Advancing Indoor Air Pollution Research: A Novel Integration of AI, IoT, and Behavioural Science for Enhanced Indoor Air Quality Monitoring and Behaviour Change

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ABSTRACT

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Keywords: Indoor Air Quality (IAQ), Low-Cost Sensors (LCS), Internet of Things (IoT), Calibration, Behavioural Change, COM-B Model, Artificial Intelligence (AI), Digital Interventions, Web Platform Engagement, Air Pollution Awareness

This thesis addresses global concerns over air quality, focusing on Indoor Air Quality (IAQ). It presents an interdisciplinary exploration into the integration of Artificial Intelligence (AI), the Internet of Things (IoT), and Low-Cost Sensors (LCS) for air quality monitoring. The research evaluates LCS, augmented by AI and IoT, as an alternative to expensive monitoring systems, tackling challenges like sensor selection and calibration. Various AI techniques, including Random Forest and Neural Networks, are employed for calibration. The study also delves into the impact of human behaviour on IAQ, utilising the COM-B model to design digital interventions. Case studies with IoT-based devices in volunteer households showed significant IAQ improvement and increased awareness due to these interventions. The thesis further examines a digital visualisation platform's effectiveness in raising IAQ awareness, applying the Technology Acceptance Model (TAM) to understand technology adoption factors. The research underscores the potential of digital interventions in promoting better IAQ practices. It emphasises leveraging LCS-based IoT technologies, digital platforms, and citizen engagement to address IAQ challenges. The findings provide insights into AQ monitoring and improvement's technical, behavioural, and digital dimensions. This comprehensive exploration showcases how behavioural models, combined with IoT and AI, can drive behavioural change, offering valuable guidance for researchers, policymakers, and public health officials on IAQ.

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AH - Absolute Humidity

AI - Artificial Intelligence

AI - Attitude Intention

ANN - Artificial Neural Networks

AQ - Air Quality

AURN - Automatic Urban and Rural Network

BCW - Behaviour Change Wheel

BI - Behavioural Intention

BMDC - Bradford Metropolitan District Council

CO - Carbon Monoxide

CO_2 - Carbon Dioxide

COM-B - Capability, Opportunity, Motivation-Behaviour

COVID-19 - Coronavirus Disease 2019

DT - Digital Transformation

DIY - Do-It-Yourself

DIT - Do-It-Together

EPA - Environmental Protection Agency

GA - Google Analytics

GDPR - General Data Protection Regulation

GT - Google Tag Manager

GSM - Global System for Mobile Communications

HEPA - High-Efficiency Particulate Air

IAQ - Indoor Air Quality

IoT - Internet of Things

KS-Statistics - Kolmogorov-Smirnov Statistics

LCS - Low-Cost Sensors

LBS - Location-Based Services

MLR - Multiple Linear Regression

MAE - Mean Absolute Error

NDIR - Non-Dispersive Infrared

NICE - National Institute for Health and Care Excellence

NO_2 - Nitrogen Dioxide

NO_x - Nitrogen Oxides

O_3 - Ozone

OAQ - Outdoor Air Quality

OPC - Optical Particle Counter

PEU - Perceived Ease of Use

PM - Particulate Matter

PU - Perceived Usefulness

RPi - Raspberry Pi

RF - Random Forest

RH - Relative Humidity

RQ - Research Questions

RMSE - Root Mean Square Error

R^2 - Coefficient of Determination

SARS-CoV-2 - Severe Acute Respiratory Syndrome Coronavirus 2

SD - Standard Deviation

SES - Socio-Economic Status

SO_2 - Sulfur Dioxide

SOx - Sulfur Oxides

SVR - Support Vector Regression

T - Temperature

TAM - Technology Acceptance Model

TTM - Transtheoretical Model

UCD - User-Centred Design

UX - User Experience

VOCs - Volatile Organic Compounds

WHO - World Health Organization

WiFi - Wireless Fidelity

WS - Wind Speed

CHAPTER 1: INTRODUCTION

1.1 Overview

The necessity for access to clean, breathable air in all environments, encompassing both indoor and ambient (outdoor) contexts, is increasingly being recognised as a fundamental human right [1]. Amid escalating concerns over air quality, healthcare institutions, community organisations, and local governing bodies have manifested a heightened interest in the implications of air pollutant exposure. It is imperative to emphasise this topic as compelling evidence indicates that air pollution dramatically contributes to the development and exacerbation of respiratory issues in humans [2]. Key air pollutants such as Carbon Dioxide (CO_2), Carbon Monoxide (CO), particulate matter ($PM_{2.5}$ and PM_{10}), Sulphur Oxides (SO_x), Nitrogen Dioxide (NO_2), and certain uncombusted hydrocarbons have been identified as elements that compromise air quality and, consequently, human health. Exposure to these pollutants has been linked to a range of respiratory and cardiovascular health problems, including, but not limited to, asthma. Furthermore, in more severe scenarios, long-term exposure can be a catalyst for carcinogenic conditions [3-5]. A common misconception that persists within the public consciousness is that outdoor air quality has a more significant impact on human health than indoor air quality. Experimental study data belie this perception; multiple studies have demonstrated that indoor air can be 3-5 times more polluted than outdoor air. Moreover, the importance of indoor air quality becomes even more salient when considering that individuals typically spend over 90% of their time in indoor environments [6, 7]. In light of the above points, IAQ has gained considerable traction over the past decade. This increased focus is not merely an academic endeavour. Still, it plays a vital function in driving policy decisions and public health initiatives to mitigate the adverse health effects of poor air quality.

Furthermore, IAQ directly affects human behaviour, performance and productivity, especially for those who primarily work indoors [8]. Also, indoor activities such as cooking, cleaning and how frequently windows are opened during cooking influence IAQ. Human behaviour plays a significant role in affecting IAQ; factors such as human attitudes and beliefs, socioeconomic status, and education level are crucial in shaping an individual's behaviours towards air quality awareness [9]. Several studies [10-14] have been conducted using sensor technologies to monitor IAQ and raise citizens' awareness. However, methodological approaches that utilise well-known behaviour models to influence behaviours with the help of sensor data visualisation are an open subject of exploration.

Low-cost sensor (LCS) technologies are changing the conventional way of monitoring and measuring instances in real-time with the help of micro-scale sensing techniques [15]. LCS are affordable and compact sensing devices designed to detect and measure specific environmental parameters, such as air or water quality, temperature, humidity, etc. LCS provide a more accessible means for widespread data collection, especially in community-driven or citizen science projects, enabling broader monitoring and data acquisition in various settings. The use of LCS has benefits in terms of cost-effectiveness, compactness, and portability, making these devices an efficient alternative to high-cost monitoring systems [16]. For example, building an LCS-based air quality monitoring device to deploy against high-cost air quality monitoring stations in a city is more feasible regarding high spatio-temporal and instantaneous data monitoring to the user at any specific location. Also, LCS has appeared as an economical substitute for high-cost sensor devices in many applications, including air quality monitoring (Indoor-Outdoor), flood monitoring, and observing health status. In recent years, with the enhancement in sensor technology, many alternative sensors have performed the same tasks while developing LCS-based applications. However, there has not been a universal single type of LCS implementation as the LCS have different working principles such as electrochemical, Optical particle counters (OPC), Non-Dispersive Infra-Red (NDIR), metal-oxide-semiconductor, or solid-state microsensors designed to monitor air pollutants [17-19]. This diversity in the working principles of sensors adds complexity to the process of LCS selection while building the monitoring systems using LCS-based devices. Apart from the working principle of LCS devices, meteorological parameters such as temperature and humidity make LCS data unreliable and less accurate when they have been used in an open environment [20, 21]. Furthermore, LCS monitor various components from the environment according to their function, which can cause sensitivity issues [22, 23]. For example, when the LCS is used to monitor air pollutants, the sensor responds more to other gas compounds than the actual gas detection [24]. Besides, LCS have characteristics that cannot give a stable performance over a certain period due to drift of sensitivity and ageing, which can cause increased data inaccuracy [23, 25]. Apart from the issues discussed earlier, LCS also often face challenges in detecting measured levels below a point where it cannot differentiate between sensor noise and actual sensed values in the environment [23, 26, 27]. This is because the sensor is designed in a range called dynamic boundary. When the sensor faces the actual data level near or below the dynamic boundary, it often fails to monitor the data accurately. In addition to these challenges, LCS data quality and consistency under the same environment are other factors that make the LCS selection task even more complex. To overcome these issues, it is a prerequisite to calibrate LCS before the on-field application is required [28].

The lower feasibility of high-cost air quality monitoring sensors to deploy at many strategic locations within a small area makes LCS-based devices a feasible solution for many applications. However, using LCS brings forth challenges regarding sensor selection, data quality and measurement accuracy [23, 29]. Different applications have used LCS for real-time monitoring, but these applications do not talk about the sensor selection process [17, 19, 22-24, 30]. Furthermore, the market availability of sensors in different forms to measure the same component challenges LCS selection. To the best of this research exploration, no standard methodologies have been encountered for selecting LCS-based devices on availability and data quality factors. Calibration techniques have been systematically incorporated into the operational framework to augment the fidelity of devices utilising LCS technology. The overarching aim of this integration is to mitigate issues associated with inaccuracies in data acquisition and interpretation. Over the years, there have been different calibration methods, such as MLR [19, 31], RF [32, 33], SVR [17], and ANN [34] have been used to improve data quality. Finding an accurate calibration method for the LCS selection based on the LCS deployment environment has made the calibration task further complex, as various LCS have different working principles and configurations [23]. To encounter all the mentioned issues, different calibration methodologies have been applied to improve data quality to the LCS-based monitoring applications. However, there is a need for a more precise and comparable approach to calibrating LCS to ascertain data quality assurance with respect to industry scale high cost, high-quality reference data. Since the calibration is dependent on the type of LCS-based devices, applications, deployment environment and meteorological parameters, there is a need for a well-defined methodology for sensor selection and calibration.

This thesis also delineates a methodological framework for selecting the most appropriate LCS based on its application. The approach is divided into two discrete yet complementary steps, each aimed at addressing the complexities and challenges inherent in LCS selection processes. To begin with, an exhaustive review of scholarly literature and comprehensive market research is conducted. This helps in identifying multiple potential LCS candidates suitable for the research. Moreover, the availability of these LCS options in the marketplace is also examined to ensure that the recommendations are timely and relevant. The rigorous nature of this two-pronged approach instils a high degree of confidence in the selection process, thereby increasing the chances of identifying an LCS that perfectly aligns with the specific requirements of the study. Following this, data-driven analytical approaches: i) Statistical approach, ii) KS-Statistics for drift analysis, iii) KL-Divergence and JS-Divergence for drift analysis comparison, and iv) Euclidean Distance have been applied. The analytical results of these approaches give the confidence to select the most consistent LCS for building LCS-based devices. Furthermore, calibration of each sensor has been applied to improve data quality as a second step. In this research, considering the air quality monitoring application, a comparative analysis has been explored among the widely used calibration methods by applying Absolute Humidity (AH) and Relative humidity (RH) along with temperature and measured air pollutants. Four different AI-based calibration methods: i) MLR, ii) MLP, iii) CNN and iv) RF have been compared with both AH and RH as calibration parameters to find the best-suited calibration method for the selected LCS in a real-world use case application. The selected LCS has been calibrated with reference to a high-cost air quality monitoring station from Urban Observatory, Sheffield (https://urbanflows.ac.uk/). Among different calibration models, the RF model performs better regarding the coefficient of determination (R^2), root means square error (RMSE) and means absolute error (MAE). In addition, the research has demonstrated that utilising AH as a calibration parameter yields more precise calibration processes than using RH for the selected LCS. This is due to AH providing more dependable and stable metrics, enhancing calibrated instruments' accuracy and dependability. This is because AH gauges water vapour density in the air, irrespective of temperature, while RH is influenced by both temperature and moisture content. This implies that AH is a more consistent and lucid parameter for calibration, leading to greater accuracy. This discovery underscores the significance of selecting AH over RH when optimising calibration techniques. Also, it offers opportunities for further investigation to comprehend the mechanisms behind the observed difference in calibration accuracy.

Furthermore, this thesis also has an experimental investigation that was executed involving ten volunteer households in the Bradford metropolitan area. The overarching objective of this research was twofold: First, to improve citizen awareness regarding IAQ, and second, to understand the relationship between indoor activities and air quality metrics. To facilitate the attainment of these objectives, each participating household was equipped with a calibrated IoT-based air quality monitoring device. The IoT device was designed to monitor several key air quality parameters in real-time, including $PM_{2.5}$ and PM_{10}. This real-time IAQ data was subsequently made available to the participating households through an interactive digital visualisation platform, aiding an educational purpose by making the participants aware of their immediate IAQ data. This real-time feedback mechanism is hypothesized to engage the participants actively in understanding the pivotal role that air quality plays in overall well-being and health. In addition to the monitoring and data acquisition, participants were requested to maintain a daily digital diary. This diary was designed to capture qualitative information regarding various indoor activities such as cooking, cleaning, and ventilation systems. This qualitative dataset was a complementary asset, providing a contextual landscape in which the quantitative IAQ data can be more comprehensively understood. The real-time IAQ data and the daily digital diaries collectively offer an integrated methodology for assessing indoor air quality's objective and subjective dimensions. This research aims to contribute a nuanced understanding of IAQ and its multiple determinants by coupling the quantitative measurements with the contextual understanding gained through the diaries. This integrative approach enhances public awareness and advances scholarly understanding of the complex interplay between human activities and IAQ. The study was conducted with participants from the Horton Park area in Bradford, UK. The analysis revealed an improvement in IAQ in the second month compared to the first. This improvement was attributed to changes in indoor activities, mainly the increased frequency of window openings. The analytical results from this study have shown that there has been an increase in window opening hours ranging from 11% to 39%, reflecting self-awareness towards IAQ. Additionally, a semi-structured post-study interview indicated heightened awareness among participants regarding the impact of indoor activities on IAQ. From analyses of this study data, it has been observed that there has been an appreciable increase in citizens' awareness towards IAQ. Participants demonstrated a clear understanding of the correlation between their actions and indoor pollution levels, emphasising the effectiveness of the study in raising IAQ awareness.

Despite the manifestation of noticeable behavioural changes among citizens regarding their awareness of IAQ, previous research does not provide conclusive evidence that isolates the influential factors responsible for this observed change. The second case study delineated eight diverse participants in subsequent research to address this shortfall. The methodological framework employed the COM-B model as a foundational paradigm in behavioural science, which stands for 'Capability,' 'Opportunity,' 'Motivation,' and 'Behaviour.' This model provides a comprehensive approach to understanding and influencing behaviour changes, particularly relevant to our investigation into IAQ monitoring and improvement strategies. A detailed exploration of the COM-B model's application to our research, including its theoretical underpinnings and practical implications for IAQ interventions, is provided in Chapter 5. This later discussion delves into how the COM-B model guides the development and implementation of our methodological approach, ensuring a structured and effective strategy to influence behavioural outcomes. This model was instrumental in shaping digital interventions, which were then accurately measured for their efficacy in modulating behaviour through IoT technology. The primary objective of this research was unambiguous: to initiate and rigorously scrutinise nuanced variations in participants' behaviours to IAQ. The digital interventions implemented in this study yielded a significant change in participant behaviour, consequently impacting their indoor activities and improving IAQ. Quantitative analyses revealed that levels of indoor air pollutants, precisely $PM_{2.5}$ and PM_{10}, showed a notable reduction. Specifically, decreases ranged from 27.79% to 91.27% for $PM_{2.5}$ and 27.66% to

90.59% for PM_{10} across all households involved in the study. However, analysis of the daily percentage change in indoor air pollution readings across the participant households disclosed a lack of consistent improvement. Despite this irregularity, an upward trajectory in IAQ was observed as the week progressed, attributed to the interventions deployed prior to the commencement of the second week. Significantly, to the best of this research and knowledge, this study is pioneering in leveraging the COM-B model to design and operationalize digital interventions within a digital tool framework. The implications are profound, marking an influential contribution to the literature on behavioural change concerning IAQ. By employing an evidence-based behavioural psychology model, this research suggests a systematic methodology for influencing behavioural change, thereby providing a more robust understanding of the mechanisms that help to raise citizens' awareness and engagement with IAQ.

