstrate that the odds of *younger individuals (under 36)*, men, those who have children under 18 and non-white individuals of accessing digitally available AQ information are greater than those who do not fall into these categories. Additionally, the odds of accessing any AQ information for those with a health condition or who caring for someone with a health condition are greater than for those who do not. Individuals are also more likely to adopt a greater number of ERBs if they access information daily, from the internet or via a mobile app.

The following subsections contextualize the findings emerging from each Chapter amidst the broader theoretical discussions emanating from the sociology, demography, and human geography literatures.

2. The AQ information landscape: sustaining structures that perpetuate outdated messaging about air pollution exposure vulnerability

Chapters II and III characterized the current landscape of “real-time” air quality information sources available to individuals across London. They delivered insights into how specific technical design and informational features across AQ channels might sustain or exacerbate existing inequalities relating to AQ information acquisition. Situating this within the broader science, technology, and society (STS) and communications literature, findings from Chapter II demonstrate that the AQ Channel innovation has diffused among specific population subgroups, with uptake being associated with individuals who have health conditions and in the more populous areas. The findings in these Chapters are brought into conversation with Roger’s description of the innovation decision process and the theory of “co-production” to conceptualize how the AQ channel innovation has been taken up in London, UK. This is expanded upon in the subsections below (Rogers, 1983 and Jasanoff, 2004).

2.1 Chapter II – Systematic review of “freely” available AQ Channels in London, UK

The systematic technology review presented in Chapter II demonstrated that despite a proliferation of channels for conveying information, methods for representing air pollution and associated risk remain aligned with conventional, narrow definitions of air pollution and limited demographic parameters first conceived by landmark epidemiological studies in the 1990s (Schulte, 2022). Perpetuation of conventional understandings of air pollution are tied to the technical structural conditions underpinning AQ channel delivery. Findings from Chapter II demonstrate how 29 of the 54 AQ channels sampled could be traced back to five models operated by the UK or the European Union, which estimate and report air pollution concentrations through conventional methods. The innovation may have a new “digital skin”, yet the insides maintain structures that perpetuate conventional framings of air pollution originating in the early 20th century and air pollution related risk originating in the 1990s

(Mosley, 2009). In other words, AQ channel infrastructure co-produces understandings of air pollution throughout society (Jasanoff, 2004). By adhering status quo air pollution data management infrastructures, the AQ channel innovation is missing out on its opportunity evolving understandings and knowledge flow around pollution exposure and risk to better reflect the experiences of vulnerable and disproportionately affected individuals.

Contrary to diffusion theory and discussions throughout the literature surrounding technological advancement, visual and numerical content delivered across the AQ channels reviewed in Chapters II and III predominantly adhere to conventional quantifications air pollution and associated exposure “risks.” Conventional definitions of “at-risk” populations miss out on pertinent approaches that re-define vulnerability to pollution exposure and intensified effects according to key social and demographic indicators, including SES, geography, educational attainment, digital literacy, and the intersections of these factors (Fairburn et al., 2019; Koman et al., 2018). The proliferation and promotion of AQ channels that maintain conventional risk messaging have the potential to feed into the failure of the AQ information landscape to underserve key vulnerable population groups (Haraway, 1988). The failure of AQ channels to consider intersectional risk factors, coupled with social, demographic, and digital barriers, threaten the ability for certain population groups to obtain health benefits associated with exposure reducing behavioral messaging (Cutler & Lleras-Muney, 2010; Pampel et al., 2010) and exacerbate social inequalities in health.

Barriers to engagement with AQ Channels were further exemplified by findings from Chapter II, demonstrating that a key driver of access to AQ channels in London, UK were news media articles from the Guardian. Guardian readership is demographically stratified, with higher educated individuals demonstrating significantly higher readership (Chan & Goldthorpe,

2007). This Chapter emphasizes that, despite evidence from controlled studies that access to AQ channels can translate into adoption of exposure reducing behaviors and improved downstream health outcomes, there are several structural barriers that can limit uptake of AQ channel recommendations and maintain exposure inequality (D’Antoni et al., 2019; Neidell & Kinney, 2010; Rappold et al., 2014, 2019).

Adherence to the information deficit model, coupled with the growing emphasis on self-monitoring expressed across AQ channels, sets up a paternalistic system characterized by a clear imbalance as to who in society is responsible for mitigating air pollution exposures. Such conditions help sustain a market of concerned individuals who are willing to pay for devices and access to information advertised as something that can mitigate their exposures. This in turn shifts the burden of responsibility onto the individual and away from centralized regulation. This also further widens the gap between those who have the financial resources to access clean air and better health with those who do not (Pampel et al., 2010; Sun et al., 2017). The findings of these chapters suggest the importance of greater transparency surrounding the aims of commercial AQ channel providers and reinforces the need for extensive, critical reviews of how government AQ channels are framing air pollution exposure risk and the division of responsibility for mitigating those exposures.

2.2 Chapter III – Variation in air pollution representations across AQ Channels at six hospital locations

Chapter III further scrutinizes the “digital skin” and internal infrastructural processes, or “guts”, of AQ channels. This Chapter highlights how specific features may contribute to inequality regarding access and engagement with ERB messaging and behavioral transformations. Building on findings from Chapter II, which raised questions around the consistency of health-protective messaging, Chapter III explored variability in air pollution

readings across AQ channels at selected geographic locations and discussed the implications of this variability. This drew on computational methods and semiological theory to deliver insights around how variation across visual and numerical representations of air pollution can convolute the AQ information landscape. In essence, the unique configuration of back-end Application Programming Interface (API), alongside front-end AQI and visual features can result in a situation where two individuals standing in the same place receive different air pollution readings and ERB recommendations. The results demonstrated that in certain instances, both “low” and “moderate” pollution readings were reported for the same geographic location, depending on which AQ channel was being consulted.

This demonstrates the pitfalls of both numerical and visual representations of air pollution in the vicinity of hospitals where more physiologically vulnerable individuals are present. Specifically, it indicates the potential for an individual with health or other vulnerabilities to receive varying exposure reducing behavioral advice for the same physical location depending on which AQ channel they choose to consult. This reinforces the pitfalls of strong reliance on digital air pollution informational interventions, which places the onus on the individual to mitigate their exposure to deliver optimal health outcomes (Neff, 2016).

The findings from this Chapter amplify the importance that non-technical audiences can select and interact with AQ channels that supply clear information on the methods they use to estimate air pollution, that are able to meet users informational or ERB advice needs, and that are transparent about the spatiotemporal limitations of air pollution “readings”. The results from Chapter segue into the focus of the final two Chapters, which aim to systematically identify sociodemographic, health and psychosocial motivations for interacting with the AQ information landscape.

3. Stratification in AQ Channel access and ERB adoption by sociodemographic and health status group

Chapters IV and V build on existing theories of social inequality presented throughout the sociology and demography literature. Specifically, they advance understandings of the “social origins of health behavior” within the context of air pollution (Pampel et al., 2010; Phelan et al., 2010). The findings in these Chapters reinforce that certain sociodemographic groups demonstrate greater access to AQ information, in turn linked to greater ERB uptake. The proceeding sections dissect the pathways by which this phenomenon ensues, while highlighting which groups are most likely to miss out on the potential health benefits associated with access to AQ channels and ERB messaging. The final two Chapters also help address the demographic limitations associated with digital trace data analyzed in Chapters II.

3.1 Chapter IV – Psychosocial, demographic and health status predictors of ERB adoption in the UK

Chapter IV examined patterns of concern, awareness, self-efficacy, and outcome expectancy with respect to air pollution at the UK population level, in addition to which groups adopted the greatest number of ERBs. Certain psychosocial characteristics such as awareness, concern, and sense of self-efficacy/outcome expectancy with respect to air pollution were significantly associated with greater adoption of ERBs. The results from this Chapter showed that women, older individuals, and those with higher educational attainment had the greatest awareness about air pollution. These findings connect with discussions throughout the social and health inequality literature, which demonstrates an empirical link between educational status and health outcomes, and the “opportunity” and protective effect that higher educational status

enables (Pampel et al., 2010; Phelan et al., 2010). This reinforces that more educated individuals have a greater potential to pursue exposure-reducing benefits associated with AQ channels. Any comprehensive strategy or policy for expanding awareness around air pollution and ultimately, exposure mitigation by way of ERB adoption, will need to critically approach persistent educational inequalities throughout the UK.

The finding that a greater sense of self-efficacy with respect to making a difference in the air one breathes highlights the potential for the development of communication strategies. It also points to the promise of additional research and interventions aimed at amplifying notions of response efficacy/outcome expectancy and instilling a sense of self-confidence or empowerment.

Findings from Chapter IV highlight that both conventionally, (i.e. older individuals, individuals with pre-existing health conditions), and the unconventionally vulnerable (i.e. from income, social grade, geography, educational attainment, or digital literacy standpoints) are either less aware, concerned, have a strong sense of self-efficacy, or adopt less ERBs around air pollution. This signals the importance of considering how the “sensitive” and “at risk” classifications are currently framed, and whether they should be expanded to account for additional categories of air pollution risk. For example, AQ channels might include additional information to signal that if individuals reside near busy roadways, work in certain jobs, or fall into other high exposure categories, they are at greater risk to short- and long-term effects of air pollution than those who do not experience these circumstances.

Finally, Chapter IV reinforces the important point regarding the narrow focus of public health literature and environmental governance on individual-led behavioral transformation to

mitigate air pollution exposures. Placing the burden on already burdened individuals to mitigate pollution exposures is unethical and likely ineffective. Comprehensive approaches to reducing air pollution exposures requires clear commitment from central institutions to stringent and widespread regulation of pollution. In addition, resources should be channeled towards research and programs for building knowledge about air pollution that are co-created alongside the most disproportionately affected individuals.

3.2 Chapter V – Demographic predictors of AQ channel access and ERB adoption in the UK

The final Chapter fills the gap in information resulting from the use of demographically poor digital trace data, which precludes analysis of sociodemographic inequalities permeating patterns of access to the AQ channel innovation. By leveraging data from the CAPIT survey, this study revealed that younger age groups accessed digital AQ information sources. It also demonstrated that individuals who access AQ information more frequently, which is easily achieved via digital AQ channels, was more closely associated with greater ERB adoption. This demonstrates that this demographic group, while being less vulnerable from a physical health perspective, but not necessarily from socioeconomic or geographic perspectives, have greater potential to experience exposure reducing benefits associated with AQ channel access.

4. Limitations and solutions

As with all research that is at the cusp of new technologies and measurements, there are several limitations. By focusing exclusively on the city of London when looking at AQ channels, this research neglects patterns of engagement with AQ channels occurring across of the rest of the UK and the world. AQ channels have become increasingly widely used in Asia, particularly China and India, where a greater number of individuals are exposed to more dangerous

concentrations of air pollution (Sun et al., 2017). Given that this is an emerging area of research, the goal was to begin by focusing on particular locations, like London and the UK more broadly, where ample, granular air pollution data and socio-demographic data already exists. Ultimately, in future research I will partner with institutions where large portions of the population are exposed to high levels of air pollution, and to harmonize research designs with socio-cultural patterns and contexts present in those parts of the world.

The use of cross-sectional survey data and intervention-based research design precluded any causal analysis of patterns of AQ channel access and ERB uptake according sociodemographic, health and psychosocial factors. Time and funding constraints did not allow for an independently led, intervention-based experimental research design. However, a future aim is to test variations on the hypotheses presented in this thesis in research throughout app or other digital intervention-based experimental research projects. For this the descriptive results from the survey-informed analyses serve as a first step towards testing potential interventions.

There were also certain limitations associated with the retrieval of data through scheduled API queries. Several of the APIs failed to return values for certain specified pollutants. One API (API 1) failed to return AQI estimates, while another (API 5) failed to return AQI estimates for the locations of Kingston hospital, Central Middlesex hospital and Great Ormond Street hospital. This prevented the comparative analysis of specific pollutants across all locations. However, the study was able to deliver important comparative findings for a subset of the APIs. Future studies should analyze a larger sample of AQ channels to examine variation in estimates for specific pollutants at precise geographic locations.

5. Future research & policy recommendations

Findings from the empirical studies presented in this thesis raised key considerations and provided recommendations around how to implement digital AQ channels in a manner that does not exacerbate existing sociodemographic, health, environmental or digital inequalities. A central recommendation is the need for participatory methods, where the co-design of technologies and research aimed at generating knowledge and evidence about air pollution are informed by the lived experiences of those who are disproportionately impacted. This thesis challenges conventional framings of “at risk” groups presented across AQ channels. It calls for a shift towards intersectional framings of vulnerability, alongside more opportunities for individuals to “self-identify” as vulnerable to avoid individuals being cut off from pertinent ERB recommendations.

Crucially, standards surrounding reporting requirements should be mandated for any parties that leverage publicly funded air pollution estimates. AQ channel providers need be more transparent about the limitations of air pollution data, specifically the geographic and temporal resolutions at which they are reported. At present, the information presented across AQ channels does not reflect the major responsibility these entities have with respect to co-producing understandings and governance of air quality in the UK. Furthermore, the analysis presented in Chapters II and III raised questions around whether AQ channels that are now available add more to the AQ information landscape. In many ways, it appears that AQ channels are duplicating existing information, and so greater oversight might improve AQ channel capabilities and the accountability of developers.

Future research and communication strategies led by academics, government and industry alike must include diverse groups throughout the co-design of tools and content feeding into the AQ

information landscape. Such methods warrant additional resources and should be incorporated throughout the training of environmental civil servants and engaging with the commercial producers and providers of these AQ channels. Employing participatory, co-design methods throughout the development of AQ channels and information delivery formats can supply a more comprehensive, equitable approach towards exchanging and co-producing knowledge about air quality conditions (Jasanoff, 2004; McCarron et al., 2022; Pritchard & Gabrys, 2016). This will also lend itself to greater, more sociodemographically diverse patterns of access.

Findings from Chapter II point to how the framing of AQ channels illuminate an emerging market of individuals who are able and willing to pay for what is currently privileged insight (via personal sensors) or privileged access (masks and air filters) to healthy air quality conditions. This reinforces an inequality in who can mitigate exposures, while highlighting how the onus is being placed on the individual to manage pollution exposures. AQ channel providers should consider pointing more directly to mechanisms where individuals can encourage elected officials and government agencies to support policies that reduce air pollution. Examples of this could be linking to online petitions, highlighting other community groups or social media spaces dedicated to addressing local air quality concerns. Such efforts will require clear commitment from all levels of government, in partnership with industry. One approach proposed in this Chapter involves shifting the lexicon from “air pollution” to “air quality”. This could enable a shift away from focusing exclusively on pollutant concentrations, and invite consideration of contextualizing socio-cultural and demographic insights, when developing policy and ERB messaging.

In line with the broader social inequality literature, findings from Chapters IV and V that more educated individuals possess more of the psychosocial characteristics conducive to ERB uptake

helps make a strong case for supporting the UK educational system with additional financial, policy and staff resources. The results from this thesis effectively add air pollution exposure mitigation to the list of social and economic benefits gained from bolstering the national educational infrastructure. Findings from these Chapters also signal opportunities for further research surrounding what types of messaging most effectively boost response efficacy/outcome expectancy with respect to air pollution, and how this can lead to even greater ERB adoption over time.

Future research around engagement with the AQ information landscape should involve the collection of survey and other types of data from AQ channel users directly that includes variables to capture patterns of engagement with publicly available AQ Channels over time. Current analytics data is demographically poor. In addition, future research designs, which will require long-term, longitudinal studies, should be developed to examine whether AQ channel ERB interventions can be causally linked to improve downstream health improvements. Researchers should consider looking to lessons learned from designing studies to examine improvements in health associated with app-enabled messaging interventions with individuals who use asthma inhalers, “fit bits” or other internet-connected devices.

6. Conclusion

This thesis demonstrated that AQ channel features, as a component of the broader AQ information landscape, can sustain or even further exacerbate disproportionate experiences of air pollution. Specifically, access to AQ channels can aid one’s ability to mitigate pollution exposures, as well as navigate the burden of associated health conditions. The evidence presented throughout this thesis demonstrates social, economic, and demographically stratified access to AQ channels, and stratified uptake of ERBs following engagement with AQ channels.

The interplay of social, digital, and environmental-political structures appears to sustain disproportionate opportunities to access AQ channels and thus the exposure reducing benefits associated with messaging. To combat these conditions, this thesis highlights how AQ channels must evolve to become more reflexive regarding the equity of the structures, understandings, and framings of air pollution they perpetuate amidst the broader AQ information and exposure landscape.

Inevitably, all humans around the world are exposed to air pollution. From wildfires to dust storms, from road traffic to industrial practices, the sources of air pollution are multiple and socio-environmentally entrenched in our world. Empirical evidence demonstrating the adverse health and psychosocial burdens of air pollution continues to pile up, yet it is unlikely the challenges posed by air pollution will disappear anytime soon. Proliferating, digitally channeled AQ information are pitched by their producers as being capable of mitigating exposures and burden of pollution, as showcased throughout the visual content analysis in Chapter III, despite a lack of robust evidence causally linking specific behavioural recommendations to exposure reduction and improved health outcomes (Breezometer, 2022; AirVisual, 2022). Additionally, as was shown in Chapters IV and V, AQ channel diffusion throughout society is stratified by age, gender, the possession of certain psychosocial traits, having certain health conditions, or caring for someone with certain health conditions. In their current formats, both commercial and government delivered AQ channels in the UK risk sustaining structural inequalities or unintended consequences if they cannot skillfully account for greater nuance in exposure vulnerability and information access inequality.

The potential for AQ information to facilitate ERB practices and improve health outcomes in an equitable fashion across social, economic, and demographic fault lines, particularly in areas that regularly experience hazardous air pollution conditions, warrants critical attention. This thesis also emphasizes that pollution levels are not the only dimension of the air that warrants critical attention. Shifting towards conceptualizing the air in terms of “quality” as opposed to “pollution” creates space to consider more than pollution-centric indicators of risk, while paving the way for co-design opportunities to incorporate social and demographic insights.

Reframing social, environmental, and political discussion of air in terms of quality, from a linguistic and meaning-making standpoint, helps characterize this earthly phenomenon as something simultaneously personal and communal, good and bad, something that exists on a spectrum, shared among yours and my body, and a collective responsibility. The air is “the most pervasive presence I can name” (Abram, 1997:225). Holding this, while bringing in the voices and experiences of those who are disproportionately exposed and burdened by poor air quality and enforcing standards and inquiry upon the current AQ informational landscape, is fundamental towards the generation of equitable knowledge, evidence and practices aimed at improving our air.