Besides, the thesis aimed not only to assess the effectiveness of an IoT device in IAQ monitoring but also to examine the role of a human-centred digital visualisation platform in raising participant awareness levels based on digital interventions. This additional investigation also examined which digital interventions have significantly impacted participants' behaviour to improve IAQ. This engagement has led to an increased consciousness about IAQ, prompting the adoption of healthier practices and behaviours. The advent of digital health and behavioural change interventions has provided new avenues for improving IAQ and raising awareness about its impact on human health [35]. These interventions leverage digital platforms to deliver personalised health messages, provide access to specific data, and facilitate behavioural change towards healthier practices. However, the effectiveness of these interventions is contingent on their ability to engage citizens and influence their behaviours. In this case study, seven volunteer households in Bradford were engaged. The study used the COM-B model as one component to design an improved human-centred digital visualisation platform incorporating IoT technology. The analytical findings indicate that the digital interventions significantly impacted participants' behaviour, resulting in changes in indoor activities and overall improvements in IAQ. In this context, citizens' behavioural science role in environmental monitoring and awareness-raising has gained prominence as the citizens' behavioural science initiatives empower individuals and communities to participate in scientific research for IAQ monitoring and raising awareness on it. However, the adoption and use of these technologies are influenced by various factors, including their perceived usefulness and ease of use. For this case study, the methodology incorporates the use of Google Analytics (GA) and Google Tag (GT) Manager technologies, which provide instrumental assistance in comprehending the behavioural tendencies of users on our digital visualisation platform under the TAM framework. The TAM offers a theoretical framework for understanding these factors and predicting user acceptance of these technologies.

Furthermore, the research has highlighted the potential of digital interventions in promoting better IAQ practices. The platform has enhanced user engagement and effectiveness by personalising the interventions to cater to each user's unique needs and preferences. Therefore, this study provides a strong foundation for using digital tools in environmental awareness promotion and sets the stage for further exploration into how these tools can be optimised to foster healthier living environments. This research analyses the growing focus on integrating IoT, digital health interventions, citizen science, and the TAM. The integration of these areas offers opportunities for improving IAQ, raising awareness, and promoting behavioural changes. As a result, the analytical findings have the potential to shape the strategical guidance to the researchers and policymakers to address IAQ challenges, enhance public awareness, and ensure a healthier and sustainable indoor environment by leveraging LCS-based IoT technologies, digital platforms, and citizen engagement.

Moreover, guided by the COM-B model, a behavioural change framework, the interventions were designed to raise participants' awareness about the state of their indoor air, enhance their ability to improve it, provide opportunities for change, and motivate them towards sustained behavioural change as it has been proven in the previous study. After three weeks of careful monitoring and intervention, the study achieved its objective, recording a notable positive change in participants' behaviours and a significant improvement in IAQ using a digital platform and interventions. The findings, based on an LCS-based IAQ monitoring device's quantitative data and qualitative analysis of interviews conducted at the end of the study, reaffirmed the approach's efficacy. Participants demonstrated increased awareness and understanding of indoor air pollution and made meaningful behavioural changes. A year after the intervention, another study was conducted among the participants from the study's second phase to determine if the participants' behavioural changes had persisted. The follow-up phase investigated the intervention's long-term effects on the participants' IAQ-conscious behaviours. The Transtheoretical Model (TTM) and the Stages of Change Questionnaire (SOCQ) have been used for the investigation. Based on the analysis, personalised interventions are crucial for changing behaviour related to IAQ.

1.2 Motivation

The motivation for undertaking this extensive research is multifaceted and deeply rooted in both academic and societal imperatives. A paramount concern in our modern world is the urgent need to address the escalating public health crisis caused by inadequate air quality. This thesis aims to contribute to this crucial endeavour by creating enhanced air quality monitoring techniques and advocating for behavioural changes to heighten the public consciousness of IAQ.

Secondly, the research is situated at the confluence of several rapidly evolving technological domains: IoT, AI, and behavioural science. By synthesizing these disparate yet complementary fields, the research not only pushes the boundaries of what is currently achievable in air quality monitoring but also introduces new ways to help the citizens. This interdisciplinary approach can act as an intellectual stimulant and provide a rich, varied research experience. Moreover, the potential for policy impact provides a compelling motivator. Integrating real-time AQ monitoring with citizen awareness initiatives could catalyse more stringent air quality regulations and the implementation of targeted public beneficiary policies. Thus, the research can promise tangible, real-world impact, extending beyond academic circles to influence public policy and health outcomes.

From an academic perspective, the research has the potential to address several gaps in the existing literature. It can offer novel insights into data-driven analytical approaches for sensor calibration, explore the efficacy of digital interventions in effecting sustained behavioural change, and investigate the long-term impacts of such interventions. In doing so, it can also contribute substantively to the academic discourse, extending the existing body of knowledge in this critical area. Furthermore, the research delves into the complex realm of behavioural change, one of the most intractable challenges in citizen perspectives. By employing an evidence-based behavioural psychology model, the research provides the opportunity to present a systematic methodology for influencing behavioural change, offering a more robust understanding of the mechanisms contributing to citizen awareness and engagement with air quality issues.

1.3 Research Questions

The growing concern about the negative impacts of air pollution on human health has underscored the importance of a comprehensive understanding of IAQ. One promising avenue to achieve this goal involves the integration of AI, IoT, and Behavioural Science. A set of carefully crafted research questions (**RQ**) has been formulated to guide this research. These questions investigate the interplay of technological innovation, human behaviour, and environmental health to deepen understanding of IAQ. By embracing an interdisciplinary approach, expanding the knowledge base in this domain, and devising more effective strategies to mitigate air pollution would be easy.

RQ1. How can data-driven approaches be applied for selecting and calibrating LCS to monitor IAQ?

RQ2. To what extent does real-time IAQ monitoring, facilitated by IoT-based devices, influence citizen engagement and awareness?

RQ3. How effective are COM-B model-based digital interventions in promoting sustained behaviour changes for improving IAQ?

RQ4. How to design a human-centred digital platform that can improve IAQ by influencing human behaviour?

RQ5. How to measure persistent behaviour for IAQ improvement influenced by the technology?

This research aims to explore the multifaceted relationship between technology, behavioural science, and IAQ through a series of interconnected research questions. RQ1 delves into the efficacy of data-driven analytical approaches in selecting and calibrating LCS for IAQ monitoring, laying the technological foundation for subsequent exploration. Building upon this, RQ2 examines the role of IoT-based LCS devices in enhancing citizen engagement and awareness through real-time IAQ monitoring. RQ3 extends the discourse to the behavioural domain, investigating the impact of digital interventions conceptualized through the COM-B model on IAQ-related behaviours. RQ4 helped design a human-centred digital platform that can improve IAQ by influencing human behaviour, which requires a deep understanding of user needs, preferences, and behaviours. Creating an intuitive, engaging, and informative platform can empower users to take control of their indoor environment and improve their health and well-being. Finally, RQ5 determine the methods for assessing long-term behavioural changes related to IAQ driven by digital interventions. Collectively, these research questions aim to provide a comprehensive understanding of how advancements in technology and behavioural science can be synergistically employed to address challenges in IAQ.

1.3.1 How can data-driven approaches be applied for selecting and calibrating LCS to monitor IAQ?

This research question aims to identify the most effective data-driven methods for selecting and calibrating LCS for IAQ monitoring. Given the increasing reliance on LCS due to their cost-effectiveness and portability, understanding the best data-driven analytical approaches for their selection and calibration becomes crucial. This question explored various statistical and AI-based calibration models by comparing their efficacy in terms of accuracy, reliability, and ease of implementation. The findings contributed to optimising IAQ monitoring systems, making them more accessible and reliable.

1.3.2 To what extent does real-time IAQ monitoring, facilitated by IoT-based devices, influence citizen engagement and awareness?

This research question seeks to assess the impact of real-time IAQ data on citizen's engagement and awareness. With the advent of IoT devices capable of monitoring IAQ in real-time, there is a potential for increased citizen awareness and engagement. This question examined how real-time data influences people's understanding of IAQ issues, their engagement with monitoring platforms, and any subsequent changes in their indoor activities. This research question provided insights into the effectiveness of IoT-based IAQ monitoring systems in fostering citizen awareness.

1.3.3 How effective are COM-B model-based digital interventions in promoting sustained behaviour changes for improving IAQ?

This question evaluated the effectiveness of digital interventions designed through the COM-B model in bringing about continuing behavioural changes related to IAQ. The COM-B model provided a comprehensive framework for understanding behaviour change, making it an ideal intervention design tool. This question explored how well interventions based on this model succeed in effecting sustained changes in behaviour and whether these changes lead to improvements in IAQ.

1.3.4 How to design a human-centred digital platform that can improve IAQ by influencing human behaviour?

This question examined the features that make a digital visualization platform effective, how users interact with these platforms, and the extent to which these interactions lead to identifying the acceptance and significance of the intervention to improve IAQ. Also, this question investigated the effectiveness of human-centred digital visualization platforms in influencing behavioural changes and improving IAQ. With the increasing availability of real-time IAQ data, digital platforms that visualize this data understandably and engagingly played a significant role in citizen awareness.

1.3.5 How to measure persistent behaviour for IAQ improvement influenced by the technology?

This question rigorously explored digital interventions' long-term sustainability and efficacy on IAQ and health-conscious behaviours. It employed quantitative and qualitative metrics for a comprehensive analysis after a specific duration from the initial interventions. The focus has been on understanding the durability of behavioural changes and the long-term impacts on IAQ. This research question provided valuable insights into the effectiveness of digital interventions and their potential for bringing about lasting improvements in IAQ.

1.4 Research Publications

The following articles have been published in journals and conferences during the PhD period.

1. **Kureshi, R.R.**; Mishra, B.K.; Thakker, D.; Mazumdar S.; Li X.*“Acceptance of Digital Visualisation Platform and IoT device towards raising IAQ awareness and Behavioural Change: A User-Centric Study”* **(In-press)**

2. Mishra, B.K.; John R.; **Kureshi, R.R.**; Ahmed B.; Thakker, D.; Li X.*“Monitoring Linkage Between Indoor Air Quality, Indoor Activity and Severity of Breathing Issues in Asthma Symptoms”* **(In-press)**

3. **Kureshi, R.R.**; Thakker, D.; Mishra, B.K.; Barnes, J. *"From Raising Awareness to a Behavioural Change: A Case Study of Indoor Air Quality Improvement Using IoT and COM-B Model"*. Sensors 2023(Impact factor: 3.9), 23, 3613. https://doi.org/10.3390/s23073613

4. **Kureshi, R.R.**; Mishra, B.K.; Thakker, D.; John, R.; Walker, A.; Simpson, S.; Thakkar, N.; Wante, A.K. *"Data-Driven Techniques for Low-Cost Sensor Selection and Calibration for the Use Case of Air Quality Monitoring"*. Sensors 2022 (Impact factor: 3.9), 22, 1093. https://doi.org/10.3390/s22031093

5. **R. R. Kureshi**, D. Thakker, B. K. Mishra, and R. John. 2022. *"AQ-SCIENCE: Air Quality – Smart Cities with IoT-Enabled Citizen Engagement Approach"*. In Proceedings of the 11th ACM International Conference on the Internet of Things (IoT '21). Association for Computing Machinery, New York, NY, USA, 177–180. https://doi.org/10.1145/3494322.3494354

6. R. John, **R. R. Kureshi**, D. Thakker, and B. K. Mishra. 2022. *"Internet of Things (IoT) and Indoor Air Quality (IAQ) Monitoring in the Health Domain"*. In Proceedings of the 11th ACM International Conference on the Internet of Things (IoT '21). Association for Computing Machinery, New York, NY, USA, 215–218. https://doi.org/10.1145/3494322.3494704

7. **R. R. Kureshi**, D. Thakker, B. K. Mishra and B. Ahmed, "Use Case of Building an Indoor Air Quality Monitoring System," 2021 IEEE 7th World Forum on Internet of Things (WF-IoT), New Orleans, LA, USA, 2021, pp. 747-752, https://doi.org/10.1109/WF-IoT51360.2021.9596006

8. **Kureshi, R.R.**; Thakker, D.; Mishra, B.K.; Mazumdar S.; Osman M.; Ainsworth B. *"Harnessing Digital Visualization Platforms For Indoor Air Quality Awareness And Behavioural Change"* **(Under internal review)**

1.5 Research Contribution Summary

1.5.1 Data-driven approaches for LCS Selection and Calibration for AQ monitoring.

This thesis has contributed effective data-driven methods for selecting and calibrating LCS for IAQ monitoring using IoT technology. Accurate and reliable IAQ monitoring is of paramount importance to give confidence to authorities and citizens who rely on it. By exploring various statistical and AI-based calibration models, the research has compared their efficacy in terms of accuracy, reliability, and ease of implementation. The findings from this exploration have the potential to revolutionise the way IAQ monitoring systems are designed, making them more accessible to the citizens and more reliable for researchers and policymakers. This contribution lays the technological foundation for subsequent exploration in the domain of IAQ.

1.5.2 Enhanced citizen engagement and awareness through real-time monitoring

The advent of the IoT has brought about a paradigm shift in how we perceive and interact with our indoor environment. This research has tapped into this potential by assessing the impact of real-time IAQ data, facilitated by IoT devices, on citizen engagement and awareness. By examining how real-time data influences citizens' understanding of IAQ, their engagement with monitoring platforms, and any subsequent changes in their indoor activities, the research provides invaluable insights into the effectiveness of IoT-based IAQ monitoring systems. As highlighted by the research, the potential for increased citizen awareness and engagement can pave the way for more informed citizen health interventions and policies.

1.5.3 COM-B Model-Based Digital Interventions for behavioural change to improve IAQ.

Behavioural change is a complex process influenced by a myriad of factors. The COM-B model is an excellent and constructive framework for understanding behaviour change, providing innovative and timely insights that can be applied to various situations. However, a significant research challenge exists in operationalising such a theoretical model as part of a digital platform. As far as we know, this thesis represents the first and early work on using the COM-B model for building a digital platform targeting activities that impact IAQ. The research delves deep into the intricacies of IAQ-related behaviours by evaluating the effectiveness of digital interventions designed using this model. The findings of this study highlight the usefulness of the COM-B model as a tool for designing interventions. By examining the effectiveness of interventions based on this model to succeed in achieving sustained behavioural changes and whether these changes lead to improvements in IAQ, the research contributes to the broader discourse on behavioural science and its implications for citizen health.

1.5.4 Designing and evaluating digital interventions using Human-Centred Digital Platforms

Information presentation is as crucial as the information itself in today's digital age. With this in mind, this research has endeavoured to identify the elements that make a digital visualisation platform effective. After a thorough investigation, it was discovered that a platform's user-centric qualities and the way users engage with it are critical to its success. The study highlighted that user interactions with these platforms play a pivotal role in determining the acceptance and significance of initiatives to improve IAQ. Furthermore, it emphasised the importance of presenting real-time IAQ data in an understandable and captivating way, as it significantly contributes to raising awareness among citizens. By combining insights from user experience, real-time data visualisation, and behavioural science, this research has laid out a plan for designing future digital platforms. When developed with a human-centric approach, these platforms have the potential to inform and influence behavioural changes, ultimately leading to tangible improvements in IAQ.

1.5.5 Measuring Persistent Behaviour Influenced by Technology

Any intervention must be effective over the long term. This research recognises this fact and investigates digital interventions' long-term sustainability and efficiency in improving IAQ. By conducting a longitudinal study, participants from an earlier study have been invited to evaluate persistent behavioural change. The research adopted the TTM to track the evolution and persistence of IAQ-related behavioural changes over time. The study used 20 custom-designed questionnaires rooted in the SOCQ to gather nuanced data. These questionnaires were tailored to capture specific nuances of behaviours, motivations, and perceived barriers, ensuring a comprehensive understanding of the participant's journey. To our knowledge, this thesis is one of the early works that uses TTM to evaluate sustained behaviour change using digital platforms. The primary objective of the research was to observe initial behavioural changes and critically assess the long-term maintenance of these changes, especially in the context of participants' consistent concerns and awareness about IAQ. This research bridges the gap between short-term behavioural changes and long-term behavioural maintenance in IAQ, presenting a significant contribution to indoor environmental research.

1.6 Research Methodology Overview

The research that I will be discussing focuses on the enhancement of IAQ through the integration of AI, IoT and behavioural sciences. The study's objective was to address the complexity of research questions that evaluate the efficacy of technological interventions and understand human behavioural change towards IAQ. The research adopted a mixed-methods approach that combined quantitative and qualitative research strategies to achieve these objectives. To begin with, LCSs were employed for continuous IAQ monitoring. These sensors focused on key pollutants such as PM, and the data generated from these IoT-enabled LCS devices were analysed using machine learning algorithms to uncover patterns and predict IAQ conditions. The advantage of using machine learning algorithms is that they can analyse vast amounts of data and identify complex patterns that may not be easily discernible through traditional methods. In addition to monitoring IAQ, structured surveys and semi-structured interviews were conducted to explore user perceptions of IAQ and the technology used for monitoring. This qualitative data was complemented by case studies in selected households, which provided more profound insights into the subjective experiences and perceptions of individuals interacting with these technologies.

The holistic methodological framework facilitated data triangulation, which enriched the reliability and validity of the findings and provided a nuanced understanding of the technological and behavioural interplay in IAQ improvement efforts. Ethical considerations, such as informed consent and data protection, were meticulously followed, ensuring research integrity. The research comprehensively examines IAQ improvements, leveraging the synergistic value of integrating quantitative and qualitative findings to bridge technological innovation and behavioural science for impactful IAQ enhancements. While acknowledging methodological limitations, such as potential biases and sensor accuracy challenges, the research offers valuable insights into IAQ improvements. By adopting a mixed-methods approach, this research contributes to understanding IAQ improvement efforts, which can inform policy decisions and the design of future interventions.

1.7 Thesis Outline

The structure of this thesis has been carefully crafted to ensure that readers gain a comprehensive understanding of the research that has been undertaken. The content has been presented logically and coherently, so each section builds upon the previous one to provide a complete picture of the thesis. In **Chapter 2**, an exhaustive review of the relevant literature is presented. This chapter aims to situate the current research within the broader academic discourse, highlighting fundamental studies, methodologies, and findings that have shaped the field. **Chapter 3** is dedicated to elucidating the data-driven methodologies that have been employed. Specifically, this chapter delves into the stepwise procedures for sensor selection and calibration, providing both these techniques' theoretical underpinnings and practical applications. **Chapter 4** focuses on an in-depth analysis of citizen engagement and behavioural change using LCS-based IoT devices and digital visualisation platforms. Using the Horton-Park Region, Bradford, UK, as a representative case study, this chapter offers insights into the dynamics of community interaction and the factors influencing IAQ. Moreover, a comprehensive examination of the experimental results is undertaken, with discussions centred on the implications and significance of the findings. **Chapter 5** embarks on a journey from initial enlightenment to tangible behavioural change. Here, the intricate exploration of IAQ enhancement is presented, particularly at the intersection of the rapidly increasing IoT technology and the COM-B Model. The chapter underscores the transformative potential of integrating these domains. In **Chapter 6**, the narrative pivots to digital visualisation platforms. The chapter explores how these platforms can be harnessed to foster a heightened awareness of IAQ and evaluate digital interventions. Drawing from a user-centric investigation, the chapter elucidates user perceptions, interactions, and the potential for instigating meaningful behavioural changes. **Chapter 7** presents a longitudinal perspective, examining the nuances of IAQ over an extended timeframe. The chapter underscores the enduring influence of behavioural interventions, probing into the long-term impacts and the sustainability of such initiatives. Concluding the thesis, **Chapter 8** synthesises the research's key findings, contributions, and implications. The chapter not only offers a reflective overview but also charts out prospective avenues for future research, highlighting areas that warrant further exploration and investigation.

CHAPTER 2: LITERATURE REVIEW

Air pollution, a growing global concern, has received significant attention in modern discourse, mainly due to its undeniable impact on human health [36]. As the ramifications of deteriorating air quality become increasingly evident, a pressing need emerges to address the technological challenges inherent in the air quality (AQ) domain. Central to this challenge is developing sophisticated AQ monitoring systems capable of real-time monitoring of specific gases and PM, both within IAQ and outdoor air quality (OAQ) contexts. This literature review delves deeply into the intricate nexus between air pollution and human activities. It comprehensively explores LCS employed in AQ monitoring and its analogous applications. Furthermore, the review highlights the myriad calibration methodologies to enhance the data accuracy of LCS-based IoT devices. Moreover, it is equally crucial to do the public's engagement in AQ monitoring and their consequent awareness, a facet that this review thoroughly examines. Additionally, this review elucidates the transformative potential of behaviour change models, such as the COM-B and the Transtheoretical Model (TTM), in steering societal behaviour towards proactive IAQ improvement measures. The overarching role of technology in enhancing IAQ and the sustainability of behaviour changes for long-term IAQ awareness are also critically assessed within this review.

2.1 Outdoor and Indoor Air Pollution

Air pollution, both outdoor and indoor, has emerged as a primary concern, especially for inhabitants of urban regions. The primary sources of outdoor air pollution can be attributed to vehicular emissions, industrial activities, and urban planning. In contrast, indoor air pollution predominantly arises from routine human indoor activities [37]. Numerous studies have underscored the harmful effects of outdoor air pollution on human health [38, 39]. Similarly, research has also highlighted the adverse health implications of indoor air pollutants [40, 41]. Intriguingly, a reciprocal relationship exists between indoor and outdoor air quality, with each influencing the other [37].

The body of research encompassed in references [42-46] provides compelling evidence that the primary determinant of particulate matter (PM) concentration within indoor environments is the prevailing concentration of outdoor PM. However, other factors, such as the type of windows and specific human activities, including cleaning practices, cooking methods, and heating choices, also play pivotal roles in shaping IAQ [41, 47, 48]. Notably, a positive correlation exists between Indoor-Outdoor (I/O) PM concentrations, suggesting that outdoor pollution levels dominate indoor air quality. Li et al. [49] explored the interplay between urban street canyons (defined by the ratio of building height to road width) and vehicular pollution. Their findings revealed that taller buildings hinder the effective dispersion of pollutants by obstructing wind flow, thereby exacerbating air pollution levels. This observation aligns with the findings of Tong et al. [50], who demonstrated that the proximity of buildings to roads significantly impacts IAQ. Additionally, ambient wind conditions and building ventilation strategies can substantially mitigate indoor pollution levels, particularly concerning particulate matter. An intriguing revelation from this study is that a noteworthy 22.5% can reduce indoor particle concentration from the baseline by merely keeping windows facing the road closed. In a related study, Wang et al. [51] delved into the cross-transmission dynamics of gaseous pollutants, examining the roles of buoyancy and wind speed in buildings with single-sided ventilation. Their research underscored that variations in window sizes and the degree of window openings can significantly modulate IAQ.

In summary, the intricate relationship between outdoor and indoor air pollution is influenced by many factors, ranging from urban design to routine human activities. While outdoor pollutants predominantly shape indoor air quality, specific indoor practices and architectural considerations can exacerbate or mitigate these effects. As urbanisation intensifies, understanding and addressing these dynamics becomes paramount to safeguarding public health and ensuring sustainable urban living.

Research Gap: Existing research has established the harmful effects of both indoor and outdoor air pollution on human health. However, there is a gap in the literature when it comes to investigating the enduring consequences of indoor pollutants that arise from particular household activities and their interplay with outdoor pollution.

2.2 Low-Cost Sensors for AQ Monitoring: Selection and Calibration

Traditional air quality monitoring stations such as Automatic Urban and Rural Network (AURN) have more than 1,500 sites across the UK. These stations have installed large, expensive and calibrated sensor devices which can monitor several air pollutants such as oxides of nitrogen (NO_x), sulphur dioxide (SO_2), particles (PM_{10} & $PM_{2.5}$), carbon monoxide (CO) and ozone (O_3). Also, in many cases, these stations are located away from traffic areas or a little far from city centres, limiting this station's coverage to monitor air quality. To overcome this limitation, the use of LCS becomes a practical alternative approach to monitoring air quality (Indoor-Outdoor) and allows real-time exposure assessment from many locations. No universal definition is agreed upon for LCS. Still, Rai et al. [27] acknowledged that *"anything costing less than the instrumentation cost required for demonstrating compliance with the air quality regulations can be termed as low-cost"*. Comparing LCS with those high-cost monitoring stations, LCS are less expensive and easy to access and deploy. Predominantly, the data collected from LCS devices are easy to handle and process and can be analysed by experts, sharing the monitoring outcomes with the public or stakeholders to spread awareness and other purposes [15]. However, the data from LCS are generally less reliable and low quality [23, 29, 52].

Several challenges have been underscored in the existing literature, notably data reliability and performance evaluation, posited as pivotal areas for future advancements in LCS development. LCS-based air quality monitoring systems are predominantly integrated with low-power computational devices, such as the Raspberry Pi [53-55] and the Arduino board [56, 57]. These devices facilitate sensor communication and interface with web or mobile platforms, enabling data acquisition, storage, analysis, and visualisation. Furthermore, they employ specific communication protocols, including WiFi and GSM [58], to transmit data from diverse locations following information collection via LCS.

In recent years, the proliferation of micro-sensor technology has significantly augmented the utilisation of LCS in monitoring and measurement applications, enabling broader spatial coverage across various domains [59]. When compared with high-end monitoring stations, LCS offer a cost-effective alternative that is both accessible and easily deployable. However, a notable drawback is a potential compromise in data reliability and quality associated with LCS [23, 29, 52], as discussed earlier. Notably, data procured from LCS devices are amenable to processing and can be carefully analysed by specialists. The resultant insights can then be disseminated to the public and stakeholders, supplying a conduit for raising awareness and facilitating other significant endeavours [15]. The versatility of LCS has been demonstrated in many different applications, including air quality [60], road traffic [61], water quality [62], and human health [63], thereby highlighting their demand. Castell et al. [24] embarked on an evaluative study of LCS (specifically AQMesh) and delved into the complexities of data quality. Furthermore, they enumerated several funded initiatives that leverage LCS, including OpenSense (https://gitlab.ethz.ch/tec/public/opensense), Everyaware (http://www.everyaware.eu/), Citi-Sense-MOB, and Citi-Sense [64]. These initiatives predominantly involve devices affixed to vehicles or stationary locales, transmitting real-time data to web platforms from eight European cities for subsequent analysis. It’s noteworthy that these devices were equipped with individual gas sensors, priced between €20 and €100, culminating in an aggregate device cost ranging from €500 to €5000. Chojer et al. [60] conducted a comprehensive review spanning works from 2012 to 2019 centred on LCS-based monitoring systems. Their analysis gathered 35 salient research applications, with a particular emphasis on meteorological parameters such as temperature and relative humidity (RH). Their findings revealed that a mere ten out of the 35 applications were dedicated to sensor performance, encompassing facets like validation, calibration, and testing. A core advantage of LCS-based systems lies in their affordability and market availability [65]. Kumar et al. [66] extolled the virtues of LCS, highlighting their capacity for real-time data access, enhanced spatial resolution, uncertainty reduction, investigative emission sources from indoor activities, and the health benefits they confer when compared with conventional monitoring systems. However, they also underscored challenges intrinsic to LCS, particularly concerning data quality and the performance evaluation imperative for LCS device evolution.

Several studies have investigated the influence of temperature and RH on LCS performance. Notably, references [67-69] have indicated that neither temperature nor RH significantly impacts LCS performance. In a comprehensive study, Zou et al. [70] assessed eight distinct low-cost Particulate Matter (PM) sensors to discern the relationship between temperature and humidity in a controlled laboratory setting. Their findings underscored that while temperature had a negligible effect on LCS functionality, RH levels ranging from 10% to 90% could potentially alter the sensor's output magnitude. However, they posited that such discrepancies could be rectified through meticulous calibration. Similarly, Zamora et al. [71] elucidated that the meteorological parameter RH has a pronounced effect on LCS performance. This observation was further corroborated by Jayaratne et al. [72], who noted that sensor performance deteriorates when RH surpasses the 75% threshold. Spinelle et al. [73, 74] introduced an innovative approach by employing Absolute Humidity (AH) as a substitute for RH and temperature in the LCS calibration process. Their research accentuated the pivotal role of environmental parameters and the intrinsic working principles of LCS, necessitating advanced calibration techniques to ensure data reliability.

Calibration is a crucial process in the realm of sensor technology. It involves meticulously adjusting the sensor to achieve unmatched accuracy and eliminate possible discrepancies. This process is essential as it ensures that the sensor operates within its optimal parameters, consistently producing reliable and precise results. Maag et al. [23] conducted an exhaustive review of prevalent calibration methodologies, bifurcating them into two primary categories: pre-deployment calibration (or calibration models) and post-deployment calibration (encompassing network recalibration strategies). Their review further delineated sensor calibration models into three distinct types: i. Offset and Gain calibration, ii. Temperature and Humidity Correction, and iii. Sensor Array Calibration. The Offset and Gain calibration approach addresses calibration inaccuracies stemming from uncertain boundaries and systematically eliminates potential non-linear responses. The Temperature and Humidity Correction method enhances recorded values by comparing them with extant data to fine-tune the LCS. Sensor Array Calibration, a more advanced technique, extends the principles of temperature and humidity correction by incorporating interfering gases and other environmental variables into the calibration process. Understanding that sensor calibration can happen in controlled or uncontrolled environments is essential. In a controlled environment, the sensor is calibrated using state-of-the-art instruments or sensors that have been calibrated before. On the other hand, in an uncontrolled environment, sensor parameters are adjusted based on readings from different sensors, especially when the measurement in a controlled setting is not possible. However, this approach is prone to data inaccuracies [73, 75].

It has been observed that current research relies heavily on monitoring stations equipped with expensive and high-end devices, usually placed at fixed locations. Although these instruments are highly reliable, their deployment in various locations could be more economically feasible [24]. In this scenario, it has been presented with a choice between high-cost, high-fidelity equipment and their more affordable but often less precise counterparts. As a result, the challenge is to identify an optimal LCS system that can effectively bridge this gap and provide reliable and accurate data. One common concern when using LCS is ensuring data integrity and quality [19, 32]. Maag et al. [23] conducted an extensive review of challenges associated with LCS and deduced that the quality of data derived from LCS depends on many factors. These include the nature and operational principles of the sensors, prevailing meteorological conditions, sensor sensitivity, and consistency. Similarly, Kotsev et al. [76] elucidate the methodologies to ensure dependable data quality derived from LCS. They further highlight several parameters known to influence the response of electrochemical sensors. Factors such as temperature, humidity, and cross-sensitivity are pivotal in affecting sensor outcomes.

In addressing the challenges inherent to LCS, calibration emerges as a pivotal solution [77, 78]. While some calibrations, like those conducted by Wang et al. [79], have been executed in laboratory settings, others, such as those by Spinelle et al. [74], have been applied in the field, placed alongside a reference station. The selection of an appropriate calibration model depends upon various parameters, including the sensor's type, the device's operational phenomena, the resources it necessitates, and the sensors' storage, computational, and communicative capabilities [75]. Various methodologies have been proposed and employed in statistical modelling and calibration to achieve accurate and reliable outcomes. These methods, each with unique strengths and limitations, cater to diverse data structures and requirements. Among them, Multivariate Linear Regression (MLR) stands out as a frequently employed calibration method [19, 31]. Multiple covariates are predominantly harnessed in utilising MLR for calibration to derive the desired variable outcomes. While the MLR model's implementation is straightforward, it is not without its constraints. Specifically, MLR operates on a linear equation, the coefficients predicated on assumptions encompassing linearity, residual error, and co-linearity. Another prevalent model is the Random Forest (RF) [32, 33]. The RF model enhances stability by randomly sampling multiple observations during training, reserving a subset of the data for model validation. Predictions are subsequently derived from the mean outcomes in various decision trees. However, as the dataset expands, so does the size of the tree, leading to increased time complexity during model training. Support Vector Regression (SVR) has also been introduced as a calibration technique [17]. SVR-based models employ kernel functions for training with provided datasets. The Support Vector Machine (SVM) component delineates an optimal hyperplane to differentiate between classes, facilitating outcome prediction. A notable limitation of the SVM-based model is the users' need to specify the quantity of support vectors. Artificial Neural Networks (ANN) have also gained traction as calibration models [34]. ANNs are particularly advantageous when datasets are noisy. However, training an ANN demands numerous iterations and the specification of specific parameters, including the number of nodes, hidden layers, activation functions, and weights. The efficacy of the ANN model is intrinsically linked to these user-defined parameters.

In recent academic discourse, statistical calibration models have been extensively discussed in calibration processes. The challenge, however, lies in selecting appropriate sensors, given the vast array of LCS available in the market. Williams et al. [80] offer a comprehensive guide for LCS selection. Nonetheless, their research posits that sensor choice is predominantly contingent upon user preferences, as delineated in sensor manuals. Supporting this perspective, another study [81] underscores that sensor selection is inherently subjective, primarily on the end-user's discretion and the specific application's scope. Sousan et al. [82] empirically examined the consistency of PM sensors, specifically the Sharp GP sensors, employing the average slope method. Their findings revealed that averaging multiple measurements over an extensive frequency spectrum can mitigate random noise, thereby enhancing data quality.

A detailed review of extant literature reveals an increasing trend in developing applications harnessing LCS. Notably, the application spectrum of LCS is expansive, transcending specific domains. The widespread use of LCS-based applications in different fields is due to the development of various LCS variants, each designed for particular tasks. The literature also highlights the use of multiple sensors in other applications, emphasising the importance of selecting suitable sensors for LCS-based devices. As the number of LCS options increases, selecting the appropriate sensors will become more complex. Therefore, there is a growing need for a robust sensor selection strategy to maximise the effectiveness of LCS-based applications.

Data quality is a significant concern when it comes to LCS-based applications. Despite various calibration methods being used, it is still unclear which approach is the most effective. This is because the calibration process's efficiency depends on several factors, including the calibration parameters, the sensor's working principles, and the application domain. Therefore, selecting the right sensor and calibrating it correctly is crucial in improving LCS-based systems' effectiveness and data quality, ultimately ensuring the successful deployment of LCS-based devices for specific applications.