Literature cited

- 1956 UK Clean Air Act. Retrieved electronically on 18 March 2021
< <https://www.legislation.gov.uk/ukpga/Eliz2/4-5/52/enacted>>
- Abram, D., 1997. Spell of the sensuous: perceptual language in a more-than-human world. *Vintage, New York, New York, USA*.
- Aether, (2017). Updated Analysis of Air Pollution Exposure in London. GLA. Retrieved electronically <https://www.london.gov.uk/WHAT-WE-DO/environment/environment-publications/updated-analysis-air-pollution-exposure-london-final>
- Adey, P. (2013). Air/Atmospheres of the Megacity: <https://doi.org/10.1177/0263276413501541>, 30(8), 291–308. <https://doi.org/10.1177/0263276413501541>
- Alburez-Gutierrez, D., Zagheni, E., Aref, S., Gil-Clavel, S., Grow, A., & Negraia, D. V. (2019). Demography in the Digital Era: New Data Sources for Population Research. *SocArXiv*.
<https://doi.org/10.31235/OSF.IO/24JP7>
- Amoore, L. (2011). Data Derivatives. *Theory, Culture & Society*. <https://doi.org/10.1177/0263276411417430>
- Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behavior. *Journal of Environmental Psychology*, 27(1), 14–25. <https://doi.org/10.1016/J.JENVP.2006.12.002>
- Ban, J., Zhou, L., Zhang, Y., Brooke Anderson, G., & Li, T. (2017). The health policy implications of individual adaptive behavior responses to smog pollution in urban China. *Environment International*, 106, 144–152. <https://doi.org/10.1016/J.ENVINT.2017.06.010>
- Barnes, J., Hayes, E., De Vito, L., Williams, B. (2020). *Cleaner Air for Scotland – Air Quality Public Attitudes & Behavior Review*.
- Barry, A. (2002). The anti-political economy. *Economy and Society*.
<https://doi.org/10.1080/03085140220123162>
- Bartington, S.E., Bakolis, I., Devakumar, D., Kurmi, O.P., Gulliver, J., Chaube, G., Manandhar, D.S., Saville, N.M., Costello, A., Osrin, D. and Hansell, A.L., 2017. Patterns of domestic exposure to carbon monoxide and particulate matter in households using biomass fuel in Janakpur, Nepal. *Environmental pollution*, 220, pp.38-45.
- Bell, M. L., & Davis, D. L. (2001). Reassessment of the lethal London fog of 1952: Novel indicators of acute and chronic consequences of acute exposure to air pollution. *Environmental Health Perspectives*.
<https://doi.org/10.2307/3434786>
- Bickerstaff, K., & Walker, G. (2001a). Participatory local governance and transport planning. *Environment and Planning A*. <https://doi.org/10.1068/a33173>
- Bickerstaff, K., & Walker, G. (2001b). Public understandings of air pollution: The “localisation” of environmental risk. *Global Environmental Change*. [https://doi.org/10.1016/S0959-3780\(00\)00063-7](https://doi.org/10.1016/S0959-3780(00)00063-7)
- Bickerstaff, K., & Walker, G. (2003c). The place(s) of matter: Matter out of place - Public understandings of air pollution. *Progress in Human Geography*. <https://doi.org/10.1191/0309132503ph412oa>
- BinDhim, N. F., McGeechan, K., & Trevena, L. (2014). Who Uses Smoking Cessation Apps? A Feasibility Study Across Three Countries via Smartphones. *JMIR MHealth and UHealth*, 2(1).
<https://doi.org/10.2196/MHEALTH.2841>
- Bol, N., Helberger, N., & Weert, J. C. M. (2018). Differences in mobile health app use: A source of new digital inequalities? *Information Society*, 34(3), 183–193. <https://doi.org/10.1080/01972243.2018.1438550>
- Breezometer. (2021). *Clients Case Studies - Successful Air Quality Integrations | BreezoMeter*.
<https://www.breezometer.com/use-cases>
- Briscoe, S. (2015). Web searching for systematic reviews: A case study of reporting standards in the UK Health Technology Assessment programme. *BMC Research Notes*. <https://doi.org/10.1186/s13104-015-1079-y>
- Brody, S. D., Zahran, S., Vedlitz, A., & Grover, H. (2008b). Examining the relationship between physical vulnerability and public perceptions of global climate change in the United States. *Environment and Behavior*. <https://doi.org/10.1177/0013916506298800>
- Browning, K. A., & Collier, C. G. (1989). Nowcasting of precipitation systems. In *Reviews of Geophysics*.
<https://doi.org/10.1029/RG027i003p00345>
- Brunekreef, B., & Holgate, S. T. (2002b). Air pollution and health. In *Lancet* (Vol. 360, Issue 9341, pp. 1233–1242). Elsevier Limited. [https://doi.org/10.1016/S0140-6736\(02\)11274-8](https://doi.org/10.1016/S0140-6736(02)11274-8)
- Burnett, R. T., Arden Pope, C., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., Shin, H. H., Singh, G., Hubbell, B., Brauer, M., Ross Anderson, H., Smith, K. R., Balmes, J. R., Bruce, N. G., Kan, H., Laden, F., Prüss-Ustün, A., Turner, M. C., Gapstur, S. M., ... Cohen, A. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental Health Perspectives*. <https://doi.org/10.1289/ehp.1307049>

- Cepeda, M., Schoufour, J., Freak-Poli, R., Koolhaas, C.M., Dhana, K., Bramer, W.M. and Franco, O.H., 2017. Levels of ambient air pollution according to mode of transport: a systematic review. *The Lancet Public Health*, 2(1), pp.e23-e34.
- Chen, J. and Hoek, G., 2020. Long-term exposure to PM and all-cause and cause-specific mortality: a systematic review and meta-analysis. *Environment international*, 143, p.105974.
- Clayton, S., Devine-Wright, P., Swim, J., Bonnes, M., Steg, L., Whitmarsh, L., & Carrico, A. (2016). Expanding the role for psychology in addressing environmental challenges. *American Psychologist*, 71(3), 199–215. <https://doi.org/10.1037/a0039482>
- COMEAP. (2011). *Review of the UK Air Quality Index. A report by the Committee on the Medical Effects of Air Pollutants*.
- COMEAP. (2010). *The Mortality Effects of Long-Term Exposure to Particulate Air Pollution in the United Kingdom A report by the Committee on the Medical Effects of Air Pollutants*.
- COMEAP. (2009). Long-Term Exposure to Air Pollution: Effect on Mortality. In *A report by the Committee on the Medical Effects of Air Pollutants*.
- Conte Keivabu, R., Rüttenauer, (2022). London congestion charge: the impact on air pollution and school attendance by socioeconomic status. *Population and Environment* 2022 43:4, 43(4), 576–596. <https://doi.org/10.1007/S11111-022-00401-4>
- Cross, E.S., Williams, L.R., Lewis, D.K., Magoon, G.R., Onasch, T.B., Kaminsky, M.L., Worsnop, D.R. and Jayne, J.T., 2017. Use of electrochemical sensors for measurement of air pollution: correcting interference response and validating measurements. *Atmospheric Measurement Techniques*, 10(9), pp.3575-3588.
- Cruz, T. M. (2020). Perils of data-driven equity: Safety-net care and big data's elusive grasp on health inequality. *Big Data and Society*, 7(1). <https://doi.org/10.1177/2053951720928097>
- Daly, A. and Zannetti, P., 2007. An introduction to air pollution—definitions, classifications, and history. *Ambient air pollution. P. Zannetti, D. Al-Ajmi and S. Al-Rashied, The Arab School for Science and Technology and The EnviroComp Institute*, pp.1-14.
- D'Antoni, D., Auyeung, V., Walton, H., Fuller, G. W., Grieve, A., & Weinman, J. (2019). The effect of evidence and theory-based health advice accompanying smartphone air quality alerts on adherence to preventative recommendations during poor air quality days: A randomised controlled trial. *Environment International*. <https://doi.org/10.1016/j.envint.2019.01.002>
- D'Antoni, D., Smith, L., Auyeung, V., & Weinman, J. (2017). Psychosocial and demographic predictors of adherence and non-adherence to health advice accompanying air quality warning systems: A systematic review. In *Environmental Health: A Global Access Science Source* (Vol. 16, Issue 1). BioMed Central Ltd. <https://doi.org/10.1186/s12940-017-0307-4>
- Delmas, M. A., & Kohli, A. (2019). Can Apps Make Air Pollution Visible? Learning About Health Impacts Through Engagement with Air Quality Information. *Journal of Business Ethics*. <https://doi.org/10.1007/s10551-019-04215-7>
- De Nazelle, A., Bode, O. and Orjuela, J.P., 2017. Comparison of air pollution exposures in active vs. passive travel modes in European cities: A quantitative review. *Environment international*, 99, pp.151-160.
- Derrida, J., & Spivak, G. C. (n.d.). *Of Grammatology* (1981st ed.).
- di Bella, E., Leporatti, L., & Maggino, F. (2018). Big Data and Social Indicators: Actual Trends and New Perspectives. *Social Indicators Research*. <https://doi.org/10.1007/s11205-016-1495-y>
- Diez, S., Lacy, S.E., Bannan, T.J., Flynn, M., Gardiner, T., Harrison, D., Marsden, N., Martin, N.A., Read, K. and Edwards, P.M., 2022. Air pollution measurement errors: is your data fit for purpose?. *Atmospheric Measurement Techniques*, 15(13), pp.4091-4105.
- Dimaggio, P., & Hargittai, E. (n.d.). *From the "Digital Divide" to "Digital Inequality": Studying Internet Use as Penetration Increases**.
- Dockery, D. W., Pope, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris, B. G., & Speizer, F. E. (1993). An Association between Air Pollution and Mortality in Six U.S. Cities. *New England Journal of Medicine*. <https://doi.org/10.1056/NEJM199312093292401>
- Dockery, D. W., Pope, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris, B. G., & Speizer, F. E. (1993). An Association between Air Pollution and Mortality in Six U.S. Cities. *New England Journal of Medicine*, 329(24), 1753–1759. <https://doi.org/10.1056/nejm199312093292401>
- Noonan, D.S. (2011). *Smoggy with a Chance of Altruism: Using Air Quality Forecasts to Drive Behavioral Change* | American Enterprise Institute - AEI. AEI Outlook Series. American Enterprise Institute. AEI Working Paper. <https://www.aei.org/research-products/working-paper/smoggy-with-a-chance-of-altruism-using-air-quality-forecasts-to-drive-behavioral-change/>
- Eliasson, L., Barber, N., & Weinman, J. (2014). Applying COM-B to medication adherence: a suggested framework for research and interventions. *The European Health Psychologist*.
- Elliot, A. J., & Maier, M. A. (2013). *Color Psychology: Effects of Perceiving Color on Psychological Functioning in Humans*. <https://doi.org/10.1146/annurev-psych-010213-115035>

- Elliott, S. J., Cole, D. C., Krueger, P., Voorberg, N., & Wakefield, S. (1999b). The power of perception: Health risk attributed to air pollution in an urban industrial neighbourhood. *Risk Analysis*, 19(4), 621–634. <https://doi.org/10.1023/A:1007029518897>
- Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing*, 62(1), 107–115. <https://doi.org/10.1111/j.1365-2648.2007.04569.x>
- Emissions Analytics (2021). Exposure to particles and volatile organic compounds across multiple transportation modes. Report for TRANSITION Clean Air Network. 31 July 2021 (Updated 14 January 2022). Retrieved electronically < <https://transition-air.org.uk/wp-content/uploads/TRANSITION-DI-Project-Report-Nick-Molden.pdf>>
- UK Health Security Agency (2022). *Air pollution: applying All our Health*. Retrieved July 8, 2022, from <https://www.gov.uk/government/publications/air-pollution-applyingall-our-health/air-pollution-applying-all-our-health#why-we-focus-on-the-health-effects-of-air-pollution-in-your-professional-practice>
- European Society for Medical Oncology (2022). ESMO Congress Press Release. Retrieved electronically <https://www.esmo.org/newsroom/press-releases/scientists-discover-how-air-pollution-may-trigger-lung-cancer-in-never-smokers>
- Fairburn, J., Schüle, S. A., Dreger, S., Hilz, L. K., & Bolte, G. (2019). Social Inequalities in Exposure to Ambient Air Pollution: A Systematic Review in the WHO European Region. *International Journal of Environmental Research and Public Health* 2019, Vol. 16, Page 3127, 16(17), 3127. <https://doi.org/10.3390/IJERPH16173127>
- Fatehkia, M., Kashyap, R., & Weber, I. (2018). Using Facebook ad data to track the global digital gender gap. *World Development*. <https://doi.org/10.1016/j.worlddev.2018.03.007>
- Fecht, D., Fischer, P., Fortunato, L., Hoek, G., De Hoogh, K., Marra, M., Kruize, H., Vienneau, D., Beelen, R., & Hansell, A. (2015). Associations between air pollution and socioeconomic characteristics, ethnicity and age profile of neighbourhoods in England and the Netherlands. *Environmental Pollution*, 198, 201–210. <https://doi.org/10.1016/j.envpol.2014.12.014>
- Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, 87(417), 178–183. <https://doi.org/10.1080/01621459.1992.10475190>
- Fuller, R., Landrigan, P.J., Balakrishnan, K., Bathan, G., Bose-O'Reilly, S., Brauer, M., Caravanos, J., Chiles, T., Cohen, A., Corra, L. and Cropper, M., 2022. Pollution and health: a progress update. *The Lancet Planetary Health*.
- Gabrys, J. (2017). Program Earth. In *Program Earth*. <https://doi.org/10.5749/minnesota/9780816693122.001.0001>
- Gabrys, J. (2020). Smart forests and data practices: From the Internet of Trees to planetary governance. In *Big Data and Society* (Vol. 7, Issue 1). SAGE Publications Ltd. <https://doi.org/10.1177/2053951720904871>
- Gabrys, J., Pritchard, H., & Barratt, B. (2016). Just good enough data: Figuring data citizenships through air pollution sensing and data stories. *Big Data and Society*. <https://doi.org/10.1177/2053951716679677>
- Gifford, R., & Nilsson, A. (2014). Personal and social factors that influence pro-environmental concern and behavior: A review. *International Journal of Psychology*, 49(3), 141–157. <https://doi.org/10.1002/IJOP.12034>
- Global Action Plan, 2022. Clean Air Public Insight Tracker. Retrieved electronically 1 August 2022 <https://www.actionforcleanair.org.uk/capit>
- Global Burden of Disease (2019). Ambient Particulate Matter Pollution – Capstone Appendix. Retrieved electronically < https://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_GBD_2019_PM_RISK_MODELING_DESCRIPTION_Y2021M01D06.PDF>
- Goldthorpe, J.H. and McKnight, A., 2006. The economic basis of social class. *Mobility and inequality: Frontiers of research in sociology and economics*, pp.109-136.
- Gordon, S.B., Bruce, N.G., Grigg, J., Hibberd, P.L., Kurmi, O.P., Lam, K.B.H., Mortimer, K., Asante, K.P., Balakrishnan, K., Balmes, J. and Bar-Zeev, N., 2014. Respiratory risks from household air pollution in low and middle income countries. *The Lancet Respiratory Medicine*, 2(10), pp.823-860.
- Graham, S. (2015). Life support: The political ecology of urban air. *City*. <https://doi.org/10.1080/13604813.2015.1014710>
- Grieve, A. (2017). Clean Air Walking Routes Monitoring Report. King's College London. Retrieved electronically < <https://crossriverpartnership.org/wp-content/uploads/2019/04/clean-air-walking-routes-air-quality-monitoring-report-1-1.pdf>>
- The Guardian (2022). Demographic profile of Guardian online site users. Accessed electronically < <https://www.theguardian.com/advertising/advertising-demographic-profile-guardian-users>>
- Gulliford, M., & Alageel, S. (2019). Digital health intervention at older ages. *The Lancet Digital Health*, 1(8), e382–e383. [https://doi.org/10.1016/S2589-7500\(19\)30194-3](https://doi.org/10.1016/S2589-7500(19)30194-3)

- H, B., J, B., SJ, J., JWS, L., G, S., & E, H. (2017). Air pollution, deprivation and health: understanding relationships to add value to local air quality management policy and practice in Wales, UK. *Journal of Public Health (Oxford, England)*, 39(3), 485–497. <https://doi.org/10.1093/PUBMED/FDW084>
- Hammerton, G. and Munafò, M.R., 2021. Causal inference with observational data: the need for triangulation of evidence. *Psychological medicine*, 51(4), pp.563–578.
- Hano, M. C., Prince, S. E., Wei, L., Hubbell, B. J., & Rappold, A. G. (2020). Knowing Your Audience: A Typology of Smoke Sense Participants to Inform Wildfire Smoke Health Risk Communication. *Frontiers in Public Health*, 8, 143. <https://doi.org/10.3389/fpubh.2020.00143>
- Haraway, D. (1988). Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective. *Feminist Studies*, 14(3), 575. <https://doi.org/10.2307/3178066>
- Hargittai, E. (2010). Minding the digital gap: why understanding digital inequality matters. In S. Papathanassopoulos (Ed.), *Media Perspectives for the 21st c. Entury Routledge.*, 231–240.
- Hargittai, E., Piper, A. M., Meredith, ., & Morris, R. (2019). From internet access to internet skills: digital inequality among older adults. 18, 881–890. <https://doi.org/10.1007/s10209-018-0617-5>
- Hart, P. S., & Nisbet, E. C. (2012). Boomerang Effects in Science Communication: How Motivated Reasoning and Identity Cues Amplify Opinion Polarization About Climate Mitigation Policies. *Communication Research*. <https://doi.org/10.1177/0093650211416646>
- Hilfiger, J. J. (2015). *Graphing Data with R: An Introduction*. 250.
- Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., & Kaufman, J. D. (2013a). Long-term air pollution exposure and cardio-respiratory mortality: A review. In *Environmental Health: A Global Access Science Source*. <https://doi.org/10.1186/1476-069X-12-43>
- Hubbell, B. J., Kaufman, A., Rivers, L., Schulte, K., Hagler, G., Clougherty, J., Cascio, W., & Costa, D. (2018a). Understanding social and behavioral drivers and impacts of air quality sensor use. In *Science of the Total Environment*. <https://doi.org/10.1016/j.scitotenv.2017.11.275>
- Janke, K. (2014). Air pollution, avoidance behavior and children's respiratory health: Evidence from England. *Journal of Health Economics*, 38, 23–42. <https://doi.org/10.1016/J.JHEALECO.2014.07.002>
- Jasanoff, S. (2004). *States of knowledge: the co-production of science and the social order*.
- Jetter, J., Zhao, Y., Smith, K.R., Khan, B., Yelverton, T., DeCarlo, P. and Hays, M.D., 2012. Pollutant emissions and energy efficiency under controlled conditions for household biomass cookstoves and implications for metrics useful in setting international test standards. *Environmental science & technology*, 46(19), pp.10827–10834.
- Johnson, B. B. (2012). Experience with Urban Air Pollution in Paterson, New Jersey and Implications for Air Pollution Communication. *Risk Analysis*, 32(1), 39–53. <https://doi.org/10.1111/J.1539-6924.2011.01669.X>
- Johnston, F. H., Wheeler, A. J., Williamson, G. J., Campbell, S. L., Jones, P. J., Koolhof, I. S., Lucani, C., Cooling, N. B., & Bowman, D. M. J. S. (2018). Using smartphone technology to reduce health impacts from atmospheric environmental hazards. *Environmental Research Letters*. <https://doi.org/10.1088/1748-9326/aab1e6>
- Karanasiou, A., Viana, M., Querol, X., Moreno, T. and de Leeuw, F., 2014. Assessment of personal exposure to particulate air pollution during commuting in European cities—Recommendations and policy implications. *Science of the Total Environment*, 490, pp.785–797.
- Karppinen, P., & Oinas-Kukkonen, H. (2013). Three approaches to ethical considerations in the design of behavior change support systems. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. https://doi.org/10.1007/978-3-642-37157-8_12
- Kelly, F. J., Fuller, G. W., Walton, H. A., & Fussell, J. C. (2012). Monitoring air pollution: Use of early warning systems for public health. In *Respirology* (Vol. 17, Issue 1, pp. 7–19). <https://doi.org/10.1111/j.1440-1843.2011.02065.x>
- Kelly, F. J., & Fussell, J. C. (2015). Air pollution and public health: emerging hazards and improved understanding of risk. *Environmental Geochemistry and Health*, 37(4), 631–649. <https://doi.org/10.1007/s10653-015-9720-1>
- Kelly, F.J. and Fussell, J.C., 2019. Improving indoor air quality, health and performance within environments where people live, travel, learn and work. *Atmospheric Environment*, 200, pp.90–109.
- Kim, J., & Kwan, M. P. (2021). How Neighborhood Effect Averaging Might Affect Assessment of Individual Exposures to Air Pollution: A Study of Ozone Exposures in Los Angeles. *Annals of the American Association of Geographers*, 111(1), 121–140. <https://doi.org/10.1080/24694452.2020.1756208>
- Kitchin, R. (2014). The Data Revolution: Big Data, Open Data, Data Infrastructures & Their Consequences. In *The Data Revolution: Big Data, Open Data, Data Infrastructures & Their Consequences*. <https://doi.org/10.4135/9781473909472>

- Koman, P. D., Hogan, K. A., Sampson, N., Mandell, R., Coombe, C. M., Tetteh, M. M., Hill-Ashford, Y. R., Wilkins, D., Zlatnik, M. G., Loch-Caruso, R., Schulz, A. J., & Woodruff, T. J. (2018). Examining Joint Effects of Air Pollution Exposure and Social Determinants of Health in Defining “At-Risk” Populations Under the Clean Air Act: Susceptibility of Pregnant Women to Hypertensive Disorders of Pregnancy. *World Medical and Health Policy*. <https://doi.org/10.1002/wmh3.257>
- LAQM Technical Guidance (2022). Department for Environment, Food and Rural Affairs (Defra). Retrieved electronically < <https://laqm.defra.gov.uk/wp-content/uploads/2022/08/LAQM-TG22-August-22-v1.0.pdf>>
- Latour, Bruno. (1999). *Pandora's hope an essay on the reality of science studies*.
- Lave, R. (2015). The Future of Environmental Expertise. *Annals of the Association of American Geographers*, 105(2), 244–252. <https://doi.org/10.1080/00045608.2014.988099>
- Lewandowsky, S., & Spence, I. (2016). The Perception of Statistical Graphs: <http://Dx.Doi.Org/10.1177/0049124189018002002>, 18(2–3), 200–242. <https://doi.org/10.1177/0049124189018002002>
- Lezaun, J., & Soneryd, L. (2007). Consulting citizens: technologies of elicitation and the mobility of publics. *Public Understand. Sci*, 16, 279–297. <https://doi.org/10.1177/0963662507079371>
- Marres, N. (2017). Digital Sociology: the Reinvention of Social Research. In *Digital Sociology*.
- McCarron, A., Semple, S., Braban, C. F., Swanson, V., Gillespie, C., & Price, H. D. (2022). Public engagement with air quality data: using health behavior change theory to support exposure-minimising behaviors. *Journal of Exposure Science & Environmental Epidemiology* 2022, 1–11. <https://doi.org/10.1038/s41370-022-00449-2>
- Michie, S., van Stralen, M. M., & West, R. (2011). The behavior change wheel: A new method for characterising and designing behavior change interventions. *Implementation Science*, 6(1), 1–12. <https://doi.org/10.1186/1748-5908-6-42/TABLES/3>
- Milojevic, A., Niedzwiedz, C. L., Pearce, J., Milner, J., MacKenzie, I. A., Doherty, R. M., & Wilkinson, P. (2017). Socioeconomic and urban-rural differentials in exposure to air pollution and mortality burden in England. *Environmental Health : A Global Access Science Source*, 16(1). <https://doi.org/10.1186/S12940-017-0314-5>
- Monteiro, A., Vieira, M., Gama, C., & Miranda, A. I. (2017). Towards an improved air quality index. *Air Quality, Atmosphere and Health*, 10(4), 447–455. <https://doi.org/10.1007/S11869-016-0435-Y/FIGURES/4>
- Morawska, L., Thai, P. K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., Bedini, A., Chai, F., Christensen, B., Dunbabin, M., Gao, J., Hagler, G. S. W., Jayaratne, R., Kumar, P., Lau, A. K. H., Louie, P. K. K., Mazaheri, M., Ning, Z., Motta, N., ... Williams, R. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? In *Environment International* (Vol. 116, pp. 286–299). Elsevier Ltd. <https://doi.org/10.1016/j.envint.2018.04.018>
- Moser, S. C., & Dilling, L. (2009). Toward the social tipping point: creating a climate for change. In *Creating a Climate for Change* (pp. 491–516). Cambridge University Press. <https://doi.org/10.1017/cbo9780511535871.035>
- Mosley, S. (2009). A network of trust: Measuring and monitoring air pollution in british cities, 1912-1960. *Environment and History*. <https://doi.org/10.3197/096734009X12474738131074>
- Murray, C.J., Aravkin, A.Y., Zheng, P., Abbafati, C., Abbas, K.M., Abbasi-Kangevari, M., Abd-Allah, F., Abdelalim, A., Abdollahi, M., Abdollahpour, I. and Abegaz, K.H., 2020. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, 396(10258), pp.1223-1249.
- Neff, G., & Nafus, D. (2016). *Self-tracking*. MIT Press.
- Neff, G., Tanweer, A., Fiore-Gartland, B., & Osburn, L. (2017). Critique and Contribute: A Practice-Based Framework for Improving Critical Data Studies and Data Science. *Big Data*. <https://doi.org/10.1089/big.2016.0050>
- Neidell, M., & Kinney, P. L. (2010). Estimates of the association between ozone and asthma hospitalizations that account for behavioral responses to air quality information. *Environmental Science and Policy*. <https://doi.org/10.1016/j.envsci.2009.12.006>
- OECD, (2022). Overview of the education system: United Kingdom. Retrieved electronically < <https://gpseducation.oecd.org/CountryProfile?primaryCountry=GBR&treshold=10&topic=EO>>
- Orellano, P., Reynoso, J., Quaranta, N., Bardach, A. and Ciapponi, A., 2020. Short-term exposure to particulate matter (PM10 and PM2. 5), nitrogen dioxide (NO2), and ozone (O3) and all-cause and cause-specific mortality: Systematic review and meta-analysis. *Environment international*, 142, p.105876.
- Pampel, F. C., Krueger, P. M., & Denney, J. T. (2010). Socioeconomic Disparities in Health Behaviors. *Annual Review of Sociology*, 36, 349. <https://doi.org/10.1146/ANNUREV.SOC.012809.102529>

- Pasetto, R., Mattioli, B., & Marsili, D. (2019). Environmental justice in industrially contaminated sites. A review of scientific evidence in the WHO european region. In *International Journal of Environmental Research and Public Health*. <https://doi.org/10.3390/ijerph16060998>
- Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social Conditions as Fundamental Causes of Health Inequalities: Theory, Evidence, and Policy Implications. *Journal of Health and Social Behavior*, 51(1_suppl), S28–S40. <https://doi.org/10.1177/0022146510383498>
- Pimpin, L., Retat, L., Fecht, D., de Preux, L., Sassi, F., Gulliver, J., Belloni, A., Ferguson, B., Corbould, E., Jaccard, A., & Webber, L. (2018). Estimating the costs of air pollution to the National Health Service and social care: An assessment and forecast up to 2035. *PLOS Medicine*, 15(7), e1002602. <https://doi.org/10.1371/JOURNAL.PMED.1002602>
- Pope, D., Bruce, N., Dherani, M., Jagoe, K. and Rehfuess, E., 2017. Real-life effectiveness of ‘improved’ stoves and clean fuels in reducing PM_{2.5} and CO: Systematic review and meta-analysis. *Environment international*, 101, pp.7-18.
- Pritchard, H., & Gabrys, J. (2016). From Citizen Sensing to Collective Monitoring: Working through the Perceptive and Affective Problematics of Environmental Pollution. *GeoHumanities*. <https://doi.org/10.1080/2373566x.2016.1234355>
- Pritchard, H., Gabrys, J., & Houston, L. (2018). Re-calibrating DIY: Testing digital participation across dust sensors, fry pans and environmental pollution: <https://doi.org/10.1177/1461444818777473>, 20(12), 4533–4552. <https://doi.org/10.1177/1461444818777473>
- Ramírez, A. S., Ramondt, S., Van Bogart, K., & Perez-Zuniga, R. (2019). Public Awareness of Air Pollution and Health Threats: Challenges and Opportunities for Communication Strategies To Improve Environmental Health Literacy. <https://doi.org/10.1080/10810730.2019.1574320>, 24(1), 75–83. <https://doi.org/10.1080/10810730.2019.1574320>
- Rappold, A. G., Fann, N. L., Crooks, J., Huang, J., Cascio, W. E., Devlin, R. B., & Diaz-Sanchez, D. (2014). *Forecast-Based Interventions Can Reduce the Health and Economic Burden of Wildfires*. <https://doi.org/10.1021/es5012725>
- Rappold, A. G., Hano, M. C., Prince, S., Wei, L., Huang, S. M., Baghdikian, C., Stearns, B., Gao, X., Hoshiko, S., Cascio, W. E., Diaz-Sanchez, D., & Hubbell, B. (2019). Smoke Sense Initiative Leverages Citizen Science to Address the Growing Wildfire-Related Public Health Problem. *GeoHealth*. <https://doi.org/10.1029/2019GH000199>
- Riley, R., de Preux, L., Capella, P., Mejia, C., Kajikawa, Y., & de Nazelle, A. (2021). How do we effectively communicate air pollution to change public attitudes and behaviors? A review. *Sustainability Science* 2021 16:6, 16(6), 2027–2047. <https://doi.org/10.1007/S11625-021-01038-2>
- Rivas, I., Kumar, P., & Hagen-Zanker, A. (2017). Exposure to air pollutants during commuting in London: Are there inequalities among different socio-economic groups? *Environment International*, 101, 143–157. <https://doi.org/10.1016/j.envint.2017.01.019>
- Rogers, E. M. (1995). Diffusion of Innovations, Fourth Edition. In *Elements of Diffusion*. <https://doi.org/citeulike-article-id:126680>
- Rose, G. (2016). Visual methodologies: an introduction to researching with visual materials. *Sage Publication*, 1–4.
- Royal College of Physicians. (2016). *Every breath we take: the lifelong impact of air pollution*. <https://www.rcplondon.ac.uk/projects/outputs/every-breath-we-take-lifelong-impact-air-pollution>
- Ruggieri, M., & Plaia, A. (2012). An aggregate AQI: Comparing different standardizations and introducing a variability index. *Science of the Total Environment*. <https://doi.org/10.1016/j.scitotenv.2011.09.019>
- Ruppert, E., Harvey, P., Lury, C., Mackenzie, A., McNally, R., Baker, S. A., Kallianos, Y., & Lewis, C. (2015). *Socialising Big Data: From concept to practice*.
- Rüttenauer, T. (2019). Bringing urban space back in: A multilevel analysis of environmental inequality in Germany. *Urban Studies*, 56(12), 2549–2567. <https://doi.org/10.1177/0042098018795786>
- Rüttenauer, T. (2021). *Extreme Weather Events Elevate Climate Change Belief but not Pro-Environmental Behavior*. <https://doi.org/10.31235/OSF.IO/574UF>
- Rogers, R. (1983). Cognitive and Physiological Processes in Fear Appeals and Attitude Change: A Revised Theory of Protection Motivation. In In: Cacioppo JT, Petty RE. (eds.), *Social Psychophysiology: A Sourcebook*. New York: Guilford Press (pp. 153–76.).
- Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. In *Telematics and Informatics* (Vol. 34, Issue 8, pp. 1607–1624). Elsevier Ltd. <https://doi.org/10.1016/j.tele.2017.07.007>
- Schulte, K. (2022). “Real-time” air quality channels: A technology review of emerging environmental alert systems: <https://doi.org/10.1177/20539517221101346>, 9(1), 205395172211013. <https://doi.org/10.1177/20539517221101346>

- Schwarzer, R. (1992). Self-Efficacy in the Adoption and Maintenance of Health Behaviors Theoretical Approaches and a New Model. In *In Schwarzer, R., Ed., Self-Efficacy Thought Control of Action* (pp. 217–243). Scientific Research Publishing. Washington, DC.
- Shaw, A., & Hargittai, E. (2018). The pipeline of online participation Inequalities: The case of Wikipedia editing. *Journal of Communication*. <https://doi.org/10.1093/joc/jqx003>
- Simpson, D., Benedictow, A., Berge, H., Bergström, R., Emberson, L. D., Fagerli, H., Flechard, C. R., Hayman, G. D., Gauss, M., Jonson, J. E., Jenkin, M. E., Nyíri, A., Richter, C., Semeena, V. S., Tsyro, S., Tuovinen, J.-P., Valdebenito, A., & Wind, P. (2012). The EMEP MSC-W chemical transport model-technical description. *Atmos. Chem. Phys*, 12, 7825–7865. <https://doi.org/10.5194/acp-12-7825-2012>
- Singh, A., Bartington, S.E., Song, C., Ghaffarpasand, O., Kraftl, M., Shi, Z., Pope, F.D., Stacey, B., Hall, J., Thomas, G.N. and Bloss, W.J., 2022. Impacts of emergency health protection measures upon air quality, traffic and public health: evidence from Oxford, UK. *Environmental Pollution*, 293, p.118584.
- Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S. W., Shelow, D., Hindin, D. A., Kilaru, V. J., & Preuss, P. W. (2013). The changing paradigm of air pollution monitoring. *Environmental Science and Technology*, 47(20), 11369–11377. <https://doi.org/10.1021/es4022602>
- Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. *Ecological Economics*, 131, 468–474. <https://doi.org/10.1016/j.ecolecon.2016.06.030>
- Tainio, M., de Nazelle, A.J., Götschi, T., Kahlmeier, S., Rojas-Rueda, D., Nieuwenhuijsen, M.J., de Sá, T.H., Kelly, P. and Woodcock, J., 2016. Can air pollution negate the health benefits of cycling and walking?. *Preventive medicine*, 87, pp.233-236.
- Tian, Y., Nearing, G. S., Peters-Lidard, C. D., Harrison, K. W., and Tang, L.: Performance Metrics, Error Modeling, and Uncertainty Quantification, *Mon. Weather Rev.*, 144, 607–613, <https://doi.org/10.1175/MWR-D-15-0087.1>, 2016.
- Tonne, C., Beevers, S., Armstrong, B., Kelly, F., & Wilkinson, P. (n.d.). *Air pollution and mortality benefits of the London Congestion Charge: spatial and socioeconomic inequalities*. <https://doi.org/10.1136/oem.2007.036533>
- Tonne, C., Milà, C., Fecht, D., Alvarez, M., Gulliver, J., Smith, J., Beevers, S., Ross Anderson, H., & Kelly, F. (2018). Socioeconomic and ethnic inequalities in exposure to air and noise pollution in London. *Environment International*, 115, 170–179. <https://doi.org/10.1016/J.ENVINT.2018.03.023>
- Tsai, D. H., Riediker, M., Berchet, A., Paccaud, F., Waeber, G., Vollenweider, P., & Bochud, M. (2019). Effects of short- and long-term exposures to particulate matter on inflammatory marker levels in the general population. *Environmental Science and Pollution Research*, 26(19), 19697–19704. <https://doi.org/10.1007/s11356-019-05194-y>
- van Deursen, A. J. A. M., & Helsper, E. J. (2015). *The Third-Level Digital Divide: Who Benefits Most from Being Online?* (pp. 29–52). <https://doi.org/10.1108/s2050-206020150000010002>
- van Deursen, A. J., & van Dijk, J. A. (2014). The digital divide shifts to differences in usage. *New Media & Society*, 16(3), 507–526. <https://doi.org/10.1177/1461444813487959>
- Van Dijk, J., & Hacker, K. (2003). The Digital Divide as a Complex and Dynamic Phenomenon. In *Information Society* (Vol. 19, Issue 4, pp. 315–326). Informa UK Ltd. <https://doi.org/10.1080/01972240309487>
- Wai, S. Y., Bojei, J., Osman, S., & Hashim, N. H. (2018). Perceived Self-Efficacy and its Role in Fostering Pro-Environmental Attitude and Behaviors. *Asian Journal of Business and Accounting*, 11(2), 151–186. <https://doi.org/10.22452/AJBA.VOL11NO2.5>
- Whatmore, S. (2006). Materialist returns: practising cultural geography in and for a more-than-human world. *Cultural Geographies*, 13(4), 600–609. <https://doi.org/10.1191/1474474006cgj377oa>
- Whatmore, S. J., & Landström, C. (2011). Flood apprentices: an exercise in making things public. *Economy and Society*, 40(4), 582–610. <https://doi.org/10.1080/03085147.2011.602540>
- Whitmarsh, L. (2009). Behavioral responses to climate change: Asymmetry of intentions and impacts. *Journal of Environmental Psychology*, 29(1), 13–23. <https://doi.org/10.1016/J.JENVP.2008.05.003>
- WHO. (2019). Air quality guidelines – global update 2005. *World Health Organisation*.
- Williamson, J. (1978). *Decoding advertisements*.
- Woodall, G. M., Hoover, M. D., Williams, R., Benedict, K., Harper, M., Soo, J. C., Jarabek, A. M., Stewart, M. J., Brown, J. S., Hulla, J. E., Caudill, M., Clements, A. L., Kaufman, A., Parker, A. J., Keating, M., Balshaw, D., Garrahan, K., Burton, L., Batka, S., ... Thompson, B. (2017). Interpreting mobile and handheld air sensor readings in relation to air quality standards and health effect reference values: Tackling the challenges. *Atmosphere*. <https://doi.org/10.3390/atmos8100182>
- Zhang, Y., Bocquet, M., Mallet, V., Seigneur, C., & Baklanov, A. (2012). Real-time air quality forecasting, part I: History, techniques, and current status. In *Atmospheric Environment*. <https://doi.org/10.1016/j.atmosenv.2012.06.031>

Zhao, J., Freeman, B., & Li, M. (2016). Can mobile phone apps influence people's health behavior change? An evidence review. In *Journal of Medical Internet Research* (Vol. 18, Issue 11, p. e5692). JMIR Publications Inc. <https://doi.org/10.2196/jmir.5692>

Appendices

Appendix 1 - Chapter II: “Real-time” Air Quality (AQ) channels: A technology review of emerging environmental alert systems

Appendix 1.1: Search term permutations

Searches were conducted in February 2021 using Google, Apple App Store and Google Play Store. Appgroves.com was used as a referencing mechanism confirm whether resulting apps were available for Android, Apple iOS or both mobile operating systems. Searches were conducted using an Apple iPhone, Android emulator software and a MacBook Pro. The location for the Android emulator was “spoofed” to an address in London using GPS spoofing app GPS Joystick, while location was reset manually in the Chrome browser.