Research Gap: Despite advancements in LCS for AQ monitoring, significant gaps remain in standardising the selection and calibration processes, particularly in tailoring these methodologies to diverse environmental conditions and ensuring data reliability for public health advisories.

2.3 IAQ Monitoring Studies Using LCS

Given the significance of IAQ and the substantial duration for which individuals remain indoors, there is an imperative need for comprehensive research on IAQ. This research should elucidate the correlations between the indoor activities of residents and the consequent IAQ. In the quest for sustainable smart city solutions, a paramount concern is mitigating air pollution and enhancing citizen awareness. To this end, scholars have pioneered the deployment of infrastructures capable of monitoring air quality through the Internet of Things (IoT) framework, both in outdoor [12, 13] and indoor environments [11, 14]. Such monitoring systems can amplify awareness about AQ and foster the development of sustainable smart city strategies [83, 84]. Nevertheless, traditional AQ monitoring mechanisms cope with significant challenges, including the high costs of devices, often escalating to tens of thousands of US dollars, their spatial coverage limitations, and their substantial dimensions [7]. Given the impracticality of large-scale deployment, these impediments render the current AQ monitoring stations less expansive regarding area coverage. LCS has emerged as transformative tools in this realm in recent years, owing to their affordability, compactness, and portability. Additionally, LCS devices furnish operators with real-time, high-resolution spatiotemporal data at specific locales [16]. Thus, when compared with high-cost monitoring sensor systems, LCS emerges as a cost-effective alternative for IAQ monitoring. Nevertheless, the accuracy of data derived from LCS remains a challenge, which is currently being addressed through innovative design strategies, including calibration [23, 29].

Government bodies, local administrations, and citizens can significantly benefit from tracking air quality by fortifying urban areas with infrastructure equipped for air quality monitoring through LCS devices. This approach offers a more cost-effective solution compared to utilising high-end sensor apparatus. Moreover, LCS devices can aid in raising awareness among citizens, ultimately leading to a better understanding of AQ dynamics. For instance, Willet et al. [85] developed a framework for collecting personal air quality data through sensor monitoring and interviews. Zappi et al. [86] delved into citizen responses and their perceptions of ambient air quality. Castell et al. [64] endowed a smart city with LCS-based mobile devices to monitor AQ, simplifying citizen participation in environmental AQ governance. Jarret et al. [87] suggested that LCS-based systems generate reliable data for citizen science research. Hubbell et al. [88] explored individuals' methodologies, behaviours, and perspectives concerning AQ sensor deployment. This research also delved into the synergistic collaboration between citizen scientists and the general public, culminating in advanced sensor technology and heightened AQ awareness.

Studies have shown that the indoor activities of people can significantly affect indoor air quality, which in turn can impact human health. The lack of monitoring for indoor activities and the absence of awareness about indoor pollution levels can worsen health risks. To address this issue, a practical solution would be an indoor pollution monitoring system that tracks indoor activities and provides real-time IAQ data to raise awareness among citizens and encourage behavioural changes. IoT-enabled LCS devices, combined with interactive IoT platforms, can be a practical solution at the household level to help people reduce indoor air pollution levels and modify activities that contribute to it.

Research Gap: There is a need for comprehensive studies that monitor IAQ using LCS and integrate behavioural insights to understand how personal habits influence IAQ and how individuals can utilize IAQ data for healthier living environments.

2.4 The Impact of Indoor Air Quality on Health Outcomes During the Covid-19 Pandemic

The COVID-19 pandemic has underscored the critical importance of indoor air quality (IAQ) in public health, prompting a surge in research aimed at understanding and mitigating the airborne transmission of SARS-CoV-2. This literature review synthesises findings from ten significant studies that explore various aspects of IAQ during the pandemic, highlighting the implications for health, transmission dynamics, and mitigation strategies. Allen et al. [89] laid a foundational understanding by examining the efficiency of High-Efficiency Particulate Air (HEPA) filters in capturing SARS-CoV-2 aerosols, revealing their significant role in reducing viral load in indoor settings and thus contributing to safer indoor environments. This finding is crucial as it provides a practical solution for immediate IAQ improvement. Building upon the importance of awareness, Sekar et al. [90] explored the impact of public perceptions of

IAQ on behaviour and the adoption of mitigation measures, highlighting the need for comprehensive public education as a key element of pandemic response strategies. This underscores the link between knowledge and action, where informed communities are better equipped to implement and comply with IAQ improvements. Gaffar et al. [91] further elucidated and focused on IAQ challenges and school solutions. By implementing improved ventilation and air purification systems, schools saw a decrease in transmission rates, underscoring the importance of IAQ in educational settings. Moreover, the study by Roh et al. [92] conducted a study on the correlation between poor IAQ and increased susceptibility to COVID-19 in residential settings. Their analysis indicates that individuals in poorly ventilated homes have a higher risk of contracting the virus, emphasising the need for adequate indoor air management. The influence of environmental factors on virus survival and transmission was further detailed by Davidse et al. [93] investigated the impact of humidity on virus survival and transmission indoors. The study concluded that maintaining indoor humidity within a specific range could reduce the viability of viral particles, thus lowering transmission risk. Jones et al. [94] introduced a practical approach to assessing ventilation effectiveness in public spaces through PM monitoring. Their findings demonstrate the utility of PM levels as indicators for airborne transmission risk and underscore the need for adaptable ventilation strategies in public settings. In healthcare environments, Zia et al. [95] emphasised the role of mechanical ventilation in reducing airborne transmission, showing that enhanced ventilation systems can significantly decrease viral particle concentrations. This is particularly relevant for protecting healthcare workers and patients, indicating a direct link between IAQ management and hospital infection rates. Reflecting on the broader implications of the pandemic on workplace environments, Motuzienė et al. [96] provided a comparative analysis of IAQ in office buildings before and during the pandemic. Their research highlights the significant improvements in air quality and ventilation practices in response to COVID-19, pointing to a shift in building management priorities towards health-oriented approaches. A study conducted by Elsaid et al. [97] looked beyond the immediate response to the pandemic, evaluating the long-term health benefits of IAQ improvements. Their findings suggest that sustained attention to IAQ can contribute to broader public health benefits, such as reduced incidence of respiratory diseases, thereby underscoring the lasting value of improved indoor air management. Finally, Adam et al. [98] focused on the policy implications of pandemic-induced IAQ research, calling for the integration of IAQ standards into public health policy. This advocates for a systemic approach to ensuring lasting improvements in indoor environments, highlighting the need for policy frameworks that support sustainable IAQ management.

In conclusion, the COVID-19 pandemic has highlighted the importance of IAQ for public health. This review provides effective strategies to reduce SARS-CoV-2 transmission and emphasizes the need to include IAQ in future health policies. As we face future public health challenges, it is vital to prioritize IAQ as a fundamental element of public health strategy. The insights gained from these studies emphasize the importance of maintaining and improving IAQ for the well-being of individuals and communities.

2.5 Motivations and Engagement for Citizen Participation and Environmental Monitoring

The degree and nature of participation can vary significantly, with individuals engaging in various activities and displaying diverse behavioural characteristics [99]. These behaviours often correspond to the individual's level of involvement in the research project, from those who contribute significantly to less active participants and those who merely consume content without contributing personally. The authors [100] classify participants into three categories: Casual Workers, Community Workers, and Focused Workers, based on their contribution patterns. While the study offers valuable insights into the dynamics of online communities, it could have benefited from a more extensive exploration of the factors influencing these participation patterns. These varying definitions of participation necessitate a more in-depth exploration of participants' views on citizen science and their participatory choices. These choices are primarily driven by motivational factors closely tied to participants' emotional, behavioural, cognitive, and social experiences. The research article [101] analyses citizen science projects' participation levels and behavioural traits. The study utilises a comprehensive methodology, including a literature review, open coding, and the constant comparative method, to identify salient themes in the interviews conducted.

The encouragement for involvement in citizen science can differ among projects and individuals. A Case Study by Palacin et al. [102] reveals that the primary motivations for participation are personal interest, the desire to contribute to scientific knowledge, and the opportunity to learn. Another study [103] highlights the importance of community and social interaction as motivating factors. In contrast, the study [104] emphasises the role of environmental concern and the desire to protect local resources. Nelms et al. [105] introduce the idea of 'micro-volunteering', where participants can contribute in small, manageable ways, suggesting that ease and convenience can also be significant motivators. Finally, Fraisl et al. [106] underscore the importance of collaboration, technological development, and scientific guidance in motivating citizen science participation. To sum up, citizen science projects can attract participants for various reasons, such as personal interest, the wish to contribute to scientific research, environmental concerns, community involvement, and the convenience of participation. Nevertheless, collaboration, technological advancements, and scientific guidance are equally important factors in motivating and maintaining participation.

The research article by Robinson et al. [107] presents an innovative user-centred design (UCD) approach for communicating results in personal exposure studies. The study's strength lies in its combination of human-centred design, human-information interaction, and design thinking, which enhances participant comprehension and engagement. However, the research is geographically limited to participants in Ljubljana, Slovenia. Furthermore, the study could have provided more detail on the challenges encountered during the UCD implementation. Despite these limitations, the research offers valuable insights for future work in personal exposure studies and citizen science. The study conducted by Golumbic et al. [108] explores the development of a user-centred platform for presenting air-quality data. The study in three phases reveals a preference for map-based data interpretation and the need for contextualised information. Despite low registration rates, many users found the platform useful, highlighting the importance of user feedback in iterative design processes in citizen science projects.

Hubbell et al. [88] delve into the social science aspect of air quality sensors, examining people's perceptions, attitudes, and behaviours. They underscore the potential collaboration between citizen scientists and professionals in enhancing understanding of sensor technology use and raising air quality awareness. Pritchard et al. [109] analyse how citizen sensing can be used to develop new technologies and foster new partnerships and communities, leading to a joint effort towards addressing issues like air pollution. Another study conducted by Mahajan et al. [110] Reflections on designing a citizen-driven air quality monitoring framework in Taiwan. The study focuses on the transition from a Do-It-Yourself (DIY) approach to a Do-It-Together (DIT) approach, emphasising the importance of collective awareness and knowledge sharing. One case study highlighted in the document is the practice of incense burning in religious contexts. The research used AirBox devices to understand and discuss the relationship between cultural practices and science. The study underscores the importance of understanding the effects of cultural practices on air quality and the role of citizen science in creating this awareness. Jerrett et al. [87] demonstrate that low-cost sensors could reduce exposure measurement error and act as a valid data source for citizen science studies. This suggests that affordable technology can be crucial in citizen science initiatives. English et al. [111] emphasise the significance of community engagement in every aspect of air quality monitoring when creating a community-wide monitoring scheme. This underscores the need for participatory approaches in environmental monitoring. Castell et al. [64] introduce the Citi-Sense MOB approach, which facilitates public participation in environmental governance using mobile technologies. This highlights the potential of mobile technology to enhance public participation in environmental monitoring. Finally, Leonardi et al. [112] present a mobile crowdsensing system for air quality, aiming to monitor air pollution and also to get the participant's reflections on their pollution exposure. This underscores the potential of crowdsourcing in gathering valuable data and insights on air pollution. Commodore et al. [113] present a study driven by the community's desire to be more aware of air quality and learn about health issues due to pollution exposure. This highlights the importance of community involvement in environmental monitoring initiatives.

In summary, these studies collectively highlight the importance of citizen science, community engagement, and affordable technology in monitoring air pollution and estimating exposure. They underscore the potential of these approaches in enhancing public awareness and fostering collective action towards addressing air pollution.

Research Gap: While the literature highlights motivations behind citizen participation in environmental monitoring, there's insufficient understanding of how to effectively translate this engagement into actionable behaviour change for IAQ improvement.

2.6 Human Behaviour and Activities in Congruence with IAQ

IAQ is predominantly influenced by human indoor activities, such as cooking and cleaning, building characteristics, and external factors, including ambient environmental conditions [114]. An Institute of Medicine, UK report underscores that human behaviour and pollutant properties are pivotal in determining IAQ [115]. Activities undertaken by humans indoors are intrinsically linked to the emission of chemical components. These components react and elevate indoor pollution levels based on their environmental characteristics. For instance, activities like cooking and combustion processes, including wood burning and smoking, primarily produce PM and COx. Prolonged exposure to these pollutants indoors can result in symptoms such as chest pain, exacerbated asthma, fatigue, and diminished lung functionality [116]. Additionally, heightened concentrations of Total Volatile Organic Compounds (TVOCs) — organic compounds emanating from sources like paints, cleaners, and air fresheners — can lead to health issues ranging from ear, nose, and throat (ENT) irritation to nausea and headaches [117]. It is imperative to note that the level of pollution exposure for individuals is contingent not only on their work schedules and external weather conditions but also on their indoor behavioural patterns, including routine activities. Furthermore, other indoor actions, such as opening and closing doors and windows and operating ventilation systems, can modulate indoor pollution concentration [4, 47, 118].

Over time, academic research has highlighted various household elements that either directly or indirectly correlate with IAQ. Li et al. [119] suggested that bioaerosols, ventilation systems, and cleaning agents could escalate indoor air pollution levels [120]. Heo et al. [118] demonstrated a direct correlation between the number of occupants in space and the concentration of bacterial bioaerosols, influencing the air pollution index [121]. Several other studies [122-124] have deduced that the walking activity of indoor occupants can also modulate aerosol particle concentrations. Concurrently, research on IAQ [115, 116] has revealed that air particle filtration systems can substantially enhance indoor air quality, especially in residences housing individuals with allergies or asthma. Tran et al. [125] delineated the adverse health effects stemming from suboptimal IAQ, categorising them into four primary clusters: (i) neurotoxic effects, (ii) mucous membrane irritations, (iii) gastrointestinal and skin issues, and (iv) respiratory symptoms. The study also delved into the pronounced health impacts of poor IAQ on vulnerable demographics, including older people, infants, and those with chronic conditions. To address these concerns, global health organisations have promulgated guidelines. For instance, the World Health Organization (WHO) in 2010 released guidelines to mitigate public health risks associated with varying indoor air pollution exposure levels [126]. Similarly, the National Institute for Health and Care Excellence (NICE) England in 2020 introduced guidelines to amplify public awareness regarding optimal IAQ [127]. However, a challenge persists as these guidelines, despite their comprehensive nature, sometimes present non-cohesive or contradictory reference values [128].

The research community and governmental entities have shown significant interest in improving IAQ and promoting awareness through behavioural changes. However, the effectiveness of such awareness campaigns depends on whether the communication medium suits the intended audience. Choosing an appropriate communication medium for the target demographic is crucial to ensure better results [129]. Lin et al. [47] embarked on a study exploring the nexus between human behaviour and IAQ within a smart home setting. The research underscored a robust association between in-home human activities and IAQ, focusing on the influence of indoor temperature as an activity indicator. Other studies have accentuated the importance of ventilation practices [130-133] or underscored cooking as a predominant factor influencing IAQ [134-136].

Furthermore, socioeconomic factors, including household income [137, 138], house characteristics [139], and societal diversity [140], also play a pivotal role in affecting IAQ. Brown et al. [141] undertook a study in France, discerning a correlation between socio-economic status (SES) and IAQ, wherein households with constrained financial resources exhibited elevated indoor pollution levels. Another study by Rumchev et al. [139] in urban India highlighted the detrimental impact of limited income and indoor smoking on women’s and children’s well-being. Different nations' cultural and lifestyle diversity invariably influences IAQ [140, 142]. A study by Walton et al. [143] in East London assessed 333 children (8–9 years) of different ethnicities. This study found that prolonged air pollution exposure (PM and NOx) considerably impacted telomeres length, leading to ageing and immunological senescence later in life.

To summarise, IAQ is a multifaceted domain influenced by human activities, building attributes, and external environmental factors. While human indoor activities and building characteristics play a direct role, socio-economic and cultural nuances further complicate the IAQ landscape. Academic research underscores the health implications of poor IAQ, especially among vulnerable demographics. Despite global health organisations' efforts to establish guidelines, challenges persist due to occasional inconsistencies in reference values. The interplay between human behaviour, socioeconomic factors, and IAQ necessitates a holistic approach, emphasising awareness campaigns and technological interventions to ensure optimal indoor environments for all.

Research Gap: Current research often overlooks the nuanced ways in which diverse socioeconomic backgrounds influence individual and collective actions affecting IAQ, suggesting a gap in developing targeted interventions that address varied demographic needs.