Google:

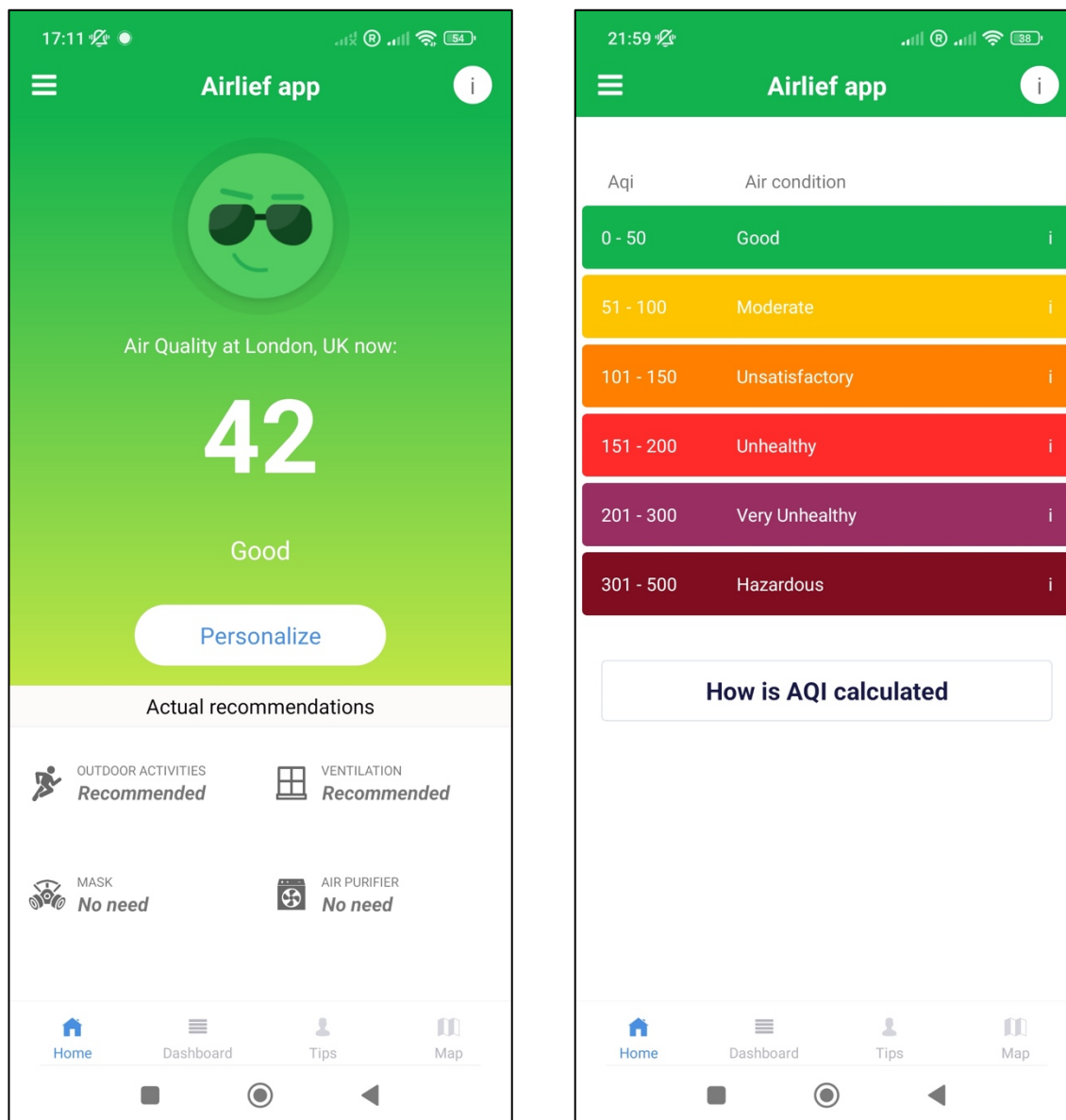
- Air quality London
- Air quality in London
- Air quality forecast
- Air quality nowcast
- Air quality alert
- Air quality map
- Air pollution London
- Air pollution in London
- Air pollution forecast
- Air pollution nowcast
- Air pollution alert
- Air pollution map
- Smog alert
- Smog forecast
- Smog nowcast
- Check air quality

Apple & Google App stores

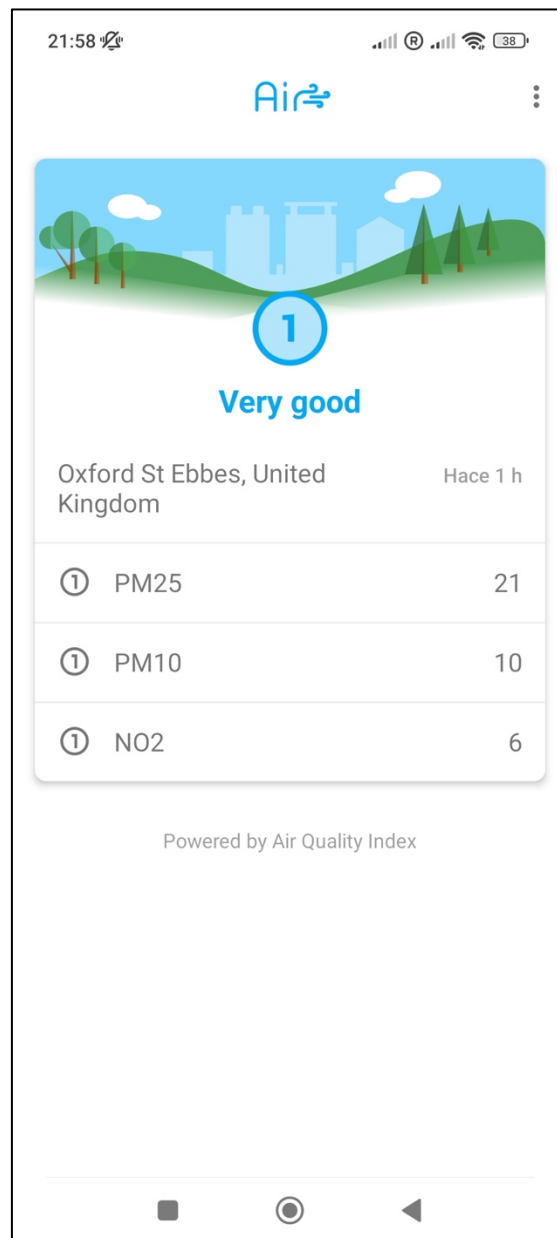
- Air quality
- Air quality app
- Air quality monitor
- Air quality index
- Air quality meter
- Check air quality
- Air quality forecast
- Air pollution forecast
- Air quality nowcast
- Air pollution nowcast
- Air monitor
- Air pollution
- Air pollution meter
- Air pollution index
- My AQI air
- Smog
- Smog app
- Smog air

Appendix 2 - Chapter III: Variation in representations of air pollution at six hospitals in London, UK

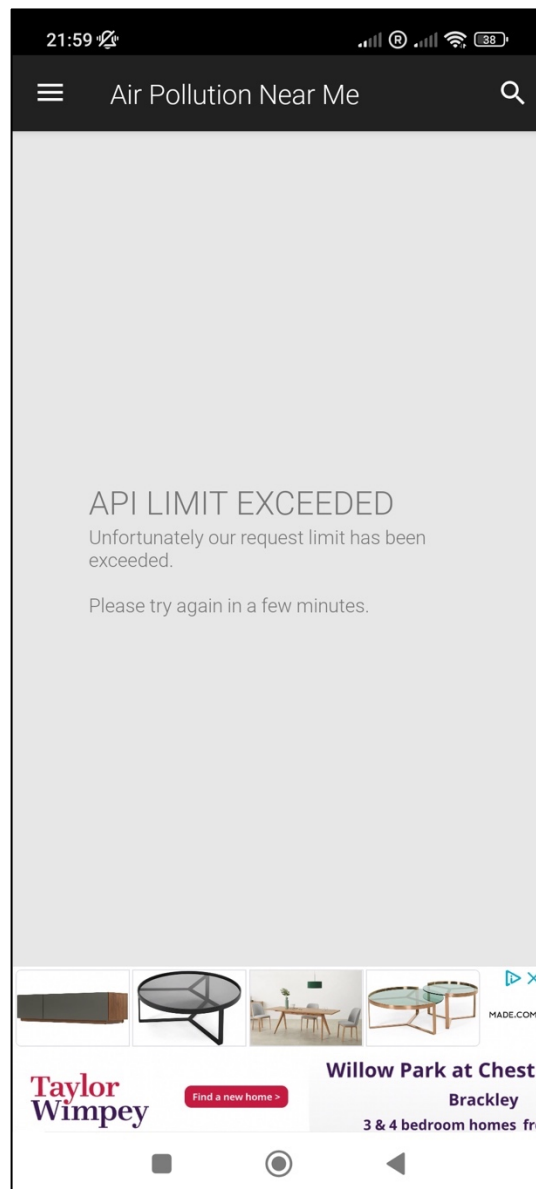
Appendix 2.1 – Additional AQ Channel screenshots



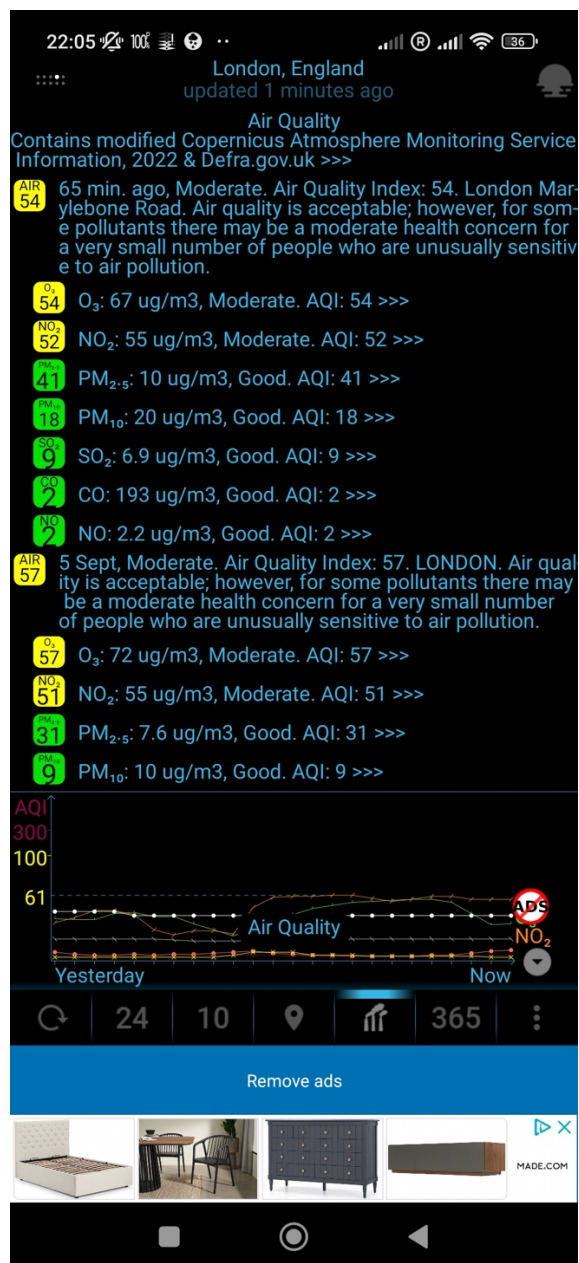
2.1.1 “Airlief” AQ channel derives air pollution estimates from API 2



2.1.2 “Air pollution around you” AQ channel derives air pollution estimates from API 2



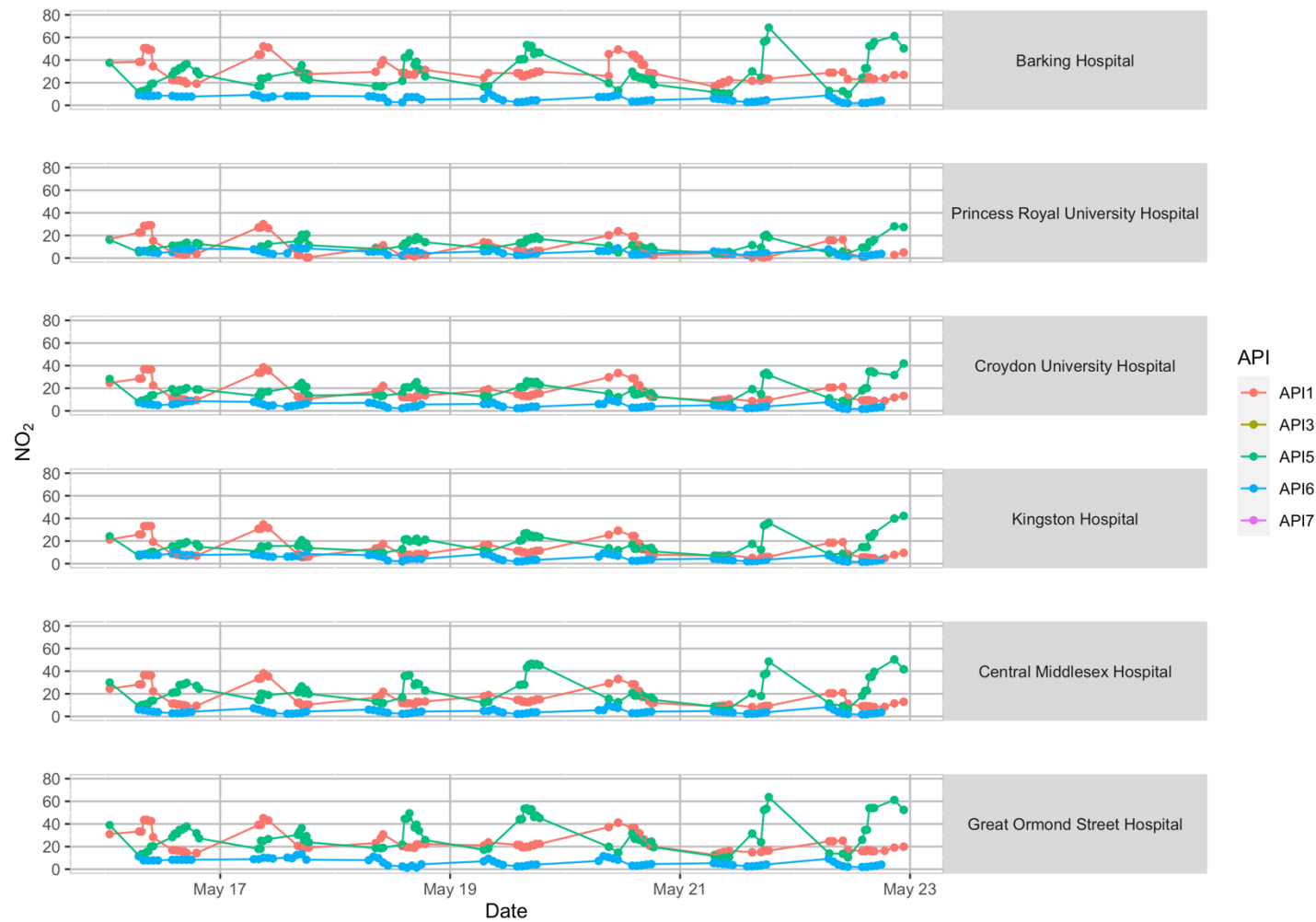
2.1.3 “Air pollution near me” AQ channel derives air pollution estimates from API 4 (non-functioning)



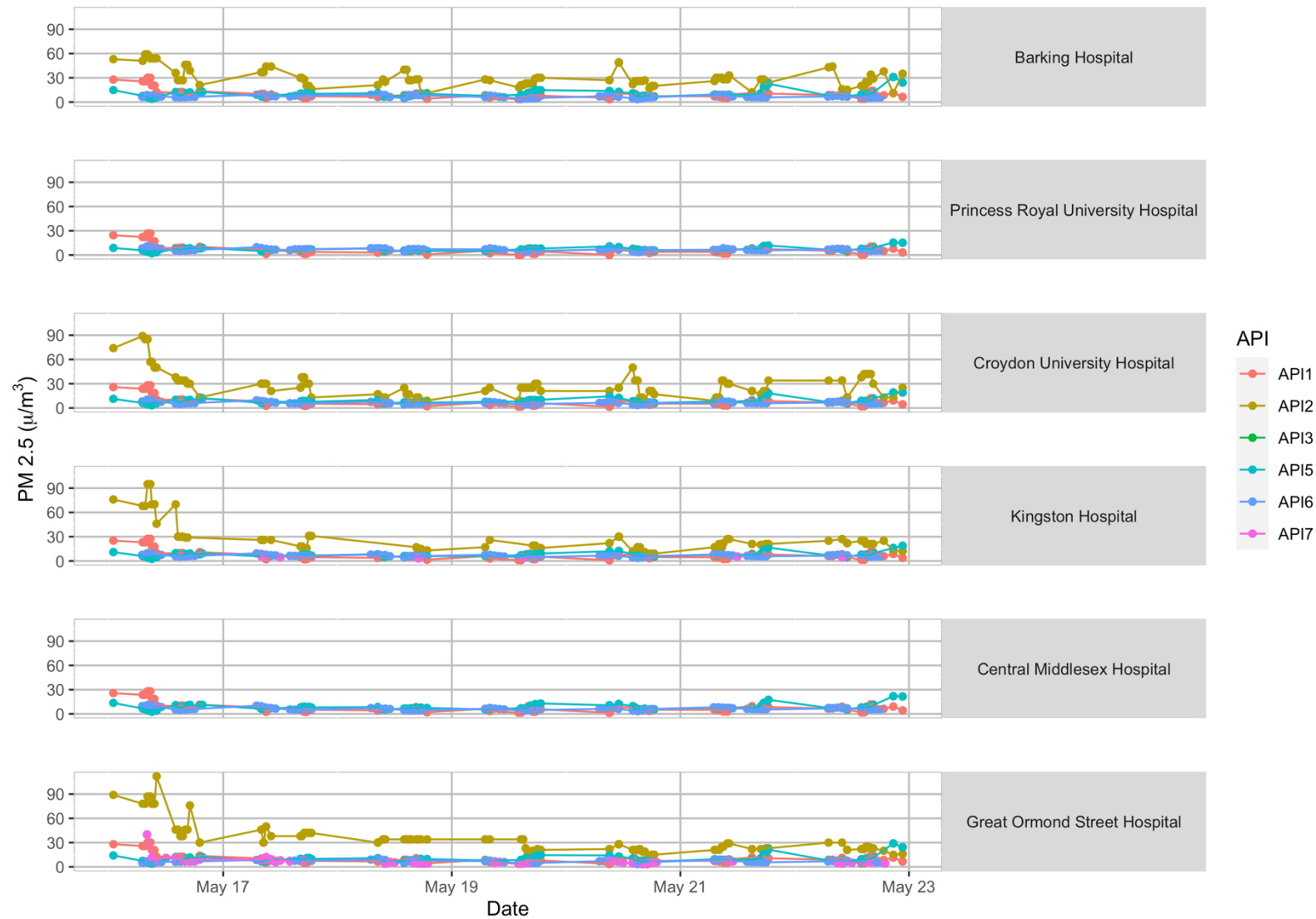
2.1.4 “eWeather hdf” AQ channel derives air pollution estimates from API 2

Appendix 2.2 – Timeseries of specific pollutant estimates by each API for the six hospital locations

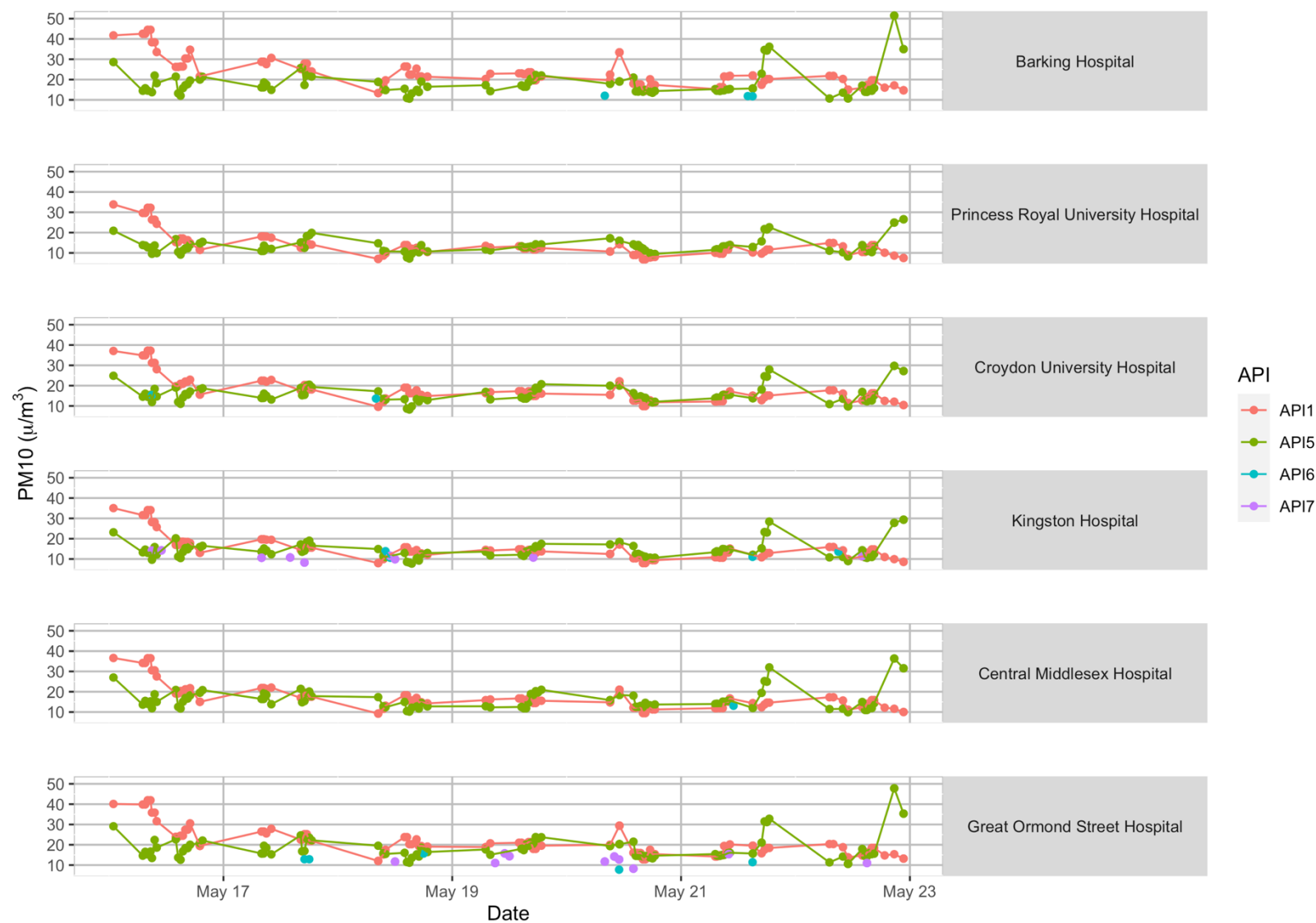
Appendix 2.2.1 NO₂ estimates from APIs 1, 3, 5, 6 and 7 for the week of May 17 – 23, 2022 at six hospital locations



Appendix 2.2.2 PM_{2.5} estimates from APIs 1, 2, 3, 5, 6 and 7 for the week of May 17 – 23, 2022 at six hospital locations



Appendix 2.2.3 PM₁₀ estimates from APIs 1, 5, 6 and 7 for the week of May 17 – 23, 2022 at six hospital locations



Appendix 3 - Chapter IV: “Examining psychosocial, health status, and demographic predictors of air pollution exposure reducing behaviors across the UK

Appendix 3.1.1 - Questions allocated to each summary index

Summary measure	Question	Sub-question	Coding scheme
ATTITUDE	To what extent do you think each of the following should be a priority for the UK? (OP11153_Q1.A.1:3)	Reducing air pollution (OP11153_Q1.A.1.1)	3 points: Should be a major priority 2 points: Should be a moderate priority 1 points: Should be a minor priority 0 points: Should not be a priority
	Which of the following, if any, do you think are the biggest contributors to indoor air pollution in the UK? Please select up to three options. (OP11153_Q11.1:16)	Boiler (OP11153_Q11.a.1)	0 points: Don't know 1 points: For each selected answer (max 3)
		Gas oven or hob (OP11153_Q11.a.2)	
		Mould (OP11153_Q11.a.3)	
		Solid fuel stove (OP11153_Q11.a.4)	
		Indoor open fire (OP11153_Q11.a.5)	
		Candles (OP11153_Q11.a.6)	
		Paint (OP11153_Q11.a.7)	
		Chipboard furniture (OP11153_Q11.a.8)	
		Carpets (OP11153_Q11.a.9)	
		Sofas (OP11153_Q11.a.10)	
		Cleaning products (OP11153_Q11.a.11)	
		Personal care products (OP11153_Q11.a.12)	
		Plastic toys (OP11153_Q11.a.13)	
		Smoking (OP11153_Q11.a.14)	
		Other (OP11153_Q11.a.15) (OMITTED)	
		Don't know (OP11153_Q11.a.16)	
		Lung cancer (OP11153_Q12.a.1[1])	
		Furring arteries (OP11153_Q12.a.1[2])	
		Cancer (OP11153_Q12.a.1[3])	
		Heart disease (OP11153_Q12.a.1[4])	

AWARENESS	Which of the following, if any, do you think are health issues associated with: Indoor air pollution (OP11153_Q12.1.1:18)	Diabetes II (OP11153_Q12.a.1[5])	0 points: Not selected/None/Don't know 1 points: For each selected answer
		Low birth weight (OP11153_Q12.a.1[6])	
		Premature birth (OP11153_Q12.a.1[7])	
		Poor lung development (OP11153_Q12.a.1[8])	
		Poor brain development (OP11153_Q12.a.1[9])	
		Worsening asthma (OP11153_Q12.a.1[10])	
		Developing asthma (OP11153_Q12.a.1[11])	
		Dementia (OP11153_Q12.a.1[12])	
		Bronchitis (OP11153_Q12.a.1[13])	
		Pneumonia (OP11153_Q12.a.1[14])	
		Worsening cognitive performance (OP11153_Q12.a.1[15])	
		Anxiety (OP11153_Q12.a.1[16])	
		None (OP11153_Q12.a.1[17])	
		Don't know (OP11153_Q12.a.1[18])	
	Which of the following, if any, do you think are health issues associated with: Outdoor air pollution (OP11153_Q12.2.1:18)	Lung cancer (OP11153_Q12.a.2[1])	0 points: Not selected/None/Don't know 1 points: For each selected answer
		Furring arteries (OP11153_Q12.a.2[2])	
		Cancer (OP11153_Q12.a.2[3])	
		Heart disease (OP11153_Q12.a.2[4])	
		Diabetes II (OP11153_Q12.a.2[5])	
		Low birth weight (OP11153_Q12.a.2[6])	
		Premature birth (OP11153_Q12.a.2[7])	
		Poor lung development (OP11153_Q12.a.2[8])	
		Poor brain development (OP11153_Q12.a.2[9])	
		Worsening asthma (OP11153_Q12.a.2[10])	
		Developing asthma (OP11153_Q12.a.2[11])	
		Dementia (OP11153_Q12.a.2[12])	
		Bronchitis (OP11153_Q12.a.2[13])	
		Pneumonia (OP11153_Q12.a.2[14])	

		Worsening cognitive performance (OP11153_Q12.a.2[15])	
		Anxiety (OP11153_Q12.a.2[16])	
		None (OP11153_Q12.a.2[17])	
		Don't know (OP11153_Q12.a.2[18])	
CONCERN	How concerned are you about the long-term impacts of air pollution on your health? (OP11153_Q9)		4 points: very concerned 3 points: somewhat concerned 2 points: not very concerned 1 points: not at all concerned
RESPONSE EFFICACY	To what extent do you think your personal actions can make a positive difference to the quality of air that you breathe? (OP11153_Q13)		4 points: major difference 3 points: moderate difference 2 points: minor difference 1 points: no difference
EXPOSURE REDUCING BEHAVIOR	And do you actively do any of the following to help reduce the level of outdoor air pollution?	Cycle or walk instead of driving	0 points: Not selected/None/Don't know 1 points: For each selected answer
		Ensure my vehicles are well maintained	
		Use public transportation instead of driving	
		Switch off the engine of my vehicle when stationary	
		Not used solid fuel stoves or open fires	
		Have fewer bonfires or barbeques	
		Use an electric lawnmower instead of diesel mowers	
		Work from home or video conference instead of commuting	
		Switched to a renewable energy tariff	
		Burn smokeless fuel/dry, well-seasoned wood on my open fire/stove	
		Bought and use low polluting car(s) such as an electric vehicle	
		N/A. I don't actively do anything to help reduce the level of outdoor air pollution	
		Opening the window	
		Making sure my boiler is well-maintained (e.g. annual service)	
		Using an extractor fan in the kitchen and/or the bathroom	
		Avoid smoking in the house	
		Keeping dust levels low	
		Not using a solid fuel stove or open fire	
		Using natural/eco air fresheners and/or cleaning products	

	And do you actively do any of the following to reduce the level of pollution inside your home?	Using fragrance free or naturally scented (e.g. without artificial ingredients) personal care products	
		Using low emission (labelled low VOC) paints, varnishes and glues (e.g. when decorating, crafting)	
		Burning smokeless fuel/dry, well-seasoned wood on my open fire/stove	
		Choosing low emission carpets and/or furniture	
		N/A. I don't actively do anything to help reduce the level of indoor air pollution	
	Have you done any of the following over the past three months?	Had a boiler service	
		Changed a journey to travel outside of rush hour	
		Chose an eco-delivery slot for online shopping	
		Switched to a green energy tariff	
		Driven in an electric vehicle	
		Actively chosen an electric taxi over another vehicle	
		None of the above	

3.1.2 Opinium respondent weighting protocol

Nat rep weighting (UK)									
	Total population:	52,673,000							
	Gender and age				Age only			Age only	
	<i>(used in weightset)</i>				-			-	
		Male	Female						
	18-34	14.12%	13.71%		18-34	27.83%		18-24	10.72%
	35-54	16.40%	16.79%		35-54	33.18%		25-34	17.11%
	55+	18.34%	20.64%		55+	38.99%		35-44	15.98%
	Other							45-54	17.21%
	Gender only							55-64	15.49%
								65-74	12.70%
		Male	Female					75+	10.80%
		48.86%	51.14%						
	Region								
	<i>(used in weightset)</i>								
	SCOTLAND	8.42%							
	NORTHERN IRELAND	2.76%							
	NORTH EAST	4.06%							
	NORTH WEST	10.97%							
	YORKSHIRE AND THE HUMBER	8.23%							
	EAST MIDLANDS	7.28%							
	WEST MIDLANDS	8.80%							
	WALES	4.79%							
	EAST	9.28%							
	LONDON	13.16%							
	SOUTH EAST	13.69%							
	SOUTH WEST	8.58%							
	Working status			Working status in more detail					
	<i>(used in weightset)</i>								
	Working full-time	46.85%		Working full-time	46.85%				
	Working part-time	13.76%		Working part-time	13.76%				
	Unemployed	2.81%		Unemployed	2.81%				
	Retired	22.95%		Student	3.93%				
	Other not working	13.62%		Retired	22.95%				
				Other not working	9.69%				

Appendix 3.2 – Descriptive statistics

3.2.1 Descriptive statistics for predictor variables in numerical format

	Sample A	Sample B	Overall
	(N=4002)	(N=4011)	(N=8013)
Indoor ERBs	2.51 2.17 (0.00, 11.00)	2.64 2.25 (0.00, 12.00)	2.58 2.21 (0.00, 12.00)
Outdoor ERBs	1.98 1.86 (0.00, 11.00)	2.05 1.89 (0.00, 11.00)	2.01 1.88 (0.00, 11.00)
ERBs in past 3 months	0.81 0.89 (0.00, 5.00)	0.69 0.84 (0.00, 5.00)	0.75 0.87 (0.00, 5.00)
All ERBs	5.37 4.04 (0.00, 28.00)	5.42 4.06 (0.00, 26.00)	5.40 4.05 (0.00, 28.00)
No ERBs adopted	0.55 0.70 (0.00, 3.00)	0.62 0.73 (0.00, 3.00)	0.58 0.71 (0.00, 3.00)

Note: Reports mean, standard deviation and confidence intervals for each ERB category

	Sample A	Sample B	Total
	(N=4002)	(N=4011)	(N=8013)
Awareness score			
Mean (SD)	6.83 (7.12)	7.50 (7.41)	7.16 (7.28)
Median [Min, Max]	5.00 [0, 32.0]	6.00 [0, 32.0]	5.00 [0, 32.0]
Concern for longterm health			
Mean (SD)	2.59 (0.832)	2.57 (0.818)	2.58 (0.825)
Median [Min, Max]	3.00 [1.00, 4.00]	3.00 [1.00, 4.00]	3.00 [1.00, 4.00]
Response efficacy/Outcome expectancy			
Mean (SD)	2.26 (0.713)	2.20 (0.724)	2.23 (0.719)
Median [Min, Max]	2.00 [1.00, 4.00]	2.00 [1.00, 4.00]	2.00 [1.00, 4.00]
Should reducing air pollution be a priority?			
Mean (SD)	3.20 (0.905)	3.28 (0.885)	3.24 (0.896)
Median [Min, Max]	3.00 [1.00, 4.00]	4.00 [1.00, 4.00]	3.00 [1.00, 4.00]

Appendix 3.3 – Sensitivity Analyses

3.3.1 VIF multicollinearity tests

3.3.1.1 – H1a – Samples A & B

	GVIF	Df	GVIF ^{1/(2*Df)}
<i>concern_longterm_num</i>	1.31954653158736	1	1.14871516555992
<i>trust_personalactions_num</i>	1.25815583204278	1	1.12167545753787
<i>priority_airpollution_num</i>	1.17992570185978	1	1.08624385009066
<i>gender_female_dummy</i>	1.06593418260625	1	1.03244088576841
<i>age_group</i>	2.08562482331827	7	1.05390771761758
<i>children_under11</i>	1.72001877406008	1	1.31149486238417
<i>region</i>	1.37629910188159	11	1.01462399424243
<i>education_simplified</i>	1.27015379229679	3	1.04066125328622
<i>white_nonwhite</i>	1.09751653428065	1	1.04762423333973
<i>income</i>	1.67237087046007	11	1.02364997829769

	GVIF	Df	GVIF ^{1/(2*Df)}
<i>concern_longterm_num</i>	1.34865757851334	1	1.16131717395092
<i>trust_personalactions_num</i>	1.25185905628524	1	1.118865075103
<i>priority_airpollution_num</i>	1.12479522412756	1	1.06056363511463
<i>gender_female_dummy</i>	1.06875831051884	1	1.03380767578832
<i>age_group</i>	2.13166593689665	7	1.05555274372756
<i>children_under11</i>	1.49669925832824	1	1.22339660712634
<i>region</i>	1.21573836157776	11	1.00891915881267
<i>asthma</i>	1.11217636572869	1	1.05459772696924
<i>asthma_child</i>	1.07595010045807	1	1.03728014560102
<i>asthma_carer</i>	1.11847865489583	1	1.0575815121757
<i>other_resp_me</i>	1.17834824882389	1	1.08551750277178
<i>other_resp_carer</i>	1.24269049100462	1	1.11476028409906
<i>other_heart_me</i>	1.17411496185605	1	1.08356585487734
<i>other_heart_child</i>	1.23733913635058	1	1.11235746788098
<i>other_heart_carer</i>	1.36315649634864	1	1.16754293126576
<i>HBP_me</i>	1.22944764266355	1	1.10880460075865
<i>HBP_child</i>	1.25715121305	1	1.12122754740062
<i>HBP_carer</i>	1.30342696240306	1	1.14167725842423
<i>other_condition_me</i>	1.21380086875849	1	1.10172631300087
<i>other_condition_child</i>	1.13045670671027	1	1.06322937633903
<i>other_condition_carer</i>	1.36862086034134	1	1.16988070346567
<i>social_grade_factor</i>	1.40073672730453	7	1.02436336205205
<i>COVID_num</i>	1.04099500937298	1	1.02029162957116

3.3.1.2 – H1b & c – Samples A & B

	GVIF	Df	GVIF ^{1/(2*Df)}
<i>awareness_score</i>	1.13098391628289	1	1.06347727586578
<i>trust_personalactions_num</i>	1.05887169457744	1	1.02901491465257
<i>priority_airpollution_num</i>	1.15246706998073	1	1.07353019053063
<i>gender_female_dummy</i>	1.06686001750045	1	1.03288916031704
<i>age_group</i>	2.06234410788159	7	1.05306303056929
<i>children_under11</i>	1.66913623508588	1	1.29195055442764
<i>region</i>	1.36549720409594	11	1.01426066379301
<i>education_simplified</i>	1.28462311856383	3	1.04262777215313
<i>white_nonwhite</i>	1.09675127538133	1	1.04725893425711
<i>income</i>	1.69695782320358	11	1.02432929437812

	GVIF	Df	GVIF ^{1/(2*Df)}
<i>awareness_score</i>	1.09355912161306	1	1.04573377186216
<i>trust_personalactions_num</i>	1.05244087153636	1	1.02588540857952
<i>priority_airpollution_num</i>	1.08394232369763	1	1.04112550813897
<i>gender_female_dummy</i>	1.06739321732583	1	1.0331472389383
<i>age_group</i>	2.12861657917428	7	1.05544481681724
<i>children_under11</i>	1.50472829195283	1	1.22667366970716
<i>region</i>	1.21894455989358	11	1.00903995073805
<i>asthma</i>	1.08149494051713	1	1.03994948940664
<i>asthma_child</i>	1.07923200580132	1	1.0388609174482
<i>asthma_carer</i>	1.11347329146676	1	1.055212439022
<i>other_resp_me</i>	1.15052475090164	1	1.07262516794155
<i>other_resp_carer</i>	1.23585494185892	1	1.11169012852454
<i>other_heart_me</i>	1.1651761047578	1	1.07943323311718
<i>other_heart_child</i>	1.28156052796437	1	1.13206030226502
<i>other_heart_carer</i>	1.33585522731541	1	1.15579203463054
<i>HBP_me</i>	1.2200725297467	1	1.1045689339044
<i>HBP_child</i>	1.29266283056425	1	1.13695331063516
<i>HBP_carer</i>	1.28880343856827	1	1.13525479015429
<i>other_condition_me</i>	1.21436262977981	1	1.10198122932281
<i>other_condition_child</i>	1.13050907035043	1	1.06325400086265
<i>other_condition_carer</i>	1.37877054551519	1	1.17421060526431
<i>social_grade_factor</i>	1.42447254487446	7	1.02559357541799
<i>COVID_num</i>	1.0394019926846	1	1.01951066335012

3.3.1.3 – H2a-c – Sample B

	GVIF	Df	GVIF ^{1/(2*Df)}
<i>awareness_score</i>	1.1467032807267	1	1.07084232299937
<i>concern_longterm_num</i>	1.36839539346061	1	1.16978433630333
<i>trust_personalactions_num</i>	1.26526963537265	1	1.1248420490774
<i>priority_airpollution_num</i>	1.14473155363289	1	1.0699212838489
<i>gender_female_dummy</i>	1.06903203737449	1	1.03394005501987
<i>age_group</i>	2.13405994099699	7	1.05563737508379
<i>children_under11</i>	1.50523377063928	1	1.22687968873858
<i>region</i>	1.21890672655941	11	1.0090385271551
<i>asthma</i>	1.11243160806842	1	1.05471873410328
<i>asthma_child</i>	1.07609638388723	1	1.03735065618489
<i>asthma_carer</i>	1.1184997677514	1	1.05759149379682
<i>other_resp_me</i>	1.17847389506738	1	1.08557537512021
<i>other_resp_carer</i>	1.24273371384314	1	1.11477967053725
<i>other_heart_me</i>	1.17437441286727	1	1.08368556918844
<i>other_heart_child</i>	1.23823978901388	1	1.11276223381902
<i>other_heart_carer</i>	1.36333376323251	1	1.16761884330141
<i>HBP_me</i>	1.22953506325473	1	1.1088440211566
<i>HBP_child</i>	1.25834017916148	1	1.12175762941978
<i>HBP_carer</i>	1.3045289773779	1	1.14215978627244
<i>other_condition_me</i>	1.22949684622194	1	1.1088267881964
<i>other_condition_child</i>	1.13274704584851	1	1.06430589862526
<i>other_condition_carer</i>	1.38063493944645	1	1.17500422954407
<i>social_grade_factor</i>	1.41372654771261	7	1.02503899345024
<i>COVID_num</i>	1.0410182845002	1	1.02030303562236

3.3.1.4 – Estimated associations between sociodemographic factors and self-efficacy/outcome expectancy