2.7 Changes in Human Behaviour for Raising Awareness on IAQ

The profound importance of IAQ and its consequential effects on human health is a topic that has been thoroughly investigated in many scholarly studies [35, 133, 144-146]. These academic explorations have consistently underscored a pivotal finding: providing readily accessible air quality data to individuals markedly amplifies their comprehension and cognisance of IAQ [147, 148]. This enhanced understanding fosters a deeper appreciation of their environment and empowers them to make informed decisions about their health and well-being [149, 150]. Ventilation, a critical component in maintaining optimal IAQ, eliminates indoor pollutants and introduces fresh air into the indoor environment [151-155]. Indoor pollutants can include common elements such as dust and humidity. However, when the ventilation systems are inadequate or the quality of the incoming air is subpar, it can lead to various health issues. These issues can range from respiratory infections to exacerbating allergies, underscoring effective ventilation systems' importance [125, 156, 157]. Creating a comfortable indoor environment is a comprehensive process involving human behaviour and architectural design [158]. Key factors that contribute to this process include the rate of ventilation, thermal comfort, lighting control, and the layout and organisation of the house. These elements uniquely shape the indoor environment and the IAQ [151, 159]. Experts have implemented various strategies to reduce indoor air pollution and improve IAQ. Among these, air ventilation has been highlighted as a significant area of focus. The current research and governmental initiatives trend is leaning towards improving IAQ and promoting behavioural changes [35]. These behavioural changes can include simple actions such as opening windows to allow fresh air in, using air purifiers, and regularly maintaining and cleaning ventilation systems.

However, these initiatives' success heavily depends on the effectiveness of the communication strategy used [125, 160, 161]. If the method fails to engage the intended audience, the awareness campaign may not yield the desired results. Therefore, ensuring that individuals understand the air quality they breathe at home is paramount. This understanding is not just about knowing the facts but also about realising the direct impact of IAQ on their health and well-being throughout their lives [145, 162].

In summary, the literature strongly advocates for increased awareness about IAQ and the integral role of ventilation in maintaining it. It also underscores the need for effective communication strategies to ensure the success of these awareness campaigns. The ultimate goal is to promote a healthier indoor environment and, by extension, healthier lives for individuals.

Research Gap: Studies focus on raising IAQ awareness through data dissemination but lack in-depth analysis of the efficacy of different intervention strategies across demographic segments to foster sustained behavioural changes.

2.8 Digital Platform, Interventions and Behavioural Change

The landscape of digital platforms is undergoing a revolutionary transformation driven by the convergence of technological advancements and increasing awareness of individuals' consciousness. Digital platforms are not just technological interventions; they represent a holistic approach that intertwines technology with citizens' behaviours to empower individuals to take charge of their daily routines. The essence of this empowerment lies in the active participation and engagement of citizens, which manifests in their behavioural attributes and perceptions [163]. The proliferation of digital platforms has ushered in an era of data-centric methodologies instrumental in shaping diverse outcomes. Digital platforms are generally equipped with cutting-edge analytical tools that offer many opportunities for professionals to devise targeted interventions, disseminate well-being messages with precision, and provide access to a treasure trove of domain-specific data. With its vast reach and scalability, the digital platform catalyses behavioural changes, fostering a culture of individual consciousness and proactive self-management [164]. Moreover, the digital platform’s adaptability and versatility make it an invaluable tool for crafting personalised interventions, bridging the gap between generic domain-specific advice and individual needs [165-167].

Air pollution, often dubbed the 'silent killer', has emerged as one of the most pressing environmental challenges to the public [168]. The insidious effects of pollutants permeate every facet of our lives, from the air we breathe to the food we consume. Addressing this immense challenge necessitates a comprehensive approach, encompassing an array of interventions tailored to safeguard the citizens. Interventions at the individual and community levels have been conceptualised and implemented with the primary objective of curtailing exposure to harmful pollutants. While diverse in their approach, such interventions share a common goal: to mitigate the associated risks with air pollution and foster a healthier living environment [169]. The role of personalised data in shaping public perception and engagement cannot be overstated. By leveraging granular data, professionals and policymakers can craft interventions that resonate with individuals, thereby driving meaningful behavioural change using digital platforms [166]. For instance, the study by Sater et al. [170] underscores the power of personalised interventions in raising awareness about indoor air pollution. Tailoring interventions to address individual needs and circumstances has been shown to be highly effective in promoting behaviour change. By customising the approach to each person's unique situation, interventions can better resonate and lead to sustained positive outcomes.

On the other hand, community-based interventions adopt a more holistic approach, targeting larger cohorts and addressing broader environmental and health challenges. The emphasis here is on collective action, with communities coming together to combat the menace of air pollution [171]. Mouri et al. [172] applied physical interventions to explore the impact of exercise among elderly citizens to explore if there is any association between changes in quality of life and behavioural change. The results showed substantial differences in quality of life between the citizens who followed the exercise schedule and those who did not. Fan et al. [173] conducted a field study of the effects of the bedroom window and door opening hours concerning IAQ, sleep quality, and next-day cognitive performance. The analytical result showed that interventions in opening windows and doors are required to achieve good IAQ, sleep quality, and individual human behaviour. As we navigate the complexities of the digital health landscape and grapple with the challenges posed by air pollution, it is imperative to adopt a forward-looking approach. The future of digital platforms lies in harnessing technology's power to craft effective interventions that resonate with individuals. By fostering a culture of human consciousness and empowering individuals with the tools and knowledge to make informed decisions, we can pave the way for a healthier, more resilient society.

In summary, the relationship between digital platforms, behavioural change, and air pollution offers a unique vantage point to address some of our most pressing health challenges. As we continue to innovate and evolve, the onus is on us to leverage the potential of technology and data to drive meaningful change and ensure a healthier future for all.

Research Gap: While digital interventions are recognised for their potential in promoting IAQ awareness, the specific mechanisms to optimise these platforms for maximum engagement and behaviour change remain underexplored.

2.9 COM-B Model & IoT: Shaping Behaviour & Air Quality Awareness

In health and well-being, many programmes have strategically employed the Behaviour Change Wheel (BCW), incorporating the COM-B model, to enhance specific behavioural patterns across a wide range of populations. This model, an integral part of the BCW, is predicated on the principles of Capability, Opportunity, and Motivation, which collectively influence Behaviour (COM-B). Simultaneously, the IoT has ushered in a new era of Location-based Services (LBS) technologies. These technologies have been instrumental in monitoring IAQ, thereby fostering a heightened awareness of air pollution among the general public. The COM-B model, a pivotal component of the BCW, offers a triad of distinct advantages to applied researchers and developers engaged in behavioural change. Foremost, it provides a comprehensive explanation of the assumptions that underpin behaviour change interventions, delineating their intricate connections to the broader theories of human motivation. This elucidation demystifies the complex mechanisms that drive behavioural change, facilitating a deeper understanding of the process.

Secondly, the theoretical framework of the COM-B model is mainly exclusive to this particular research domain. This exclusivity presents upon the model a unique set of concepts and terminologies that can be effectively communicated to individuals who may be unfamiliar with the field. This aspect of the model bridges the gap between experts in the field and those outside it, fostering a broader understanding and appreciation of the work being conducted in this area. Lastly, the COM-B model provides invaluable guidance on selecting interventions likely to yield the highest efficacy for specific groups or behaviours. This guidance can help improve behaviour by designing targeted interventions. [174].

The COM-B model has been extensively applied in public health messaging and monitoring behavioural changes [175, 176]. This includes a diverse array of interventions, both digital and traditional, aimed at achieving a variety of health-related goals. These goals include weight reduction, smoking cessation, minimising the unnecessary usage of antibiotics, and enhancing physical activity levels [177, 178]. In-depth research was conducted by Xu et al.

[179] to establish the correlation between air pollution and travel patterns. It is quite surprising to note that the study conducted on outdoor air quality and the travel behaviour of citizens did not reveal any significant correlation between the two. This unexpected outcome underscores the intricate nature of people's responses to environmental stimuli and the criticality of continuing comprehensive research in this area.

To summarise, the COM-B model is a vital aspect of the Behaviour Change Wheel that helps to decode health behaviours. As research highlights, with the increasing use of IoT-enabled technologies, it is essential to grasp the complex relationship between human behaviour and environmental cues.

Research Gap: Research applying the COM-B model in IAQ contexts is emerging, yet evidence is scarce on the model's application in real-world settings, particularly in assessing the long-term effectiveness of IoT-based interventions on behaviour change.

2.10 Technology Acceptance Model for User Acceptance and Adoption

The Technology Acceptance Model (TAM) is a theoretical model developed to explain and predict user acceptance of information systems. The model suggests that when users are presented with a new technology, their acceptance or rejection of this technology is influenced by two primary factors: perceived usefulness and perceived ease of use [180]. Over the years, TAM has been extended and modified to include additional factors that can influence technology acceptance. Despite its simplicity, TAM has been widely used in various research contexts and has proven robust in understanding and predicting user acceptance of technology. In the comprehensive review of TAM by Yousafzai et al. [181], the authors propose a unified model that integrates TAM with other user acceptance models, providing a more holistic understanding of technology acceptance. Zhou [182] applies TAM to the context of mobile payment, extending the model with perceived credibility and personal innovativeness in the domain of IT, demonstrating the model's adaptability to different technological contexts. Laukkanen [183] investigates user resistance, a factor often overlooked in TAM, identifying perceived risk, role clarity, and self-efficacy as critical factors influencing user resistance. This enriches our understanding of the barriers to technology acceptance. Kim et al. [184] introduce the concept of the user's perceived discretionary power into TAM, underscoring the importance of user autonomy in technology acceptance. Taherdoost [185] overviews various theories and models related to technology acceptance, including TAM. This work reinforces the relevance of TAM in technology adoption and underscores the importance of understanding the factors that drive users' acceptance or rejection of technologies.

Further studies have applied TAM in various contexts, such as Fintech services [186], mobile health interventions in resource-limited settings [187], e-commerce/e-business technology among small and medium enterprises [188], and educational technology [189]. Venkatesh et al. [190] develop and test a theoretical extension of TAM that explains perceived usefulness and usage intentions regarding social influence and cognitive instrumental processes. Al-Rahmi et al. [191] explore the students' behavioural intention to use social media and actual social media use in higher education. Abu-Taieh et al. [192] examine the most crucial factors that could predict Jordanian customers' continued intention toward the use of m-banking. Deng et al. [193] investigate the status of contrast-enhanced ultrasound (CEUS) utilisation and its predictors in China.

In summary, these research collectively comprehensively understand TAM and its extensions. They underscore the importance of various factors in understanding user acceptance of technology, such as perceived usefulness, perceived ease of use, perceived risk, role clarity, self-efficacy, personal innovativeness, and perceived discretionary power. These insights can guide the design and implementation of technology to ensure higher user acceptance.

Research Gap: Existing applications of the TAM in environmental monitoring are limited, indicating a gap in understanding factors influencing user acceptance of IAQ monitoring technologies.

2.11 Navigating Digital Transformation: The Role of Digital Analytics

The field of digital analytics, including Web Analytics, User Experience (UX), Predictive Analytics and social media analytics, has gained significant attention due to its potential applications in e-commerce and healthcare [194-196]. The web platform access and the online surfing process are influenced by perceived risk for virtual stores, e-store design, and the psychological state of the consumer [197]. The use of technology and media enhances user engagement in the web market. This kind of analytics benefits product development by providing real-time user feedback [198, 199]. Baishya et al. [200] have noted the influence of social factors on the adoption of smartphones and behavioural intentions. Handheld devices such as laptops and mobile, particularly those used by different ethnic groups, present new opportunities for businesses to explore [195]. Nevertheless, the implications of implementing these applications on user satisfaction and their prospective usage necessitate a more in-depth exploration [201]. Maintaining a heightened concentration level and prioritising the user's ultimate contentment is imperative for achieving a satisfactory outcome while browsing digital platforms [202]. Individuals with a wealth of knowledge and experience accessing digital platforms have developed confident expectations regarding the features and conveniences they encounter during their in-store experiences. They anticipate a comparable level of comfort and efficiency, regardless of whether they are browsing the virtual aisles or physically walking through the doors of a brick-and-mortar establishment [203]. Data privacy and security concerns persist despite the widespread adoption of web and mobile applications for user engagement. These concerns may stem from a lack of transparency regarding how app developers collect, store, and use user data. As a result, many individuals remain cautious when sharing personal information through these platforms and may prefer alternative communication and engagement methods with businesses [204].

Data analytics is crucial in strategic decision-making, offering competitive advantages in the health domain business and as a valuable tool in academic research. It transforms complex data into actionable insights, fostering innovation and knowledge creation across various disciplines [205, 206]. In the rapidly advancing area of visual analytics, the ability to convert complex data into clear, actionable insights is becoming increasingly critical for effective decision-making. This process, which leverages the visual representation of data, allows decision-makers to identify patterns and trends that might otherwise be hidden, thereby enhancing the quality of strategic decisions [207, 208].

In academic research, Google Analytics has emerged as a valuable tool for tracking the behaviour of web users [209-211]. The incorporation of this particular approach has genuinely revolutionised the way web platform designers approach their craft. Specifically, it has markedly improved the overall aesthetic appeal and user experience of websites. As a result, users can now enjoy more engaging and fulfilling interactions with the content they encounter on these sites. The benefits of this approach are clear, and it is easy to see why it has become such a popular and widely utilised technique in web design. [212]. Furthermore, Google Analytics has been instrumental in categorising website visitors, providing insights into user demographics and behaviour patterns [213]. These capabilities have facilitated a more nuanced understanding of user interactions, enabling researchers and practitioners to tailor their strategies to meet the needs and preferences of their target audience [214]. However, its use as an independent area of enquiry is limited. Most studies analysing Google Analytics data are from the domain of digital libraries [215], indicating a research gap in several disciplines. Another study examined user search behaviours in domain-specific digital libraries, revealing a preference for basic keyword searches. Notable differences emerged between the two libraries, with interface design potentially influencing user choices. The findings emphasize the need for advanced search options, guiding future digital library development and research [216]. User data analytics, encompassing user demographics and actions, is a field of significant interest to both scholars and industry professionals. This area offers valuable insights for strategic decision-making and user experience enhancement, making it a crucial tool in today's data-driven firm landscape [217].

Moreover, the digital transformation landscape focuses on the role of analytics and its impact on various sectors. Peter et al. [218] provide a roadmap for digital transformation in large organisations, emphasising the need for a holistic approach. Kutnjak et al. [219] offer a comprehensive review of case studies centred on Digital Transformation (DT) across diverse sectors, including Information and Communication, Manufacturing, and Health. The findings indicate that while DT is pervasive across industries, its adoption varies in timing and depth. Firms leverage digital technologies, from business integration to cost reduction. Yet, a strategic approach to DT is imperative for companies to enhance their market stance and remain globally competitive. Across the board, DT is perceived as an innovative strategy to address future business challenges. Reinartz et al. [220] extend the discussion to the retail sector, illustrating how digital transformation is reshaping the retailing value chain. Soto Setzke et al. [221] examines the evolving role of IT departments in digital transformation for health care and other sectors, suggesting a shift from a support function to a strategic partner. Dal Mas et al. [222] conducted a comprehensive review of research on digital transformation within healthcare from 2017 to mid-2021, emphasising the effects of the COVID-19 pandemic on healthcare entities. Their systematic literature review identified critical applications and stakeholders of innovative digital technologies in this rapidly evolving sector. The findings categorised digital technologies into five primary domains, further informing three prospective research trajectories for digital transformation in healthcare. These trajectories encompass digital healthcare services, stakeholder engagement via digital means, and the value proposition of digital transformation for healthcare participants.

Pencarelli [223] emphasises the importance of website quality in the digital age, indicating that high-quality websites can enhance user experience and contribute to any sector's success. Ucuz et al. [224] provide a comparative analysis of leading IoT cloud vendors, offering insights into the strengths and weaknesses of these platforms. Lamot et al. [225] explore the integration of audience analytics in Belgian digital newsrooms, suggesting that audience analytics can inform editorial decisions and contribute to the success of news organisations.

In summary, the reviewed literature underlines the transformative power of digital technologies and analytics in reshaping the health sector, business models, IT departments, and user experiences across various sectors. They highlight the need for organisations to adapt their strategies and operations to the digital age, leveraging analytics and other digital capabilities to enhance performance and competitiveness. Future research should focus on exploring these areas, particularly the use of Google Analytics in different domains and the potential of event-based tracking data for understanding user behaviour.

2.12 Transtheoretical Model and Stages of Change Questionnaires

The Transtheoretical Model (TTM), also known as the Stages of Change Model, is a well-established theoretical framework for understanding long-term behaviour change. Prochaska and DiClemente [226, 227] developed the model initially applied to smoking cessation [226] but has since been applied to various behaviours, including health-related behaviours [227, 228]. TTM conceptualises behaviour change as a process that unfolds over time, involving progression through six stages: pre-contemplation, contemplation, preparation, action, maintenance, and termination. Each stage represents a different level of readiness to change.

- **Pre-contemplation:** In this stage, individuals are not considering change and may not be aware that their behaviour is problematic.
- **Contemplation:** Individuals acknowledge the problem but struggle with uncertainty about change.
- **Preparation:** The individual intends to change soon and may start making small changes.
- **Action:** This stage involves active modification of the behaviour.
- **Maintenance:** The individual works to consolidate gains and prevent relapse.