Table 10: Estimated associations between sociodemographic factors and self-efficacy/outcome expectancy

	Sample A	CI
Intercept	0.03** (0.005)	0.03*** (0.02, 0.04)
awareness score	1.25 (0.13)	1.25*** (1.00, 1.50)
Concern for longterm health	2.14 (0.13)	2.14*** (1.88, 2.40)
Should reducing air pollution be a priority?	3.25 (0.16)	3.25*** (2.94, 3.56)
Gender: Female	0.15 (0.04)	0.15*** (0.08, 0.23)
Aged 26 - 35	0.19 (0.07)	0.19*** (0.06, 0.32)
Aged 36 - 45	0.18 (0.16)	0.18 (-0.13, 0.50)
Aged 46 - 55	-0.24*** (0.16)	-0.24 (-0.56, 0.08)
Aged 56 - 65	0.05** (0.16)	0.05 (-0.27, 0.37)
Aged 66 - 75	-0.33*** (0.16)	-0.33** (-0.64, -0.02)
Aged 76 - 80	-0.52*** (0.16)	-0.52*** (-0.83, -0.21)
Over 80	-0.22*** (0.24)	-0.22 (-0.68, 0.24)
Has Children under age 11	0.23 (0.34)	0.23 (-0.43, 0.90)
London	0.41 (0.10)	0.41*** (0.21, 0.61)
South East	-0.30*** (0.16)	-0.30* (-0.62, 0.02)
South West	-0.23*** (0.27)	-0.23 (-0.76, 0.31)
West Midlands	-0.15*** (0.19)	-0.15 (-0.53, 0.22)
East Midlands	-0.21*** (0.15)	-0.21 (-0.50, 0.07)
East of England	-0.51*** (0.16)	-0.51*** (-0.81, -0.20)
Yorkshire and Humberside	-0.59*** (0.15)	-0.59*** (-0.90, -0.29)
North East	0.05** (0.20)	0.05 (-0.35, 0.44)
North West	-0.19*** (0.15)	-0.19 (-0.49, 0.11)
Scotland	-0.23*** (0.16)	-0.23 (-0.54, 0.07)
Northern Ireland	-0.43*** (0.14)	-0.43*** (-0.70, -0.17)
Wales	-0.25*** (0.16)	-0.25 (-0.56, 0.06)
Education: GCSE	0.22 (0.16)	0.22 (-0.10, 0.54)
Education: Higher ed	0.06* (0.16)	0.06 (-0.25, 0.36)
Education: no formal qualification	0.22 (0.15)	0.22 (-0.08, 0.51)
Ethnicity: non-white	0.25 (0.12)	0.25** (0.01, 0.49)
Income: £10,000-£19,999	0.25 (0.15)	0.25* (-0.05, 0.56)
Income: £20,000-£29,999	0.44 (0.15)	0.44*** (0.14, 0.74)
Income: £30,000-£39,999	0.35 (0.16)	0.35** (0.04, 0.67)
Income: £40,000-£49,999	0.42 (0.17)	0.42** (0.09, 0.75)
Income: £50,000-£59,999	0.69 (0.18)	0.69*** (0.34, 1.04)
Income: £60,000-£69,999	0.37 (0.20)	0.37* (-0.02, 0.76)
Income: £70,000-£79,999	0.52 (0.20)	0.52*** (0.13, 0.92)
Income: above £80,000	0.60 (0.21)	0.60*** (0.19, 1.01)
Income: Don't Know	0.54 (0.28)	0.54* (-0.01, 1.10)
Income: None of these	0.82 (0.27)	0.82*** (0.29, 1.35)
Income: Prefer not to say	0.60 (0.16)	0.60*** (0.29, 0.92)
Observations	4,002	
Adjusted R ²	0.1242	

3.3.2 OLS regression output including all sociodemographic variables (H1a)

Table 10: Estimated associations between awareness and sociodemographic characteristics (H1a) - all variables

	Sample A	CI	Sample B	CI
Intercept	-3.53*** (0.93)	-3.53*** (-5.36, -1.71)	-2.67*** (0.91)	-2.67*** (-4.44, -0.90)
Concern for longterm health	0.96*** (0.15)	0.96*** (0.68, 1.25)	1.19*** (0.16)	1.19*** (0.88, 1.49)
Response efficacy/Outcome expectancy	0.92*** (0.18)	0.92*** (0.59, 1.24)	1.11*** (0.17)	1.11*** (0.77, 1.44)
Should reducing air pollution be a priority?	1.18*** (0.12)	1.18*** (0.93, 1.43)	1.10*** (0.13)	1.10*** (0.85, 1.36)
Gender: Female	0.46** (0.22)	0.46** (0.03, 0.88)	0.23 (0.23)	0.23 (-0.22, 0.67)
Aged 26 - 35	-1.26** (0.55)	-1.26** (-2.28, -0.23)	0.29 (0.66)	0.29 (-1.02, 1.59)
Aged 36 - 45	-0.25 (0.56)	-0.25 (-1.28, 0.78)	0.20 (0.65)	0.20 (-1.08, 1.48)
Aged 46 - 55	1.11** (0.57)	1.11** (0.09, 2.14)	0.61 (0.64)	0.61 (-0.64, 1.86)
Aged 56 - 65	1.46*** (0.55)	1.46*** (0.46, 2.46)	0.49 (0.64)	0.49 (-0.76, 1.73)
Aged 66 - 75	1.16** (0.55)	1.16** (0.16, 2.17)	0.25 (0.65)	0.25 (-1.02, 1.52)
Aged 76 - 80	0.07 (0.73)	0.07 (-1.43, 1.57)	-0.57 (0.86)	-0.57 (-2.26, 1.11)
Over 80	0.91 (0.99)	0.91 (-1.27, 3.08)	0.001 (1.12)	0.001 (-2.18, 2.19)
Has Children under age 11	-1.83*** (0.32)	-1.83*** (-2.47, -1.18)	-1.73*** (0.36)	-1.73*** (-2.45, -1.02)
London	0.02 (0.57)	0.02 (-1.03, 1.07)	-0.12 (0.52)	-0.12 (-1.13, 0.90)
South East	-0.39 (0.98)	-0.39 (-2.13, 1.34)	0.76 (0.81)	0.76 (-0.83, 2.35)
South West	0.19 (0.63)	0.19 (-1.03, 1.41)	0.33 (0.65)	0.33 (-0.93, 1.60)
West Midlands	-0.34 (0.48)	-0.34 (-1.27, 0.60)	-0.29 (0.49)	-0.29 (-1.25, 0.66)
East Midlands	-0.56 (0.53)	-0.56 (-1.56, 0.44)	0.11 (0.53)	0.11 (-0.93, 1.15)
East of England	-0.30 (0.51)	-0.30 (-1.28, 0.67)	-0.20 (0.52)	-0.20 (-1.21, 0.82)
Yorkshire and Humberside	-0.07 (0.70)	-0.07 (-1.37, 1.23)	-0.05 (0.61)	-0.05 (-1.24, 1.15)
North East	-0.30 (0.50)	-0.30 (-1.28, 0.69)	0.26 (0.50)	0.26 (-0.72, 1.23)
North West	-0.09 (0.51)	-0.09 (-1.11, 0.93)	0.69 (0.60)	0.69 (-0.48, 1.87)
Scotland	-0.02 (0.45)	-0.02 (-0.88, 0.85)	0.31 (0.45)	0.31 (-0.58, 1.20)
Northern Ireland	1.32** (0.57)	1.32** (0.30, 2.34)	0.89* (0.50)	0.89* (-0.10, 1.88)
Wales	1.24** (0.50)	1.24** (0.22, 2.26)		
Education: GCSE	0.63 (0.46)	0.63 (-0.34, 1.60)		
Education: Higher ed	2.27*** (0.44)	2.27*** (1.35, 3.18)		
Education: no formal qualification	0.07 (0.42)	0.07 (-0.72, 0.87)		
Ethnicity: non-white	0.35 (0.51)	0.35 (-0.59, 1.29)		
Income: £10,000-£19,999	0.93* (0.49)	0.93* (-0.003, 1.86)		
Income: £20,000-£29,999	0.83 (0.53)	0.83 (-0.16, 1.81)		
Income: £30,000-£39,999	0.46 (0.54)	0.46 (-0.58, 1.51)		
Income: £40,000-£49,999	0.08 (0.58)	0.08 (-1.05, 1.21)		
Income: £50,000-£59,999	0.42 (0.62)	0.42 (-0.82, 1.66)		
Income: £60,000-£69,999	-0.93 (0.62)	-0.93 (-2.21, 0.34)		
Income: £70,000-£79,999	-0.48 (0.69)	-0.48 (-1.83, 0.86)		
Income: above £80,000	0.59 (0.93)	0.59 (-1.17, 2.35)		
Income: Don't Know	0.04 (0.85)	0.04 (-1.70, 1.77)		
Income: None of these	-1.15** (0.53)	-1.15** (-2.15, -0.15)		
Income: Prefer not to say			0.32 (0.34)	0.32 (-0.34, 0.99)
Has Children Under 11			0.35 (0.47)	0.35 (-0.58, 1.28)
Has asthma themselves			-0.12 (0.45)	-0.12 (-1.00, 0.76)
Has child with asthma			0.30 (0.46)	0.30 (-0.60, 1.19)
Cares for someone with asthma			-0.19 (0.52)	-0.19 (-1.21, 0.83)
Has other respiratory condition themselves			-0.40 (0.43)	-0.40 (-1.25, 0.44)
Cares for someone with other respiratory condition			-1.74* (1.02)	-1.74* (-3.75, 0.27)
Has other heart condition themselves			0.38 (0.52)	0.38 (-0.65, 1.40)
Has child with other heart condition			-0.15 (0.29)	-0.15 (-0.72, 0.41)
Cares for someone with other heart condition			-2.22* (1.15)	-2.22* (-4.46, 0.03)
Has high blood pressure themselves			-0.75* (0.41)	-0.75* (-1.56, 0.05)
Has child with high blood pressure			1.95*** (0.27)	1.95*** (1.42, 2.48)
Cares for someone with high blood pressure			2.01*** (0.71)	2.01*** (0.62, 3.40)
Has other health condition themselves			2.24*** (0.38)	2.24*** (1.50, 2.98)
Has child with other health condition			0.39 (0.43)	0.39 (-0.45, 1.24)
Cares for someone with other health condition			0.61** (0.29)	0.61** (0.04, 1.18)
A - Higher managerial position			-0.72* (0.37)	-0.72* (-1.45, 0.002)
B - Intermediate managerial position			-1.24*** (0.44)	-1.24*** (-2.11, -0.37)
C2 -Skilled manual worker			1.10 (1.59)	1.10 (-2.02, 4.22)
D - Semi-skilled manual worker			-1.49*** (0.50)	-1.49*** (-2.47, -0.50)
Student			-0.52 (0.54)	-0.52 (-1.58, 0.53)
E - Retired/state pension only			0.07 (0.22)	0.07 (-0.37, 0.51)
Observations	4,002	4,002	4,011	4,011
R ²	0.13	0.13	0.13	0.13
Adjusted R ²	0.12	0.12	0.12	0.12
Residual Std. Error	6.66 (df = 3963)	6.66 (df = 3963)	6.96 (df = 3965)	6.96 (df = 3965)
F Statistic	15.94*** (df = 38; 3963)	15.94*** (df = 38; 3963)	12.93*** (df = 45; 3965)	12.93*** (df = 45; 3965)

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from OLS regression models examining awareness and concern (outcome variables) as predicted by demographic characteristics. Robust standard errors and standardized coefficients are shown.

Reference categories: Concern (none), Response efficacy/outcome expectancy (none), Gender (male),

Age (18 - 25), Has children under 11 (none), Region (East Midlands), Education (no formal qualification), Income (below 10,000),

Has children under 11 (none), has or cares for someone with health condition (none), Social grade (C1 - semi-skilled manual worker).

3.3.3 OLS regression output including all sociodemographic variables (H2)

Table 1: Psychosocial, sociodemographic and health predictors of ERB adoption (H2) - all variables

	Sample A	Sample B
Intercept	0.11 (0.13)	0.04 (−0.17, 0.26)
Awareness score	0.05* (0.002)	0.05*** (0.05, 0.05)
Concern for longterm health	0.06* (0.02)	0.05** (0.01, 0.08)
Response efficacy/Outcome expectancy	0.17 (0.02)	0.24*** (0.20, 0.28)
Should reducing air pollution be a priority?	0.11 (0.02)	0.13*** (0.09, 0.16)
Gender: Female	0.15 (0.03)	0.08*** (0.03, 0.14)
Aged 26 - 35	0.10* (0.07)	0.25*** (0.09, 0.40)
Aged 36 - 45	0.16 (0.07)	0.25*** (0.09, 0.40)
Aged 46 - 55	0.32 (0.07)	0.43*** (0.28, 0.58)
Aged 56 - 65	0.47 (0.07)	0.56*** (0.41, 0.71)
Aged 66 - 75	0.67 (0.07)	0.72*** (0.57, 0.88)
Aged 76 - 80	0.72 (0.09)	0.69*** (0.49, 0.89)
Over 80	0.60 (0.13)	0.68*** (0.42, 0.94)
Has Children Under 11	0.07* (0.04)	−0.02 (−0.10, 0.07)
London	0.03** (0.07)	−0.05 (−0.17, 0.07)
South East	−0.16*** (0.12)	−0.19** (−0.38, −0.0004)
South West	0.07* (0.08)	−0.01 (−0.16, 0.14)
West Midlands	−0.05*** (0.06)	0.01 (−0.11, 0.12)
East of England	−0.15*** (0.06)	0.09 (−0.04, 0.21)
Yorkshire and Humberside	−0.04*** (0.06)	−0.01 (−0.14, 0.11)
North East	−0.08*** (0.09)	−0.13* (−0.28, 0.01)
North West	0.04** (0.06)	−0.04 (−0.15, 0.08)
Scotland	0.27 (0.07)	−0.01 (−0.15, 0.13)
Northern Ireland	0.05** (0.05)	0.01 (−0.09, 0.12)
Wales	0.02** (0.07)	0.01 (−0.11, 0.13)
Education: GCSE	0.17 (0.07)	
Education: Higher ed	0.10* (0.06)	
Education: no formal qualification	0.14 (0.06)	
Ethnicity: non-white	−0.05*** (0.05)	
Income: £10,000-£19,999	0.04** (0.07)	
Income: £20,000-£29,999	0.11 (0.07)	
Income: £30,000-£39,999	0.18 (0.07)	
Income: £40,000-£49,999	0.13 (0.08)	
Income: £50,000-£59,999	0.23 (0.08)	
Income: £60,000-£69,999	0.18 (0.08)	
Income: £70,000-£79,999	0.36 (0.09)	
Income: above £80,000	−0.11*** (0.10)	
Income: Don't Know	−0.04*** (0.11)	
Income: None of these	0.06* (0.10)	
Income: Prefer not to say	−0.03*** (0.07)	
Has asthma themselves		0.07 (−0.01, 0.15)
Has child with asthma		0.12** (0.01, 0.24)
Cares for someone with asthma		−0.01 (−0.12, 0.10)
Has other respiratory condition themselves		−0.03 (−0.14, 0.08)
Cares for someone with other respiratory condition		0.002 (−0.12, 0.12)
Has other heart condition themselves		−0.05 (−0.16, 0.05)
Has child with other heart condition		−0.005 (−0.25, 0.24)
Cares for someone with other heart condition		−0.08 (−0.20, 0.05)
Has high blood pressure themselves		0.01 (−0.06, 0.08)
Has child with high blood pressure		0.25* (−0.02, 0.52)
Cares for someone with high blood pressure		0.10** (0.004, 0.20)
Has other health condition themselves		0.09*** (0.02, 0.15)
Has child with other health condition		0.08 (−0.09, 0.24)
Cares for someone with other health condition		0.11** (0.02, 0.20)
A - Higher managerial position	0.20 (0.05)	0.20*** (0.09, 0.30)
B - Intermediate managerial position	0.16 (0.04)	0.14*** (0.07, 0.21)
C2 -Skilled manual worker	0.04** (0.05)	0.03 (−0.05, 0.12)
D - Semi-skilled manual worker	−0.03*** (0.06)	−0.27*** (−0.38, −0.17)
Student	−0.04*** (0.14)	0.24 (−0.14, 0.61)
E - Retired/state pension only	−0.12*** (0.07)	−0.18*** (−0.30, −0.06)
Unemployed/long-term illness	−0.24*** (0.09)	−0.36*** (−0.49, −0.23)
COVID: post-COVID		0.12*** (0.06, 0.17)
Observations	4,002	4,011
R ²	0.31	0.32
Adjusted R ²	0.30	0.31
Residual Std. Error	0.85 (df = 3955)	0.84 (df = 3964)
F Statistic	37.99*** (df = 46; 3955)	41.07*** (df = 46; 3964)

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from OLS regression models examining awareness and concern (outcome variables) as predicted by demographic characteristics. Robust standard errors and standardized coefficients are shown.

Reference categories: Response efficacy/outcome expectancy (none), Gender (male),

Age (18 - 25), Has children under 11 (none), has or cares for someone with health condition (none).

Table 8: Estimated associations between awareness and specific ERBs adopted (H2a)

	Sample A	CI	Sample B	CI
Intercept	2.71 (2.66)	(-2.51, 7.92)	3.20*** (0.21)	(2.78, 3.61)
Improve indoor AQ: open windows/ventilation	1.52 (1.03)	(-0.50, 3.55)	1.06*** (0.23)	(0.61, 1.52)
Improve indoor AQ: use dryfuel	0.92 (1.11)	(-1.26, 3.11)	0.42 (0.49)	(-0.54, 1.39)
Improve indoor AQ: no solid fuel use	1.02 (0.81)	(-0.57, 2.60)	1.14*** (0.30)	(0.55, 1.73)
Improve indoor AQ: keep dust levels low	1.93 (1.70)	(-1.41, 5.26)	0.85*** (0.26)	(0.34, 1.35)
Improve indoor AQ: fragrance free product use	1.68 (1.79)	(-1.82, 5.18)	0.70* (0.36)	(-0.01, 1.42)
Improve indoor AQ: eco product use	0.59 (0.60)	(-0.59, 1.76)	1.12*** (0.35)	(0.43, 1.80)
Improve indoor AQ: regular boiler servicing	0.98 (0.62)	(-0.24, 2.20)	1.11*** (0.25)	(0.63, 1.59)
Improve indoor AQ: use extractor fan	0.92 (0.58)	(-0.21, 2.06)	1.39*** (0.25)	(0.91, 1.87)
Improve indoor AQ: low emission paint	0.77 (0.73)	(-0.66, 2.20)	0.74** (0.36)	(0.02, 1.45)
Improve indoor AQ: low emission furniture	1.36 (1.84)	(-2.25, 4.96)	0.30 (0.62)	(-0.91, 1.52)
Improve indoor AQ: no smoking indoors	0.94 (0.62)	(-0.27, 2.15)	0.94*** (0.25)	(0.45, 1.42)
Improve indoor AQ: other	1.29 (6.22)	(-10.91, 13.49)	4.76*** (1.39)	(2.04, 7.49)
In past 3 months: driven an electric vehicle	-1.31*** (0.12)	(-1.53, -1.08)	0.05 (0.55)	(-1.02, 1.13)
In past 3 months: chosen electric taxi	-1.31*** (0.12)	(-1.54, -1.08)	-2.15*** (0.65)	(-3.43, -0.87)
In past 3 months: chosen eco delivery	-0.22 (0.22)	(-0.66, 0.21)	0.45 (0.36)	(-0.26, 1.16)
In past 3 months: boiler service	-0.44*** (0.15)	(-0.73, -0.15)	-0.35 (0.23)	(-0.81, 0.11)
In past 3 months: switched to green energy tariff	-0.97*** (0.12)	(-1.21, -0.74)	0.09 (0.37)	(-0.63, 0.81)
In past 3 months: travelled outside rush hour	0.27 (0.34)	(-0.40, 0.93)	1.51*** (0.29)	(0.94, 2.08)
Improve outdoor AQ: chosen public transport	1.30 (0.99)	(-0.65, 3.24)	1.27*** (0.26)	(0.76, 1.78)
Improve outdoor AQ: chosen active travel	1.00 (0.63)	(-0.22, 2.23)	0.63*** (0.24)	(0.16, 1.11)
Improve outdoor AQ: teleworked	1.27 (0.99)	(-0.67, 3.20)	1.26*** (0.34)	(0.59, 1.94)
Improve outdoor AQ: regular vehicle maintenance	0.36 (0.36)	(-0.35, 1.07)	0.49* (0.26)	(-0.02, 1.00)
Improve outdoor AQ: no idling	0.58 (0.45)	(-0.30, 1.46)	0.75*** (0.26)	(0.24, 1.26)
Improve outdoor AQ: electric lawnmower use	0.12 (0.34)	(-0.56, 0.79)	0.61** (0.31)	(0.004, 1.23)
Improve outdoor AQ: use electric vehicle	0.62 (0.88)	(-1.10, 2.33)	1.15** (0.56)	(0.05, 2.26)
Improve outdoor AQ: drywood use	0.46 (0.72)	(-0.94, 1.87)	0.92* (0.53)	(-0.13, 1.96)
Improve outdoor AQ: less fires	0.14 (0.35)	(-0.54, 0.83)	-0.02 (0.32)	(-0.64, 0.61)
Improve outdoor AQ: renewable energy use	1.62 (1.52)	(-1.36, 4.60)	0.77** (0.33)	(0.13, 1.42)
Improve outdoor AQ: no solid fuel use	0.87 (0.74)	(-0.58, 2.31)	1.05*** (0.32)	(0.43, 1.67)
Improve outdoor AQ: other	3.52 (46.63)	(-87.87, 94.91)	2.71** (1.37)	(0.03, 5.39)
COVID: post-COVID		-0.31 (0.21)	(-0.72, 0.10)	

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from OLS regression models examining specific ERBs adopted (outcome variables with robust standard errors as predicted by awareness).

Table 9: Estimated associations between concern and specific ERBs adopted (H2b)

	Sample A Odds ratio	CI	Sample B Odds ratio	CI
Intercept: No impact—Slight impact	-1.96 (0.01)	(-1.97, -1.95)	-1.79 (0.01)	(-1.80, -1.77)
Intercept: Slight impact—Moderate impact	0.11 (0.06)	(0.04, 0.17)	0.41 (0.10)	(0.32, 0.51)
Intercept: Moderate impact—Major impact	2.40 (0.78)	(1.61, 3.18)	2.77 (1.27)	(1.50, 4.04)
Improve indoor AQ: open windows/ventilation	0.88*** (0.07)	(0.75, 1.02)	1.04*** (0.07)	(0.91, 1.16)
Improve indoor AQ: use dryfuel	1.02*** (0.14)	(0.75, 1.29)	0.72*** (0.14)	(0.44, 1.00)
Improve indoor AQ: no solid fuel use	0.91*** (0.09)	0.91*** (0.74, 1.09)	1.04*** (0.09)	(0.87, 1.21)
Improve indoor AQ: keep dust levels low	1.37*** (0.07)	(1.22, 1.51)	1.38*** (0.07)	(1.24, 1.52)
Improve indoor AQ: fragrance free product use	1.59*** (0.10)	(1.38, 1.79)	1.33*** (0.11)	(1.12, 1.54)
Improve indoor AQ: eco product use	1.43*** (0.10)	(1.23, 1.63)	1.41*** (0.10)	(1.21, 1.61)
Improve indoor AQ: regular boiler servicing	0.96*** (0.07)	(0.82, 1.10)	1.03*** (0.07)	(0.89, 1.17)
Improve indoor AQ: use extractor fan	0.92*** (0.07)	(0.78, 1.06)	0.96*** (0.07)	(0.82, 1.10)
Improve indoor AQ: low emission paint	1.12*** (0.10)	(0.92, 1.32)	1.32*** (0.11)	(1.11, 1.52)
Improve indoor AQ: low emission furniture	1.75*** (0.14)	(1.47, 2.04)	1.70*** (0.18)	(1.34, 2.06)
Improve indoor AQ: no smoking indoors	0.94*** (0.07)	(0.79, 1.08)	0.80*** (0.07)	(0.66, 0.94)
Improve indoor AQ: other	0.45 (0.53)	(-0.58, 1.48)	0.33 (0.41)	(-0.46, 1.13)
In past 3 months: driven an electric vehicle	1.54*** (0.13)	(1.28, 1.80)	1.28*** (0.16)	(0.96, 1.59)
In past 3 months: chosen electric taxi	1.13*** (0.13)	(0.86, 1.39)	1.56*** (0.19)	(1.18, 1.93)
In past 3 months: chosen eco delivery	1.22*** (0.08)	(1.05, 1.38)	1.36*** (0.11)	(1.15, 1.56)
In past 3 months: boiler service	1.11*** (0.07)	(0.97, 1.24)	1.26*** (0.07)	(1.13, 1.39)
In past 3 months: switched to green energy tariff	1.10*** (0.10)	(0.91, 1.29)	1.37*** (0.11)	(1.16, 1.57)
In past 3 months: travelled outside rush hour	1.50*** (0.08)	(1.35, 1.65)	1.63*** (0.08)	(1.47, 1.80)
Improve outdoor AQ: chosen public transport	1.34*** (0.08)	(1.18, 1.50)	1.43*** (0.07)	(1.29, 1.58)
Improve outdoor AQ: chosen active travel	1.20*** (0.07)	(1.06, 1.33)	1.15*** (0.07)	(1.01, 1.28)
Improve outdoor AQ: teleworked	1.23*** (0.08)	(1.07, 1.39)	0.86*** (0.10)	(0.67, 1.06)
Improve outdoor AQ: regular vehicle maintenance	0.82*** (0.08)	(0.67, 0.97)	0.86*** (0.07)	(0.71, 1.01)
Improve outdoor AQ: no idling	0.95*** (0.08)	(0.80, 1.10)	1.03*** (0.07)	(0.89, 1.18)
Improve outdoor AQ: electric lawnmower use	1.02*** (0.09)	(0.84, 1.20)	1.04*** (0.09)	(0.87, 1.22)
Improve outdoor AQ: use electric vehicle	1.01*** (0.14)	(0.73, 1.29)	1.13*** (0.16)	(0.81, 1.45)
Improve outdoor AQ: drywood use	0.93*** (0.14)	(0.66, 1.21)	1.32*** (0.15)	(1.02, 1.62)
Improve outdoor AQ: less fires	1.09*** (0.09)	(0.92, 1.27)	1.22*** (0.09)	(1.04, 1.40)
Improve outdoor AQ: renewable energy use	1.11*** (0.09)	(0.93, 1.29)	1.36*** (0.09)	(1.18, 1.55)
Improve outdoor AQ: no solid fuel use	1.03*** (0.09)	(0.84, 1.21)	0.93*** (0.09)	(0.75, 1.10)
Improve outdoor AQ: other	0.83* (0.44)	(-0.03, 1.69)	1.92*** (0.43)	(1.09, 2.76)
COVID: post-COVID			1.15*** (0.06)	(1.03, 1.27)

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates and odds ratios with 95% confidence intervals from logistic regression models examining specific ERBs adopted (outcome variables as predicted by concern.

Table 10: Estimated associations between response efficacy/outcome expectancy and specific ERBs adopted (H2c)

	Sample A Odds ratio	CI	Sample B Odds ratio	CI
Intercept: No impact—Slight impact	-1.80 (0.01)	(-1.81, -1.79)	-1.28 (0.02)	(-1.30, -1.26)
Intercept: Slight impact—Moderate impact	1.39 (0.26)	(1.13, 1.64)	1.94 (0.53)	(1.42, 2.47)
Intercept: Moderate impact—Major impact	3.41 (2.73)	(0.68, 6.14)	3.78 (4.30)	(-0.52, 8.07)
Improve indoor AQ: open windows/ventilation	1.02*** (0.07)	(0.88, 1.16)	1.16*** (0.07)	(1.02, 1.30)
Improve indoor AQ: use dryfuel	1.14*** (0.14)	(0.86, 1.41)	0.90*** (0.15)	(0.60, 1.19)
Improve indoor AQ: no solid fuel use	1.04*** (0.09)	(0.86, 1.22)	1.18*** (0.09)	(1.00, 1.36)
Improve indoor AQ: keep dust levels low	1.27*** (0.08)	(1.11, 1.43)	1.44*** (0.08)	(1.28, 1.59)
Improve indoor AQ: fragrance free product use	1.34*** (0.10)	(1.14, 1.55)	1.38*** (0.11)	(1.16, 1.59)
Improve indoor AQ: eco product use	1.26*** (0.10)	(1.06, 1.47)	1.30*** (0.10)	(1.09, 1.51)
Improve indoor AQ: regular boiler servicing	0.85*** (0.08)	(0.70, 0.99)	1.06*** (0.08)	(0.91, 1.21)
Improve indoor AQ: use extractor fan	1.02*** (0.07)	(0.88, 1.16)	0.94*** (0.07)	(0.79, 1.08)
Improve indoor AQ: low emission paint	1.10*** (0.11)	(0.89, 1.31)	1.29*** (0.11)	(1.08, 1.50)
Improve indoor AQ: low emission furniture	1.11*** (0.15)	(0.81, 1.40)	1.95*** (0.18)	(1.60, 2.29)
Improve indoor AQ: no smoking indoors	0.99*** (0.08)	(0.83, 1.14)	0.92*** (0.08)	(0.77, 1.07)
Improve indoor AQ: other	0.67 (0.54)	(-0.38, 1.72)	0.47 (0.41)	(-0.33, 1.27)
In past 3 months: driven an electric vehicle	1.55*** (0.14)	(1.29, 1.82)	1.26*** (0.17)	(0.93, 1.59)
In past 3 months: chosen electric taxi	1.39*** (0.14)	(1.12, 1.66)	2.00*** (0.20)	(1.60, 2.40)
In past 3 months: chosen eco delivery	1.45*** (0.09)	(1.28, 1.63)	1.38*** (0.11)	(1.16, 1.59)
In past 3 months: boiler service	1.01*** (0.07)	(0.86, 1.15)	1.22*** (0.07)	(1.08, 1.36)
In past 3 months: switched to green energy tariff	1.23*** (0.10)	(1.03, 1.42)	1.16*** (0.11)	(0.95, 1.38)
In past 3 months: travelled outside rush hour	1.48*** (0.08)	(1.32, 1.64)	1.15*** (0.09)	(0.98, 1.32)
Improve outdoor AQ: chosen public transport	0.98*** (0.09)	(0.81, 1.15)	1.19*** (0.08)	(1.04, 1.35)
Improve outdoor AQ: chosen active travel	1.22*** (0.07)	(1.08, 1.37)	1.23*** (0.07)	(1.09, 1.38)
Improve outdoor AQ: teleworked	1.41*** (0.09)	(1.24, 1.58)	1.13*** (0.10)	(0.93, 1.33)
Improve outdoor AQ: regular vehicle maintenance	1.03*** (0.08)	(0.87, 1.18)	1.11*** (0.08)	(0.95, 1.26)
Improve outdoor AQ: no idling	0.92*** (0.08)	(0.76, 1.08)	1.10*** (0.08)	(0.94, 1.25)
Improve outdoor AQ: electric lawnmower use	1.08*** (0.10)	(0.89, 1.27)	1.07*** (0.09)	(0.89, 1.26)
Improve outdoor AQ: use electric vehicle	1.02*** (0.15)	(0.73, 1.32)	1.18*** (0.17)	(0.84, 1.51)
Improve outdoor AQ: drywood use	1.03*** (0.14)	(0.74, 1.31)	1.28*** (0.16)	(0.97, 1.60)
Improve outdoor AQ: less fires	1.07*** (0.10)	(0.88, 1.26)	1.06*** (0.10)	(0.87, 1.25)
Improve outdoor AQ: renewable energy use	1.28*** (0.09)	(1.10, 1.47)	1.41*** (0.10)	(1.22, 1.61)
Improve outdoor AQ: no solid fuel use	1.11*** (0.10)	(0.91, 1.30)	0.97*** (0.10)	(0.79, 1.16)
Improve outdoor AQ: other	0.80* (0.44)	(-0.06, 1.67)	1.03** (0.42)	(0.22, 1.85)
COVID: post-COVID			1.17*** (0.06)	(1.04, 1.29)

Note: *p<0.1; **p<0.05; ***p<0.01

Estimates with 95% confidence intervals from logistic regression models examining specific ERBs adopted (outcome variables with robust standard errors as predicted by response efficacy/outcome expectancy).

Table 11: Estimated associations between attitudes and specific ERBs adopted (H2d)

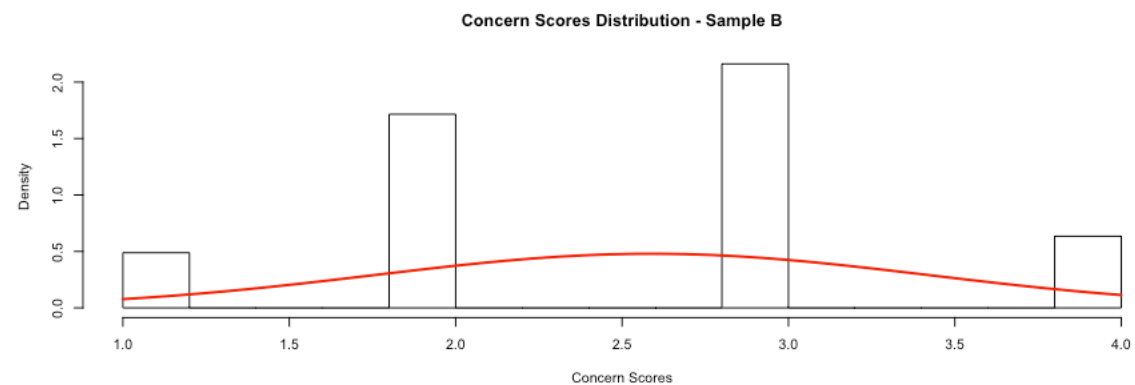
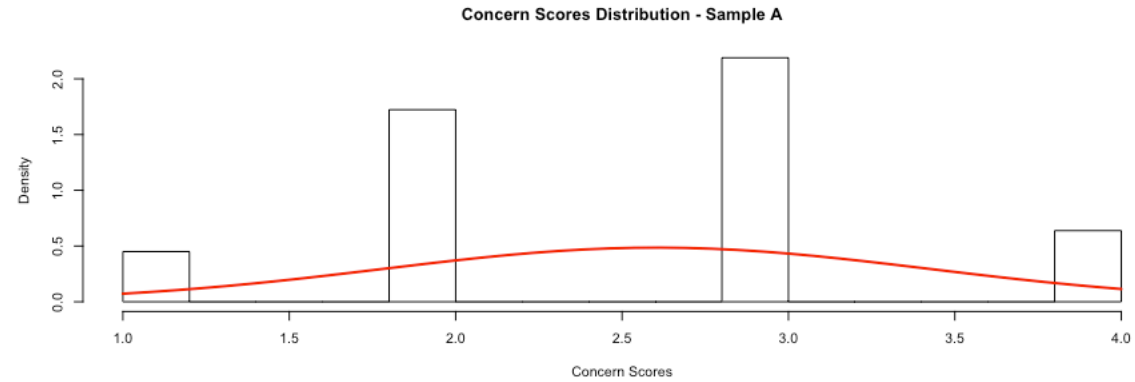
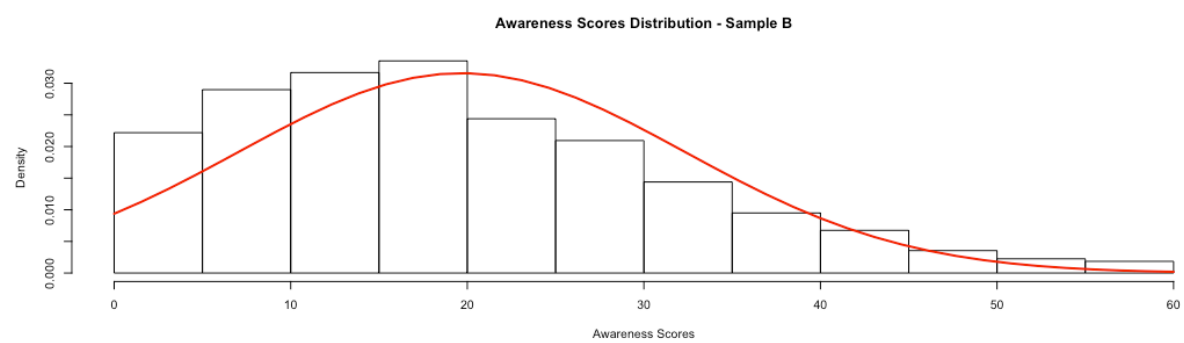
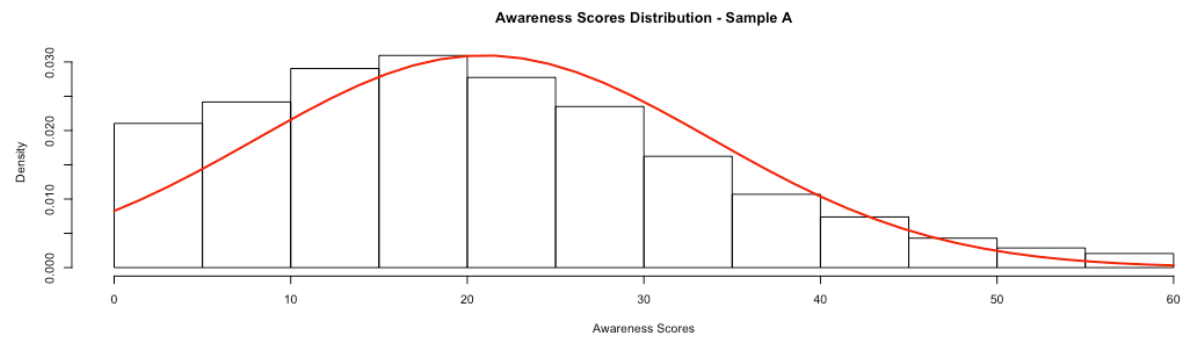
	Sample A Odds ratio	CI	Sample B Odds ratio	CI
Intercept: No impact—Slight impact	-1.80 (0.01)	(-1.81, -1.79)	-1.28 (0.02)	(-1.30, -1.26)
Intercept: Slight impact—Moderate impact	1.39 (0.26)	(1.13, 1.64)	1.94 (0.53)	(1.42, 2.47)
Intercept: Moderate impact—Major impact	3.41 (2.73)	(0.68, 6.14)	3.78 (4.30)	(-0.52, 8.07)
Improve indoor AQ: open windows/ventilation	1.37*** (0.07)	1.37*** (1.23, 1.50)	1.14*** (0.07)	1.14*** (1.01, 1.27)
Improve indoor AQ: use dryfuel	0.98*** (0.14)	0.98*** (0.71, 1.26)	1.23*** (0.16)	1.23*** (0.92, 1.53)
Improve indoor AQ: no solid fuel use	1.16*** (0.10)	1.16*** (0.98, 1.35)	1.17*** (0.09)	1.17*** (0.98, 1.35)
Improve indoor AQ: keep dust levels low	1.29*** (0.08)	1.29*** (1.14, 1.45)	1.13*** (0.08)	1.13*** (0.98, 1.29)
Improve indoor AQ: fragrance free product use	1.22*** (0.11)	1.22*** (1.00, 1.44)	1.38*** (0.12)	1.38*** (1.15, 1.61)
Improve indoor AQ: eco product use	1.37*** (0.11)	1.37*** (1.15, 1.59)	1.42*** (0.11)	1.42*** (1.20, 1.64)
Improve indoor AQ: regular boiler servicing	1.12*** (0.07)	1.12*** (0.98, 1.26)	1.28*** (0.07)	1.28*** (1.14, 1.43)
Improve indoor AQ: use extractor fan	1.05*** (0.07)	1.05*** (0.91, 1.20)	1.13*** (0.07)	1.13*** (0.99, 1.28)
Improve indoor AQ: low emission paint	1.10*** (0.11)	1.10*** (0.88, 1.32)	1.15*** (0.12)	1.15*** (0.92, 1.38)
Improve indoor AQ: low emission furniture	1.19*** (0.16)	1.19*** (0.88, 1.51)	0.91*** (0.21)	0.91*** (0.51, 1.32)
Improve indoor AQ: no smoking indoors	1.28*** (0.08)	1.28*** (1.12, 1.43)	0.97*** (0.08)	0.97*** (0.82, 1.12)
Improve indoor AQ: other	0.92* (0.51)	0.92* (-0.09, 1.92)	0.90** (0.43)	0.90** (0.05, 1.74)
In past 3 months: driven an electric vehicle	0.66*** (0.13)	0.66*** (0.40, 0.92)	0.59*** (0.16)	0.59*** (0.27, 0.91)
In past 3 months: chosen electric taxi	0.33** (0.13)	0.33** (0.08, 0.58)	0.43** (0.19)	0.43** (0.07, 0.79)
In past 3 months: chosen eco delivery	0.86*** (0.09)	0.86*** (0.69, 1.03)	0.81*** (0.11)	0.81*** (0.59, 1.03)
In past 3 months: boiler service	1.04*** (0.07)	1.04*** (0.90, 1.18)	0.92*** (0.07)	0.92*** (0.78, 1.06)
In past 3 months: switched to green energy tariff	0.79*** (0.10)	0.79*** (0.59, 0.99)	0.99*** (0.11)	0.99*** (0.77, 1.21)
In past 3 months: travelled outside rush hour	0.80*** (0.08)	0.80*** (0.63, 0.96)	1.01*** (0.09)	1.01*** (0.84, 1.19)
Improve outdoor AQ: chosen public transport	1.35*** (0.09)	1.35*** (1.18, 1.53)	1.78*** (0.08)	1.78*** (1.62, 1.94)
Improve outdoor AQ: chosen active travel	1.69*** (0.07)	1.69*** (1.54, 1.83)	1.31*** (0.07)	1.31*** (1.17, 1.45)
Improve outdoor AQ: teleworked	1.04*** (0.09)	1.04*** (0.87, 1.22)	1.17*** (0.11)	1.17*** (0.96, 1.39)
Improve outdoor AQ: regular vehicle maintenance	0.97*** (0.08)	0.97*** (0.81, 1.13)	0.89*** (0.08)	0.89*** (0.73, 1.04)
Improve outdoor AQ: no idling	1.17*** (0.08)	1.17*** (1.02, 1.33)	1.29*** (0.08)	1.29*** (1.14, 1.45)
Improve outdoor AQ: electric lawnmower use	1.13*** (0.10)	1.13*** (0.93, 1.33)	1.06*** (0.10)	1.06*** (0.87, 1.25)
Improve outdoor AQ: use electric vehicle	1.08*** (0.15)	1.08*** (0.78, 1.38)	1.10*** (0.18)	1.10*** (0.75, 1.45)
Improve outdoor AQ: drywood use	0.89*** (0.14)	0.89*** (0.61, 1.17)	1.12*** (0.17)	1.12*** (0.79, 1.45)
Improve outdoor AQ: less fires	1.03*** (0.10)	1.03*** (0.84, 1.23)	1.17*** (0.10)	1.17*** (0.97, 1.37)
Improve outdoor AQ: renewable energy use	1.66*** (0.10)	1.66*** (1.47, 1.86)	1.53*** (0.11)	1.53*** (1.32, 1.74)
Improve outdoor AQ: no solid fuel use	1.13*** (0.10)	1.13*** (0.93, 1.33)	1.11*** (0.10)	1.11*** (0.92, 1.30)
Improve outdoor AQ: other	1.15** (0.48)	1.15** (0.21, 2.10)	1.29*** (0.43)	1.29*** (0.46, 2.13)
COVID: post-COVID			1.00*** (0.06)	1.00*** (0.88, 1.12)