Each stage of change characterises the challenges and strategies needed to progress to the next stage, thereby providing a framework for developing effective interventions to promote health behaviour change. The Stages of Change Questionnaire (SOCQ) is an assessment tool derived from the TTM [229, 230]. The SOCQ is designed to determine an individual’s readiness to change a specific behaviour by identifying the stage of change that best describes their current status. By identifying an individual’s stage of change, interventions can be tailored to their current readiness to change, potentially increasing the effectiveness of the intervention.

Applying the TTM and SOCQ in the IAQ context offers a unique way to understand and influence behavioural changes associated with air quality improvement. At the core of this process is the individual’s awareness and understanding of indoor air quality and its impact on health. This stage is critical, as maintaining behaviour change over the long term can be challenging. Interventions at this stage might focus on reinforcing the benefits of improved IAQ, providing ongoing support, and helping individuals to develop strategies for maintaining behaviour change. The SOCQ can be used at different stages of the intervention to assess individuals’ readiness to change and to tailor interventions according to their needs. By identifying where an individual is on their behaviour change journey, interventions can be targeted more effectively, enhancing the likelihood of sustained behaviour change. Garner et al. [231] analysed the exercise behaviours of 178 community-dwelling stroke patients, leveraging the SOCQ to discern their readiness to initiate an exercise regimen. The findings validated the TTM as an instrumental framework in evaluating stroke patients' readiness to engage in exercise. Gonzalez et al. [232] study endeavoured to construct and validate the Health Behavior and Stages of Change Questionnaire (HBSCQ), underpinned by the TTM, focusing on health recommendations pertinent to cancer risk mitigation. Additionally, a study [233] aimed at promoting physical activities among individuals utilised the constructs of the TTM, including stages of change, processes of change, decisional balance, and self-efficacy, which were measured at three distinct time points: preintervention, three months, and six months post-intervention. These studies underscore the instrumental role of TTM and SOCQ in fostering a deeper understanding of behaviour change across varied health domains.

Furthermore, applying TTM and SOCQ allows for a more nuanced understanding of the behavioural changes associated with IAQ improvement in the IAQ context. It also provides a valuable framework for developing and implementing interventions to promote these changes and measure their effectiveness. The long-term success of any behaviour change initiative, including those related to improving IAQ, hinges on the ability of individuals to maintain the new behaviours over time [234]. Behavioural maintenance, defined as the continued adherence to behaviour after the initial behaviour change, is a critical aspect of the behaviour change process [235]. The TTM maintenance stage represents this phase where individuals strive to consolidate the gains made during the action stage and prevent a return to the old behaviours [236]. The maintenance concept is rooted in the understanding that behaviour change is not an event but a process and that sustaining the changes over the long term often requires ongoing efforts. Rothman [237] notes that the challenges faced during the maintenance stage are qualitatively different from those encountered in earlier stages. While initial behaviour change often relies on motivations such as perceived benefits of change or emotional reactions, maintenance of behaviour change is influenced more by the outcomes and the context in which the behaviour is enacted [238, 239].

For instance, in the context of IAQ, while initial changes may be motivated by the awareness of health risks associated with poor IAQ or the desire to improve well-being, maintaining these changes might depend on the perceived effectiveness of the behaviour in improving IAQ, ease and convenience of the behaviour, and support or reinforcement from others. The ability to monitor and visualise IAQ may also influence behavioural maintenance in the IAQ context, which was proven in our previous study [35]. IAQ monitoring sensors and web platforms can provide real-time feedback on IAQ, which may provide a powerful reinforcement for the continued practice of the new behaviours. Such feedback mechanisms can create a more tangible link between the new behaviours and their impact, making it easier for individuals to see the value in maintaining the behaviours.

The TTM and the SOCQ present a comprehensive framework to understand, measure, and influence behaviour change in various contexts, including IAQ. Using these models in conjunction with modern IAQ monitoring technologies offers a promising avenue to motivate individuals towards healthier behaviours concerning IAQ [236, 240]. However, as the COM-B suggests, achieving initial behaviour change is just one part of the process in our previous study [35]. The real challenge lies in maintaining these behaviours over the long term, a critical aspect that ensures the sustained health benefits associated with improved IAQ. While some behaviours may be easy to adapt and maintain, others may require substantial effort and continual reinforcement.

Current research on IAQ and behavioural change emphasises primarily the earlier stages of instability—increasing awareness about IAQ and instigating initial behaviour modifications. However, it is equally essential to focus on the maintenance stage to understand how individuals consolidate these behavioural changes and the challenges they face in doing so. More importantly, studying the maintenance stage would focus on the elements that could promote sustained positive changes, an area that is relatively under-researched at present. There are also considerable opportunities to explore the interplay of personal, social, and environmental factors that influence the maintenance of IAQ-related behaviours. For instance, an individual’s motivation and capability to maintain behaviour can be affected by social support, their beliefs and attitudes towards the behaviour, and their physical environment [174]. Exploring these factors can provide a more holistic understanding of the maintenance stage in the context of IAQ.

In summary, the literature points to the necessity of longitudinal studies that follow individuals through their journey of change regarding IAQ behaviours, paying particular attention to the maintenance stage. Despite its importance, the maintenance of behavioural change in IAQ is relatively under-studied. More research is needed to understand the factors influencing the long-term sustainability of IAQ-related behaviours and how interventions can be designed to support individuals in this critical stage of the behaviour change process. These studies would be instrumental in developing practical, sustainable interventions for IAQ improvement, ultimately contributing to improved public health.

Research gap: The TTM and SOCQ within the IAQ context are the limited explorations of long-term behaviour change maintenance. There's a crucial need for longitudinal studies that focus on the sustainability of IAQ-related behaviours beyond initial adoption, specifically investigating how interventions can support enduring behaviour change. This encompasses understanding the multifaceted influences on behaviour maintenance to develop more effective, lasting IAQ improvement strategies.

CHAPTER 3: DATA-DRIVEN SENSOR SELECTION AND CALIBRATION

The development of LCS devices has been supported by a three-step data-driven sensor selection and calibration methodology, as illustrated in Figure 1. In Step 1, a range of sensors was identified as candidate sensors based on a literature review and market availability and specifically identified popular candidate sensors for PM and CO_2 monitoring. OPC-R1, PMS5003 and PM Nova SDS011 were chosen for PM and SGP30, CJMCU-611, and CU-1106 for CO_2 monitoring. The selection process considered the sensors' availability in the UK market and the suppliers available, guided by procurement criteria established by the university regulations. In addition, the sensors' datasheets and available libraries to support their implementation with programming have also been considered. Combining these factors created a shortlist of candidate sensors for the use cases. In Step 2, a data-driven statistical analysis was employed to select sensors from the shortlisted candidates. Finally, in Step 3, a calibration process was applied to the selected sensors to enhance the quality of the data obtained in the use case.

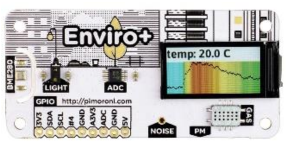
Candidate Sensors **Sensor Selection** **Sensor Calibration**

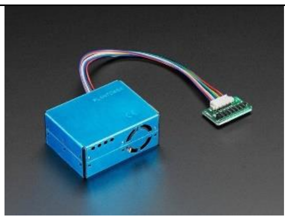
Figure 1: Process diagram for sensor selection and calibration to build AQ monitoring device.

3.1 Step 1: Selection of Candidate Sensors

The LCS-based use case aims to develop a dependable AQ monitoring system that can measure multiple pollutants, such as PM, CO_2, NO_2, NH_3, CO, and Volatile Organic Compounds (VOCs), as these pollutants heavily depend on various activities carried out in the human indoor environment [37]. For example, the concentration of pollutants depends on their emissions and meteorological conditions such as wind speed (WS), relative humidity (RH), and turbulence. Additionally, meteorological parameters and other atmospheric compounds can affect sensor measurements. Furthermore, gas sensors may also exhibit cross-sensitivity, where the concentration of a particular pollutant measured by a sensor can be influenced by the concentration of a different pollutant due to measurement techniques. However, the cross-sensitivity of sensors was not considered during the selection of gas sensors for this study. Instead, the sensor selection process relied on the information provided by the manufacturers to measure specific gases. To measure air pollutants, the following candidate sensors listed in Table 1 were considered for use either indoors or outdoors. These sensors were selected based on existing studies and market availability [241-243].

Table 1: List of candidate sensors and their information

Candidate Sensor Name	**Description**	**Sensor Specification**	**Image**
BME680	This sensor can measure temperature, humidity, barometric pressure, and VOC gas.	Temp in Celsius (*C), Humidity - %, Barometric pressure – hPa	
CJMCU-811	This sensor can be used for detecting eCO_2, VOC gases. It is a digital gas sensor integrated CCS801 sensor and 8-bit Analog-to-digital converter (ADC).	eCO2 in ppm, VOC gases in ppb.	
SGP-30	This gas sensor is mainly used to monitor eCO_2 and TVOC.	eCO2 in ppm, VOC gases in ppb.	
Envio+	This pHAT is a collection of multiple sensors such as BME280 which can measure temperature, humidity, and pressure, MICS6814	BME280: temperature (*C), pressure (hPa), humidity (%) LTR-559 light and proximity sensor MICS6814 analog gas sensor (CO, NO_2, NH_3)	

	analogue gas sensor is responsible to measure CO, NO_2 and Ammonia (NH_3) and LTR-559 light and proximity sensor. Also, it has a built-in ADS1015 analogue-to-digital convertor and 0.96"colour LCD for display.		
SDS011	This sensor is used to measure $PM_{2.5}$ and PM_{10} air pollutants. This sensor is an infrared-based laser sensor and has a fan to provide self-airflow.	$PM_{2.5}$: ug/m^3 PM_{10}: ug/m^3	
PMS5003	It is used to measure PM_1, $PM_{2.5}$ and PM_{10}.	$PM_{2.5}$: ug/m^3 PM_{10} : ug/m^3	
OPC-R1	This sensor is used to detect PM_1, $PM_{2.5}$ and PM_{10} with the help of laser scattering technology.	$PM_{2.5}$: ug/m^3 PM_{10} : ug/m^3	
MQ-2	This gas sensor is mainly used to detect CO, Methane, Butane, LPG, smoke.	LPG and propane - 200ppm-5000ppm Butane - 300ppm-5000ppm Methane - 5000ppm-20000ppm Hydrogen - 300ppm-5000ppm Alcohol - 100ppm-2000ppm	

3.2 Step 2: Data-Driven Analysis to Narrow down the Selection of Low-Cost AQ Monitoring Sensors.

The next challenge was to identify the most feasible sensors from the candidate sensors. Statistical and drift analyses were employed to provide statistical-analysis-based reasoning for selecting the most viable sensors among the candidates. For instance, to measure $PM_{2.5}$ and PM_{10}, three sensors, namely SDS011, PMS5003, and OPC-R1, were compared in a lab environment for 48 hours with a reading interval of 15 minutes to determine the best feasible sensor for PM measurement. These sensors measure PMs without any human activity, ensuring that there is no external influence on the sensor measurement. Subsequently, the sensors' consistency was also tested among themselves. SDS011 and PMS5003 sensors were deployed for 48 hours in the same lab environment to assess consistency among sensors from the same manufacturer. The purpose of deploying sensors in a human-activity-free lab environment was to ensure that devices of the same type were consistent among themselves. This deployment of three sensors was intended to ensure that sensors of the same type (from the same manufacturer) were consistent among themselves in the same environment. If sensors from the same type and manufacturer were not consistent when exposed to the same environment, they were discarded from consideration for the next step of calibration.

All the selected LCS have working limitations, as mentioned in the manufacturer's datasheet. For example, SDS011 has a particle measurement range of 0.00-999.99 $\mu g/m^3$. In the lab experimentation, general case scenarios were considered, which reflect that all the sensor ranges fall under the general working environment.

3.2.1 Statistical Approach

The statistical approach is a mathematical technique utilised to extract information through data analysis. In this approach, the measured data were statistically analysed to perform a comparative analysis for sensor selection. For instance, the $PM_{2.5}$ and PM_{10} readings were recorded for 48 hours with a 15-minute time interval using three different PM sensors: SDS011, OPC-R1, and PMS5003. As depicted in Figures 2 and 3, the data were plotted, indicating variations in readings among the sensors in the same environment.

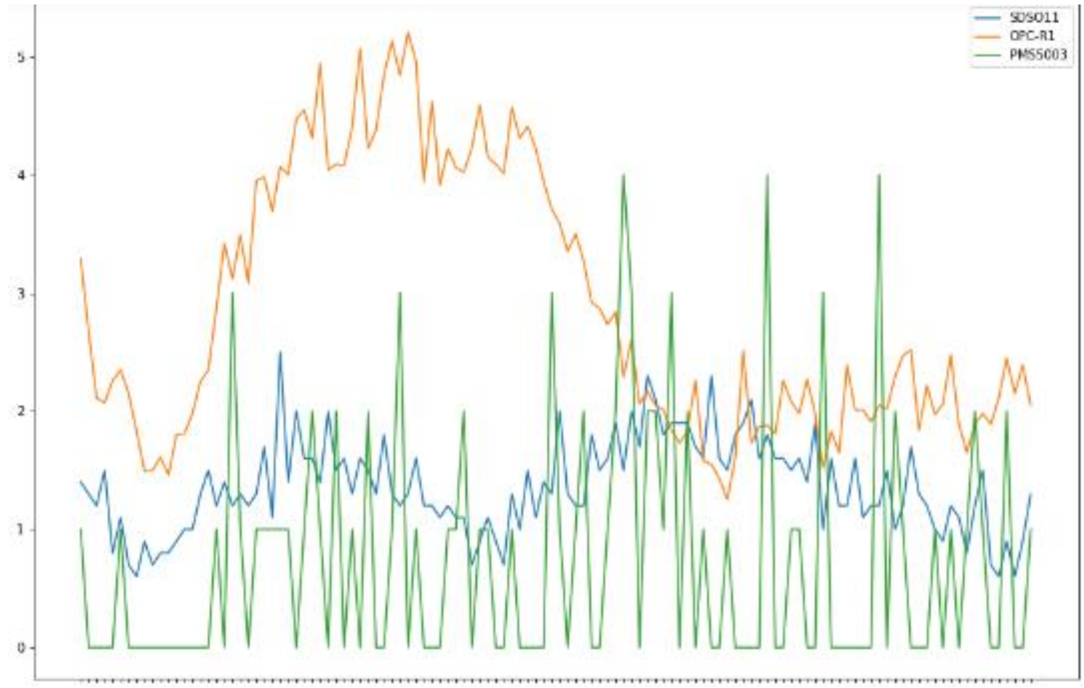


Figure 2: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in the lab environment for $PM_{2.5}$ every 15 minutes for 48 hours.

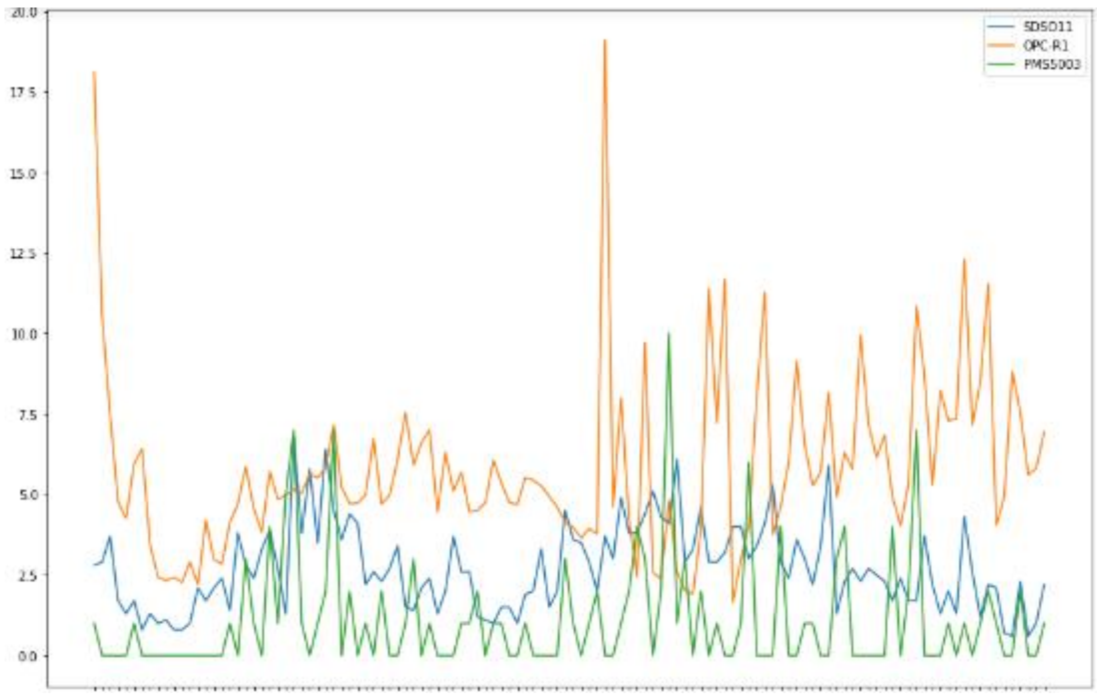


Figure 3: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in the lab environment for PM_{10} every 15 minutes for 48 hours.