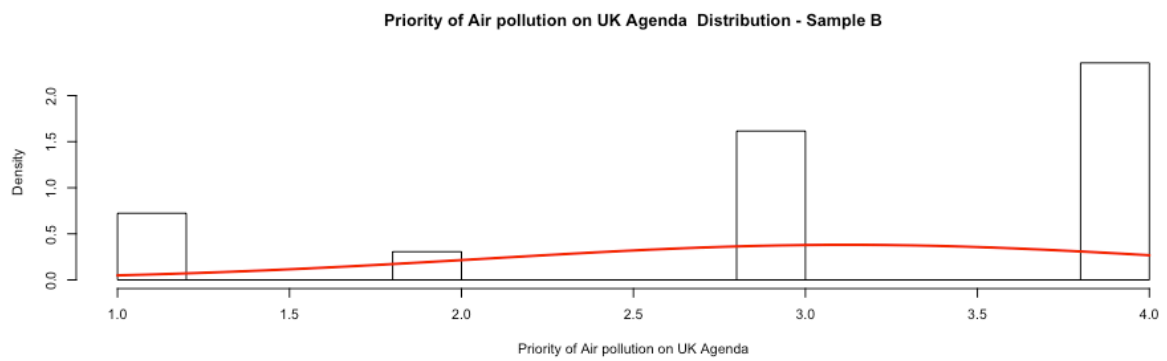
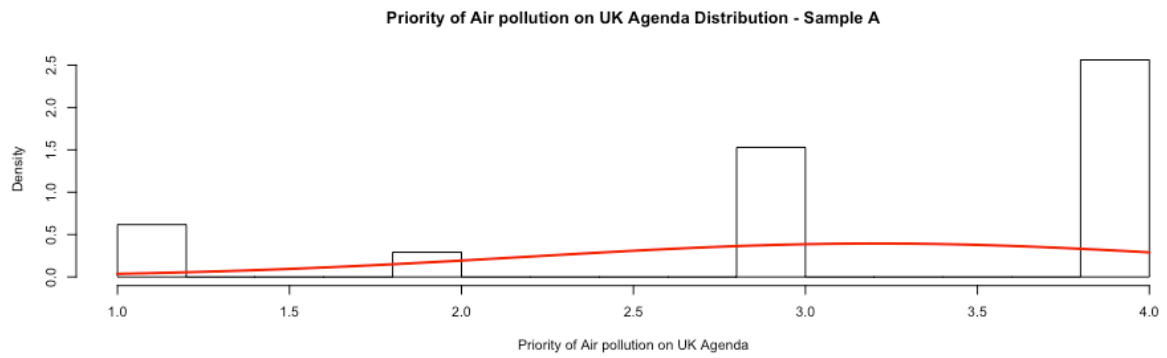
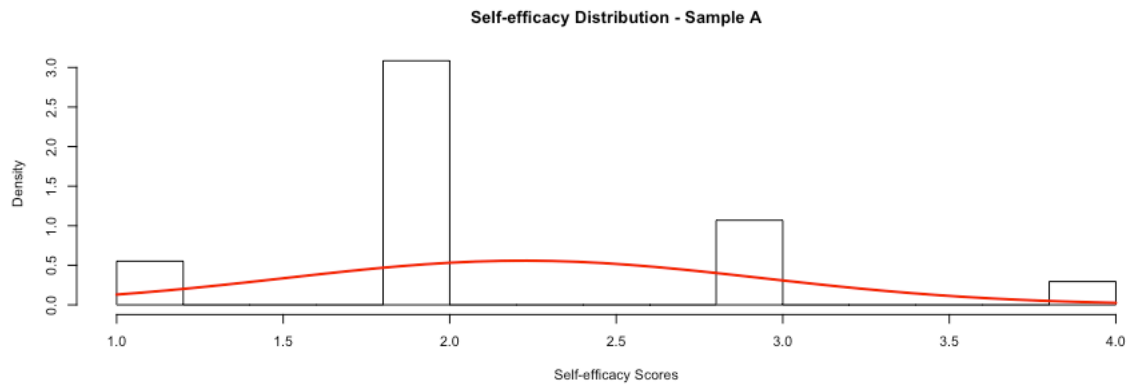
Note: *p<0.1; **p<0.05; ***p<0.01

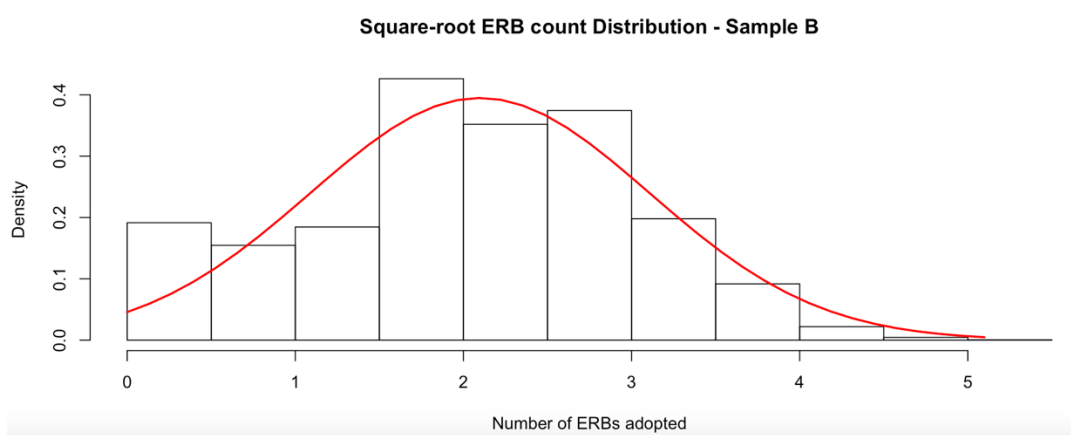
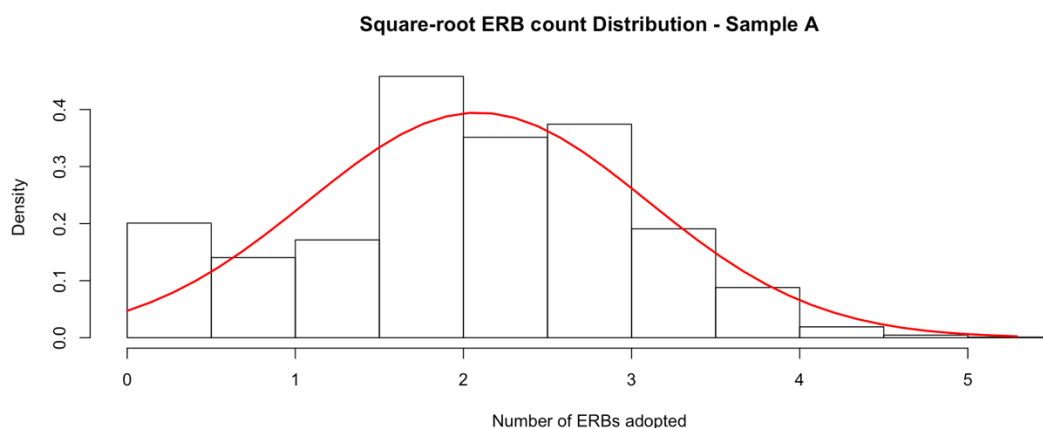
Estimates and odds ratios with 95% confidence intervals from logistic regression models examining specific ERBs adopted (outcome variables as predicted by attitudes).

Appendix 3.3 – Descriptive statistics for predictor and outcome variables

2.3.a Distribution of awareness scores across Samples A & B







Appendix 3.5 Social grade factor classification scheme⁹

- A - "Higher managerial/ professional/ administrative (e.g. established doctor, solicitor, board director in large organisation (200+ employees), top level civil servant/ public service employee, head teacher etc.)"
- B - "Intermediate managerial/ professional/ administrative (e.g. newly qualified (under 3 years) doctor, solicitor, board director of small organisation, middle manager in large organization, principal officer in civil service/ local government etc.)"
- C1 "Supervisory or clerical/ junior managerial/ professional/ administrator (e.g. office worker, student doctor, foreman with 25+ employees, sales person, student teacher etc.)"
- C2 - "Skilled manual worker (e.g. skilled bricklayer, carpenter, plumber, painter, bus/ ambulance driver, HGV driver, unqualified teaching assistant, pub/ bar worker etc.)"
- D - "Semi-skilled or unskilled manual worker (e.g. manual jobs that require no special training or qualifications, apprentices to be skilled trades, caretaker, cleaner, nursery school assistant, park keeper, non-HGV driver, shop assistant etc.)"
- "Student"
- E - "Retired and living on state pension only"
- "Unemployed for over 6 months or not working due to long term sickness"

⁹Informed by NC-SEC:

ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatistics socioeconomic classificationnssecbasedonsoc2010

Appendix 4 - Chapter V: Exploring inequalities in air quality information access and uptake of exposure reducing behaviors across the UK

Appendix 4.1 – Sensitivity Analyzes

4.2.1 VIF multicollinearity tests

4.2.1.1 H1a - Model 3

	GVIF	Df	GVIF^{1/(2*Df)}
<i>gender</i>	1.05764423278312	1	1.02841831604806
<i>age_group</i>	1.8046652373058	7	1.04307142158916
<i>children_under18</i>	1.36396185175746	1	1.16788777361417
<i>social_grade</i>	1.81309066620192	7	1.04341851134515
<i>education_simplified</i>	1.4408979630603	3	1.06276898356928
<i>white_nonwhite</i>	1.06432430649242	1	1.03166094551089

4.2.1.2 H1b – All health conditions (oneself)

	GVIF	Df	GVIF^{1/(2*Df)}
<i>age_group</i>	1.24691853640929	7	1.01588740794601
<i>asthma_me</i>	1.12382502026963	1	1.06010613632298
<i>other_resp_me</i>	1.18148124156589	1	1.08695963198542
<i>HBP_me</i>	1.29897968115994	1	1.13972789785981
<i>other_heart_me</i>	1.14196223544899	1	1.06862633106666
<i>other_condition_me</i>	1.16455204572764	1	1.07914412648526

4.2.1.3 H1c – All health conditions (carer)

	GVIF	Df	GVIF^{1/(2*Df)}
<i>age_group</i>	1.06460532231066	7	1.00448173744311
<i>asthma_child</i>	1.19304969619166	1	1.09226814299038
<i>asthma_carer</i>	1.22052836121708	1	1.10477525371321
<i>other_resp_child</i>	1.14650129557053	1	1.07074800750248
<i>other_resp_carer</i>	1.27823906406442	1	1.13059235096671
<i>other_heart_child</i>	1.0971801720537	1	1.04746368531501
<i>other_heart_carer</i>	1.29098943459578	1	1.13621715996361
<i>HBP_child</i>	1.0833821775224	1	1.04085646345805
<i>HBP_carer</i>	1.34087524296961	1	1.15796167595029
<i>other_condition_child</i>	1.12601878404028	1	1.0611403225023
<i>other_condition_carer</i>	1.33227004733917	1	1.15424003020999

4.2.1.4 H2b – All AQ channels & ages

	GVIF	Df	GVIF^{1/(2*Df)}
<i>age_group</i>	1.15744605912256	7	1.01049872205328
<i>aq_info_via_internet_num</i>	1.07160242647401	1	1.03518231557248
<i>aq_info_via_tv_radio_num</i>	1.1175875060572	1	1.05716011372791
<i>aq_info_socialmedia_num</i>	1.13597991032493	1	1.06582358311539
<i>aq_info_via_GP_num</i>	1.15451340403255	1	1.07448285422921
<i>aq_info_via_nat_paper_num</i>	1.14143979267747	1	1.06838185714541
<i>aq_info_via_local_paper_num</i>	1.12984882359067	1	1.06294347149351
<i>aq_info_via_pharmacy_num</i>	1.13276801233386	1	1.06431574841954
<i>aq_info_via_hospital_clinic_num</i>	1.09902217616701	1	1.04834258530645
<i>aq_info_via_app_num</i>	1.0514966257263	1	1.02542509513192
<i>aq_info_via_school_num</i>	1.11093808254942	1	1.05401047554064

4.2.2 Additional Regression analyses

4.2.1.5 RQ1 – Which sociodemographic groups have greatest access to AQ channels

Table 13: Odds of AQ Channel access for different demographic groups

	Dependent variable: accessed AQ info?		
	Model 1 (1)	Model 2 (2)	Model 3 (3)
Intercept	1.20*** (0.73, 1.68)	1.64*** (0.93, 2.35)	1.56*** (0.75, 2.36)
Gender: Male	1.99*** (1.59, 2.39)	1.90*** (1.49, 2.31)	1.87*** (1.46, 2.29)
Aged 26 - 35	0.45*** (0.31, 0.59)	0.35*** (0.20, 0.50)	0.36*** (0.21, 0.51)
Aged 36 - 45	0.31*** (0.21, 0.41)	0.25*** (0.15, 0.35)	0.26*** (0.16, 0.36)
Aged 46 - 55	0.18*** (0.11, 0.24)	0.17*** (0.10, 0.24)	0.18*** (0.11, 0.25)
Aged 56 - 65	0.11*** (0.05, 0.16)	0.12*** (0.07, 0.18)	0.14*** (0.08, 0.19)
Aged 66 - 75	0.11*** (0.06, 0.17)	0.12*** (0.06, 0.18)	0.14*** (0.08, 0.20)
Aged 76 - 80	0.06* (-0.001, 0.11)	0.06** (0.001, 0.12)	0.07** (0.01, 0.13)
Over 80	0.14** (0.001, 0.27)	0.15** (0.01, 0.29)	0.17** (0.03, 0.31)
Has Children Under 18		2.01*** (1.49, 2.53)	2.00*** (1.48, 2.53)
A - Higher managerial position		0.78*** (0.48, 1.07)	0.78*** (0.49, 1.08)
B - Intermediate managerial position		0.69*** (0.21, 1.16)	0.77*** (0.28, 1.27)
C2 -Skilled manual worker		0.52*** (0.26, 0.79)	0.58*** (0.30, 0.86)
D - Semi-skilled manual worker		0.50*** (0.26, 0.73)	0.53*** (0.29, 0.77)
Student		0.80** (0.13, 1.48)	0.70** (0.01, 1.38)
E - Retired/state pension only		0.50*** (0.31, 0.70)	0.51*** (0.31, 0.71)
Unemployed/long-term illness		0.50*** (0.19, 0.82)	0.57*** (0.24, 0.91)
Education: Higher ed			0.79*** (0.51, 1.07)
Education: A-level			0.93*** (0.65, 1.22)
Education: GCSE			0.68*** (0.24, 1.12)
Ethnicity: non-white			1.67*** (1.13, 2.22)
Observations	1,993	1,993	1,993
Log Likelihood	-1,054.37	-1,027.84	-1,021.80
Akaike Inf. Crit.	2,126.75	2,089.69	2,085.61

Note: *p<0.1; **p<0.05; ***p<0.01
N = 1993

Estimates with 95% confidence intervals from binary logistic regression models examining access to AQ channels (outcome variable) as predicted by demographic characteristics.

Reference categories: Gender (female), Age (18 - 25), Has children under 18 (none),
Social grade (C1 - semi-skilled manual worker).