In addition to visual analysis, statistical measures were used to compare the SDS011, PMS5003 and OPC-R1 sensors in terms of consistency. Measures such as mean, standard deviation, maximum value, minimum value and distribution were employed to validate the sensor data. The results for $PM_{2.5}$ and PM_{10} are presented in Tables 2 and 3, respectively. These measures provide confidence in the consistency of the sensor readings. The tables show that the SDS011 sensor has the lowest Standard Deviation (SD) in the experimental lab setup, indicating that its data are more uniformly distributed than the other two sensors. Furthermore, when the readings were analysed at 90% distributed values, it was found that the SDS011 sensor performed better than the other two sensors. The 90% distribution values indicate that most of the SDS011 readings are close to the mean value compared to the other two sensors, implying that the SDS011 sensor has more uniform readings than the others.

Table 2: Statistical observation of $PM_{2.5}$ from three sensors

	Name of the PM sensors		
	SDS011	***OPC-R1***	***PMS5003***
Number of Observations	96	96	96
Mean	1.358	2.871	0.725
Standard Deviation	0.394	1.108	1.003
Minimum Value	0.6	1.25	0.0
Maximum Value	2.5	5.21	4.0
90% distribution value	1.9	4.41	2.0

Table 3: Statistical observation of PM_{10} from three sensors

	Name of the sensor		
	SDS011	***OPC-R1***	***PMS5003***
Number of Observations	96	96	96
Mean	2.709	5.809	1.083
Standard Deviation	1.33	2.802	1.77
Minimum Value	0.6	1.64	0.00
Maximum Value	6.8	19.1	10.0
90% distribution value	4.4	8.853	3.00

3.2.2 Drift Analysis

In order to assess the consistency of sensors, drift analysis has been employed to identify the general trend in the data distribution [73]. This is accomplished by comparing data distribution from the same sensors in the same environment. KS-statistical analysis, KL-Divergence and

JS-Divergence, and Euclidean Distance have been utilised to conduct the drift analysis. For this purpose, two sets of sensors, SDS011 and PMS5003, have been compared in terms of their $PM_{2.5}$ and PM_{10} readings under the same lab environment to calculate drift.

- **KS-Statistical Analysis**

In the context of drift analysis, the Kolmogorov-Smirnov (KS) algorithm has been widely employed as a commonly used algorithm [244]. The KS algorithm, which considers the lowest value as representing a more consistent data distribution, has been utilized to identify the most reliable sensor among SDS011 and PMS5003 for $PM_{2.5}$ and PM_{10} measurements. Based on the results presented in Table 4, it is evident that the SDS011 sensor exhibits a lower statistical KS-value for both $PM_{2.5}$ and PM_{10} as compared to PMS5003. These findings indicate that the SDS011 sensor is more consistent than PMS5003 in monitoring PM values within the same laboratory environment.

Table 4: KS-Statistical comparison for drift analysis

	Name of the sensor	
	SDS011	***PMS5003***
$PM_{2.5}$ (KS-Statistics)	0.2163	0.2339
PM_{10} (KS-Statistics)	0.1929	0.2397

- **KL- DIVERGENCE AND JS-DIVERGENCE**

In this study, the Kullback-Leibler (KL) divergence, as described in Equation (1) and presented in previous research [245], was employed to quantify the distance between two probability distributions. However, the KL-divergence, also known as relative entropy, has limitations in determining the distance between two distributions. It does not produce a symmetrical result between them, such as in the case of, i.e., $D_{KL}\left(p \| q\right) \neq D_{KL}\left(q \| p\right)$. To overcome this challenge, the Jensen-Shannon (JS) divergence and JS distance, which build on the KL-divergence, were employed [245]. In particular, the JS approach was used to assess the consistency between the sensors themselves.

$$D_{KL}(p \| q) = \sum_{i=1}^{N} p\left(x_i\right) .log\left(\frac{p\left(x_i\right)}{q\left(x_i\right)}\right) \quad \text{……….(1)}$$

$$JS\left(p \| q\right) = \frac{1}{2} * D_{KL}\left(\mathrm{p} \| \mathrm{m}\right) + \frac{1}{2} * D_{KL}\left(q \| \mathrm{m}\right) \quad \text{………..(2)}$$

$$m = \frac{1}{2} * (p + q) \qquad \text{…………(3)}$$

$$JS - Distance\ (p \| q) = \sqrt{JS(p \| q)} \qquad \text{……..……..(4)}$$

Where D_{KL} = KL Divergence from *p* to *q*,

JS = Jensen-Shannon Divergence

p(x) and *q(x)* = data distribution of Sensor-1(A) and Sensor-1(B), respectively.

Two SDS011 and two PMS5003 sensors have been deployed to test KL-Divergence, and the result is shown in Table 5. At first, the KL-Divergence score has been calculated for the data distribution, and hence, the JS-Divergence has been calculated. The square root of the score of JS-Divergence gives the JS-distance between the two data distributions, as shown in Equations (2) and (4). The JS-Distance score varies between 0 (Identical) and 1 (max differences) when a base-2 logarithm is used. Also, the distance between two probability distributions is equal, i.e. $JS - Distance(p \| q) = JS - Distance(q \| p)$. Therefore, this method has been used for the drift analysis. From Table 5, it is observed that for both $PM_{2.5}$ and PM_{10}, SDS011 have a good score compared to PMS5003, which means SDS011 sensors have more consistency.

Table 5: JS-DISTANCE comparison for drift analysis

	Name of the sensor	
	SDS011	***PMS5003***
$PM_{2.5}$ (Sensor-1(A) and Sensor-1(B))	0.226	0.573
PM_{10} (Sensor-1(A) and Sensor-1(B))	0.408	0.550

3.2.4 Euclidean Distance

Euclidean distance (ED) is another approach to measure the consistency of the sensors, as demonstrated in Equation 5. ED is a mathematical technique commonly used to calculate the distance between two data points. In the context of sensor readings, ED is used to evaluate the accuracy of data distribution [246].

$$D_{ED}\left(p\,\|q\right)=\sqrt{\sum_{i=1}^{N}\left(p_i-q_i\right)^2}\;\ldots\ldots\ldots(5)$$

Where D_{ED} = mean distance between data points p and q.

p,q = two data distributions in Euclidean space.

After analysing the statistical approaches used in this study, it has been observed that SDS011 sensors outperform PMS5003 sensors in terms of their data distribution and drift analysis. This conclusion is based on the mean distance between the data distributions of $PM_{2.5}$ and PM_{10} recorded by both sensors, as listed in Table 6. Furthermore, the Euclidean distance analysis showed that SDS011 sensors performed better than PMS5003 sensors. Thus, it can be concluded that SDS011 sensors are more feasible than other PM sensors for measuring air pollutants in the LCS-based use case.

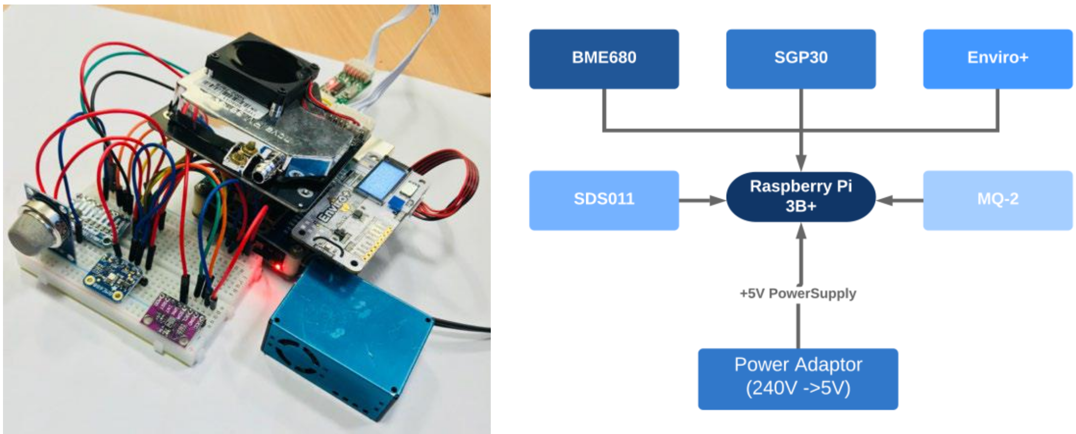
Table 6: Euclidean-Distance comparison for drift analysis

	Name of the sensor	
	SDS011	***PMS5003***
$PM_{2.5}$ (Sensor-1(A) and Sensor-1(B))	15.4735	22.4944
PM_{10} (Sensor-1(A) and Sensor-1(B))	30.9027	35.2136

In summary, step 1 helps to finalise candidate sensors for calibration based on the sensor's market availability and literature, whereas step 2 provides the statistical measures for sensor selection among candidate sensors. Other sensors are also selected for developing LCS devices for the use case, applying the same statistical approaches used in steps 1 and 2.

3.3 Step 3: Sensor Calibration Techniques

Following the completion of Step 1 and Step 2, the BME680, Enviro+, SGP30, SDS011, and MQ-2 sensors have been selected to build AQ monitoring devices for the measurement of air pollutants, as depicted in Figure 4. These sensors have been assembled with a Raspberry Pi 3B+ (RPi) for computational and connectivity purposes, thereby enabling remote access and control of the device. Additionally, the RPi facilitates data transmission to a cloud-based web server for data storage, analysis, and visualization.



(**a**) (**b**)

Figure 4: (a) Final LCS-based AQ monitoring device using RPi 3B+. (b) Block diagram of Final device with Raspberry Pi 3B+ and other LCS components.

Data quality aspects have been applied after building the AQ monitoring LCS-based device. Studies have argued that [19, 23, 32] sensor calibration is required to improve LCS-based systems' data quality. Considering this, from the calibration point of view, the two AQ devices have been deployed at "The Urban Flows Observatory (https://urbanflows.ac.uk/), Sheffield", as shown in Figure 5, for one month. Both the devices have selected sensors which monitor air pollutants such as CO, NH_3, TVOC, CO_2, NO_2, and PM ($PM_{2.5}$ & PM_{10}). Also, these devices have sensors that can measure meteorological parameters (temperature (T) and relative humidity (RH)). For $PM_{2.5}$ and PM_{10} data calibration, SDS011 PM sensors have been calibrated against the "high-end Palas Fidas 200" instrument installed at the remote van, as shown in Figure 5, by Sheffield City Council. This station monitors data at 30-minute intervals, whereas our AQ devices monitor data at every 10-minute interval. Data pre-processing has been applied to AQ data to convert it into 30-minute data using the mean value of three 10-minute readings. All the measured data have been received from the AQ devices every 10-minute time interval to the cloud-based web server (http://smartbradford.co.uk:7201/) and stored at the AQ devices in CSV (Comma-Separated Values) format.

Figure 5: LCS-based AQ monitoring devices using RPi 3B+ at Urban Observatory, Sheffield.

Different calibration models have been experimented with to compare and select the most accurate model. For example, $PM_{2.5}$ & PM_{10} data have been taken for experimental purposes and experimented with four calibration models: MLR, MLP, CNN and RF. The literature has argued that AH and RH act differently with different LCS in the calibration process. Mead et al. [247] show that the RH greatly depends on temperature; therefore, fluctuations can be observed in RH throughout the day. On the contrary, AH's value varies with changes in moisture content in the air, not remaining constant despite its independence from temperature fluctuations. Due to this factor, the calibration process is adapted based on AH as the corrections were constant and linear based on per unit change in AH. Piedrahita et al. [248] observed that temperature significantly impacts this sensor signal response. Still, the impact of AH is less on the signal response as it has been observed to be almost constant, contradictory to the RH impact on sensor signal response. However, they still consider AH in calibration modelling to improve the model performance. Also, some studies [249, 250] show that temperature and humidity have non-linear relations with particle concentrations. Research also indicates that $PM_{2.5}$ and PM_{10} values have a positive correlation with RH but a negative correlation with temperature and AH [74]. Considering these prior studies, temperature and humidity, along with the pollutant, have been applied for the calibration in this work. Regarding humidity as a factor in calibration, both AH and RH have been tested to determine which of these measures provides better results for data quality.

To find AH, the Clausius Clapeyron equation was used [251], as presented in Eq. 6,

$$AH = \frac{6.112 * e^{\left[\frac{17.67 * T}{T + 243.5}\right]} * RH * 2.1674}{273.15 + T} \quad \ldots\ldots\ldots\ldots (6)$$

Where, T = Temperature (*C)

RH = Relative Humidity (%) , e = Exponential

Using equation 6, AH has been calculated based on the two observations, T and RH, coming from the BME680 sensor and the exponential function. This AH has been used as one of the parameters for the calibration process.

$$R^2 = \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \quad \text{………. (7)}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad \text{……….(8)}$$

$$MAE = \sum_{i=1}^{n} \frac{|(\hat{y}_i - y_i)|}{n} \quad \text{……….(9)}$$

Where R^2 = R-squared

RMSE = Root Mean Square Error

MAE = Mean Absolute Error

SS_{RES} = Residual sum of squared errors of our regression model

SS_{TOT} = Total sum of squared errors

y_i = Observed value from our kit

$\bar{y}_i$ = Mean value of pollutants value from our kit

$\hat{y}_i$ = Values predicted by the model

n = Number of observations

In order to conduct a comparative analysis between AH and RH, experiments were conducted using selected models and analysed their impact on the results. Statistical measures have been used to evaluate the models presented in equations 7, 8, and 9. Specifically, performance metrics were calculated, such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) using the observed values (y_i)) recorded by LCS-based device, and the mean values ($\bar{y}_i$) of pollutant values from our devices. R^2 was computed as the ratio of our regression model's residual sum of squared errors (SS_{RES}) to the total sum of squared errors (SS_{TOT}).

1.3.1 Multivariate Linear Regression

Multivariate linear regression (MLR) is a commonly applied calibration method that involves adjusting coefficients in linear equations to account for dependencies between two or more independent variables and a single targeted variable, as illustrated by Equation 10 [252].

$$y_i = a_p * x_{ip} + \dots + a_1 * x_{i1} + a_0 + z_i \quad \dots\dots\dots (10)$$

Equation 10 is the generalised representation of MLR where a_p, a_1 and a_0 are coefficients, x_{ip}, x_{i1} are dependent variables, z_i is constant, and y_i is the calibrated targeted variable. In this study, the MLR model has been applied to the selected sensors using equations 11 and 12.

$$\hat{y}_{ref} = b_0 + b_1 * T + b_2 * PM_{raw} + b_3 * AH \quad \dots\dots\dots\dots (11)$$

$$\hat{y}_{ref} = b_0 + b_1 * T + b_2 * PM_{raw} + b_3 * RH \quad \dots\dots\dots\dots (12)$$

where $\hat{y}_{ref}$ = reference data from Palas Fidas 200, Sheffield

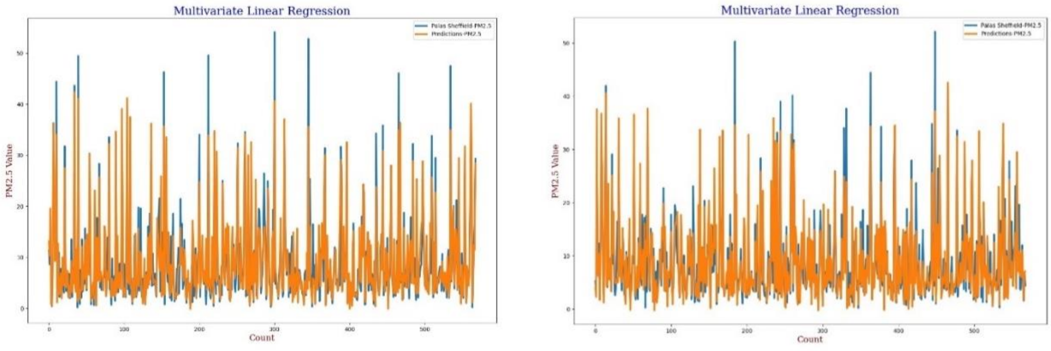
b_0 , b_1 , b_2 and b_3 = Regression coefficients

T = Temperature (*C), RH = Humidity (%) from BME680 sensor.

AH = Absolute Humidity (g/m^3)

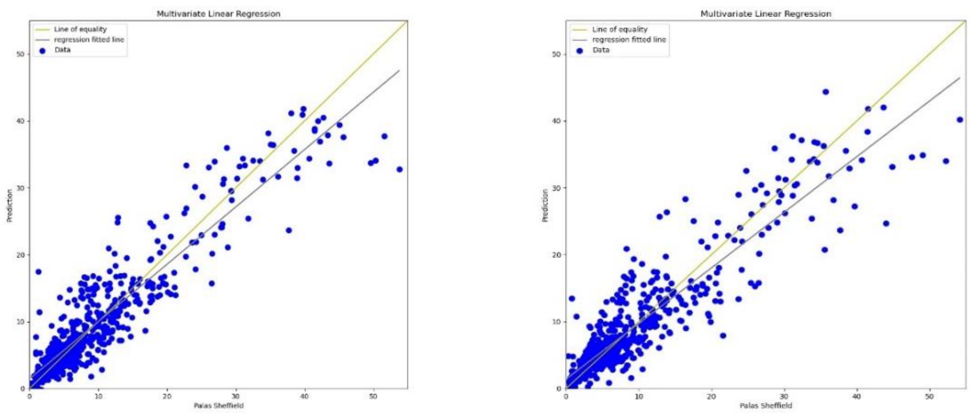
PM_{raw} = Mean PM data (from SDS011)

For the calibration analysis, line and scatter plots have been presented for both $PM_{2.5}$ and PM_{10}, as shown in Figures 6 - 9. Figures 6 & 8 are the line plots for $PM_{2.5}$ and PM_{10}, respectively, whereas Figures 7 & 9 show scatter plots for $PM_{2.5}$ and PM_{10}, respectively. From the line plots for $PM_{2.5}$ and PM_{10}, it can be observed that calibrated values are closer to the reference data when AH has been used. From the scatter plots, it can also be observed that the regression fit line is closer to the line of equality when AH has been used for the calibration compared to the RH for both $PM_{2.5}$ and PM_{10}. Analysis of these plots shows that AH performs better than RH in the calibration process.



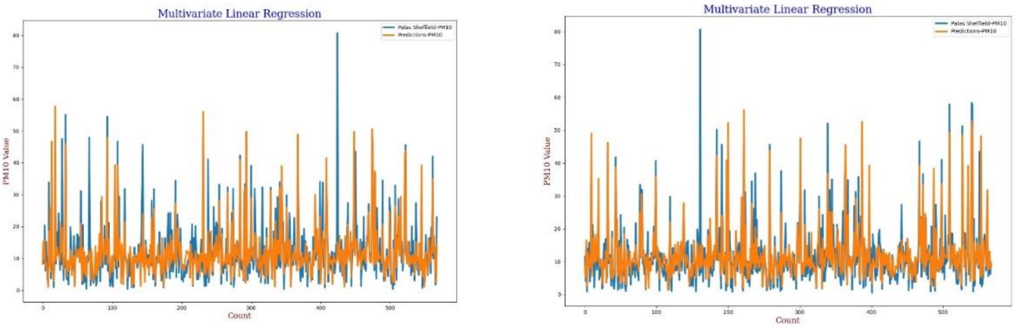
(**a**) (**b**)

Figure 6: (a) MLR calibration plot for $PM_{2.5}$ using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) MLR calibration plot for $PM_{2.5}$ using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.



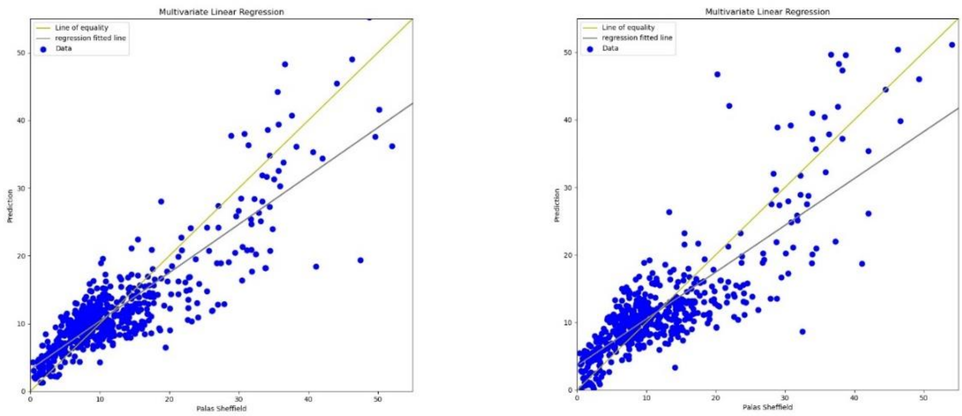
(**a**) (**b**)

Figure 7: (a) MLR calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using AH.; (b) MLR calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using RH.



(**a**) (**b**)

Figure 8: (a) MLR calibration plot for PM_{10} using AH. Blue represents the reference data, and orange represents the calibrated data; (b) MLR calibration plot for PM_{10} using RH. Again, blue represents the reference data, and orange represents the calibrated data.



(**a**) (**b**)

Figure 9: (a) MLR calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using AH.; (b) MLR calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using RH.

3.3.2 Multi-Layer Perceptron

In the field of Artificial Neural Networks, MLP is a forward-structured model that uses input vectors to produce output vectors. This method has been proven effective in solving various problems and is widely applied [253]. Figure 10 shows the design of the MLP model, which is used as the second calibration model. The input layer consists of four parameters: temperature, humidity (AH and RH), PM_{ref}, and PM_{raw}, and the calibrated PM value is obtained from the output layer. The same dataset that was used for MLR was also used for

MLP. The model has been designed as a sequential model with a relu activation function, Adam optimiser, and mean square error as a loss function with 2000 epochs for training.

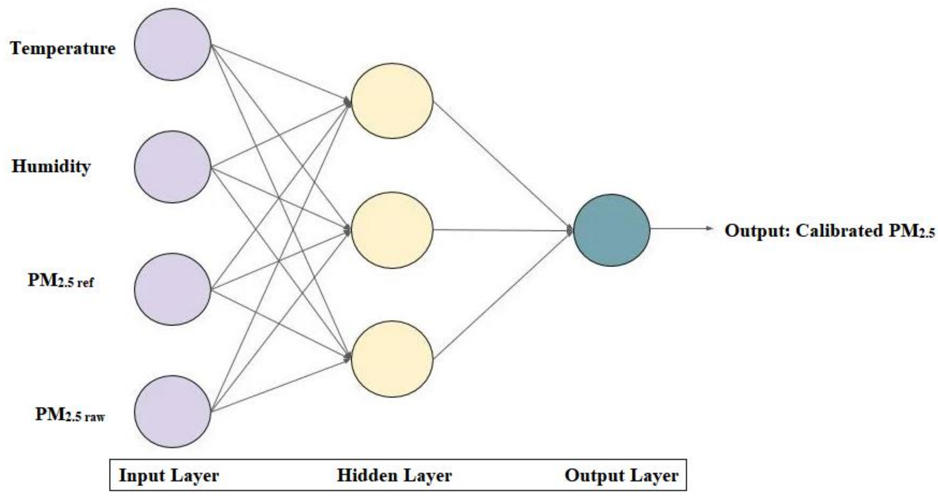
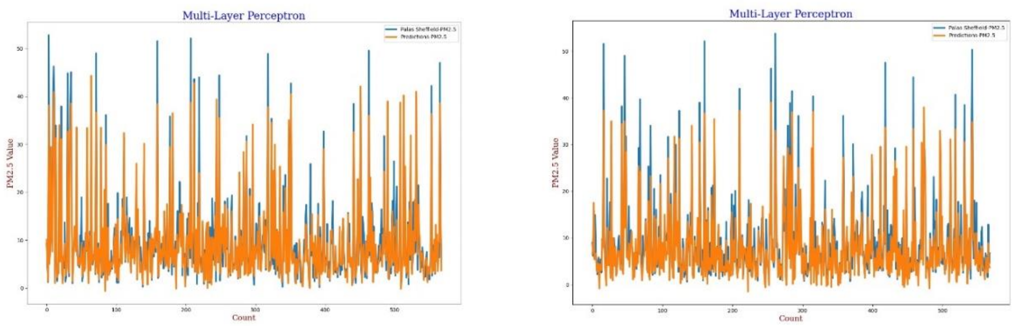


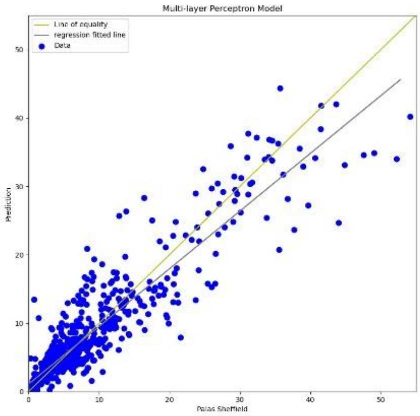
Figure 10: Block diagram of Multi-Layer Perceptron model

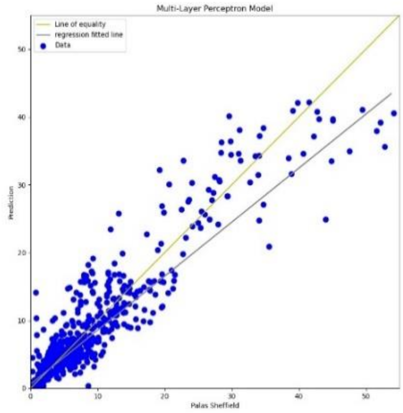
For the MLP calibration analysis, line and scatter plots have been observed for both $PM_{2.5}$ and PM_{10} as shown in Figures 11 – 14, where Figures 11 & 13 are the line plots for $PM_{2.5}$ and PM_{10}, respectively and Figure 12 & 14 shows scatter plots for $PM_{2.5}$ and PM_{10} correspondingly. Same as MLR, the calibrated line plots for $PM_{2.5}$ and PM_{10} are closer to the reference value when AH has been used. Similarly, in the scatter plots, the regression fit line is closer to the line of equality when AH has been used for the calibration in comparison to the RH for both $PM_{2.5}$ and PM_{10}. Analysis of these plots concludes that AH has better performance than RH in the calibration process in the case of MLP as well.



(**a**) (**b**)

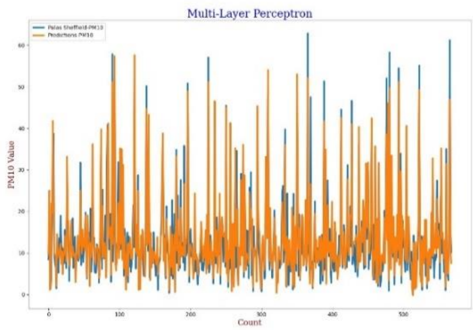
Figure 11: (a) MLP calibration plot for $PM_{2.5}$ using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) MLP calibration plot for $PM_{2.5}$ using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.

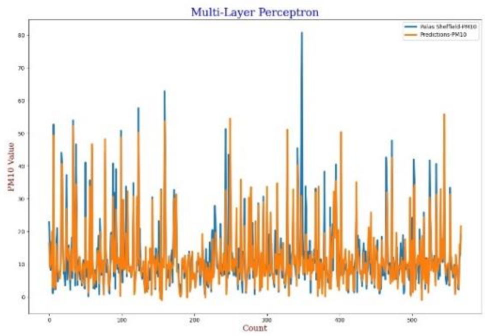




(a) (b)

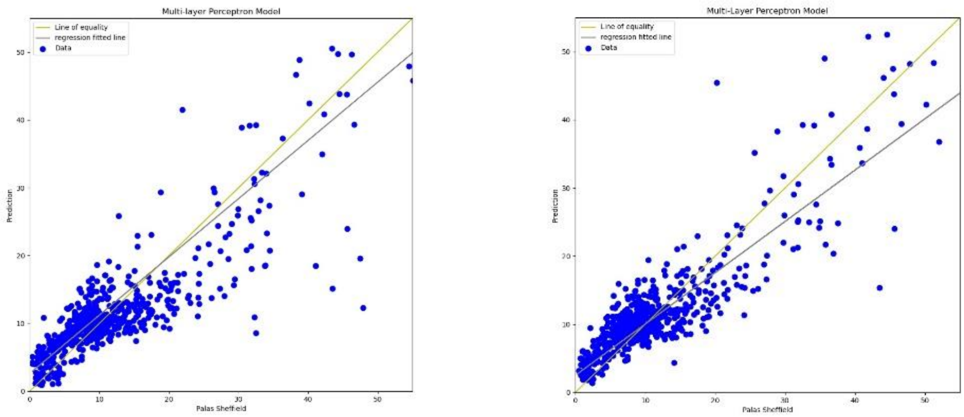
Figure 12: (a) MLP calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using AH.; (b) MLP calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using RH.





(a) (b)

Figure 13: (a) MLP calibration plot for PM10 using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) MLP calibration plot for PM10 using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.

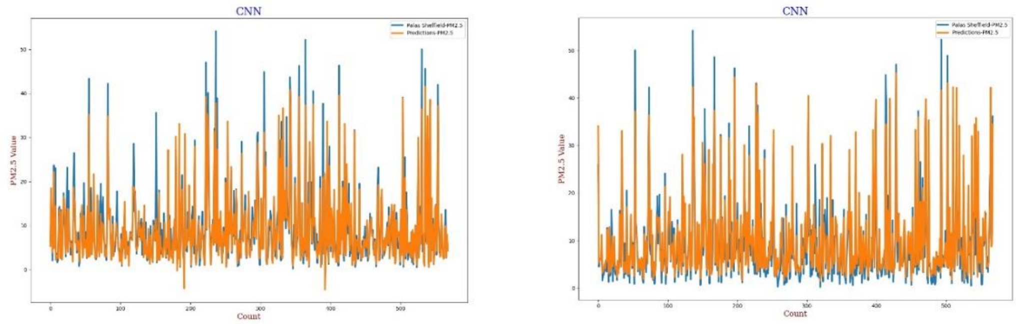


(a) (b)

Figure 14: (a) MLP calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using AH.; (b) MLP calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using RH.

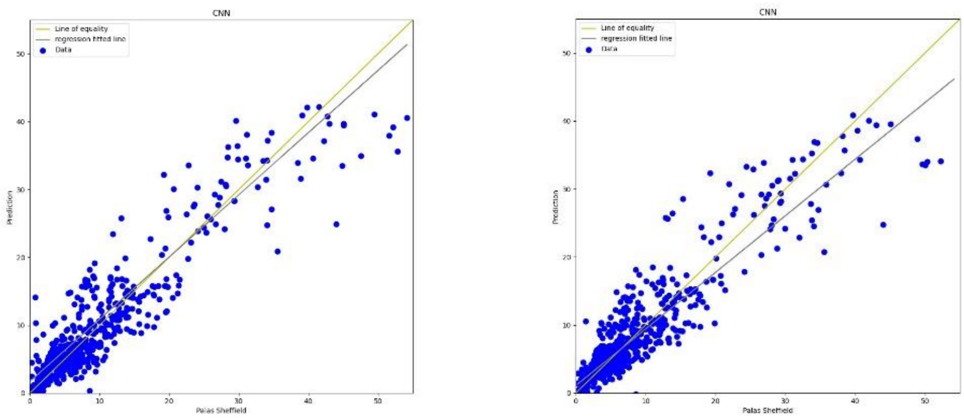
3.3.3 Convolution Neural Network

Recently, CNN architectures have been used in various sequential data modelling, such as time series [254, 255]. Moreover, CNN has appeared as one of the widely used calibration models as CNN can extract inherent information from the data set [256]. In the calibration, same as the MLP model, the CNN model has four 3-dimensional inputs, and a re-shape has been applied that gives 1 output, two hidden convolutional layers with 64 filters each and a window size of 2 is also defined for the CNN model. All layers were activated through the "relu" function with 2000 epochs support with the "adam" optimiser. The output in terms of line plots and scatter plots have been analysed for both AH and RH, as shown in Figure 15 – 18. This model also has similar results in both plottings, which support AH's calibration performance better than RH's.



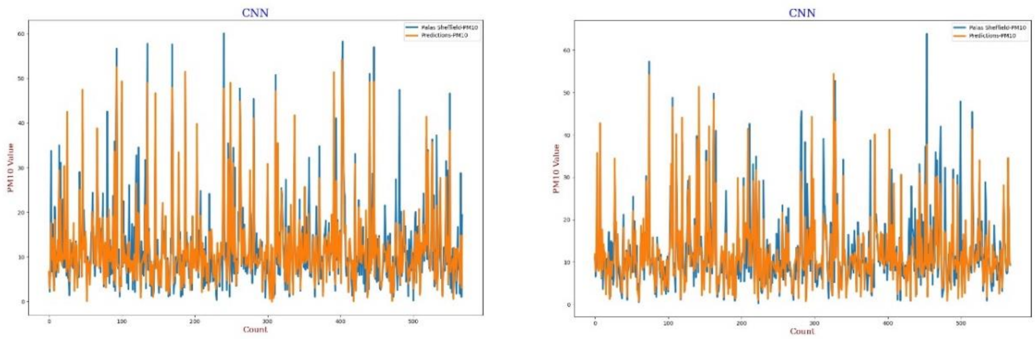
(**a**) (**b**)

Figure 15: (a) CNN calibration plot for $PM_{2.5}$ using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) CNN calibration plot for $PM_{2.5}$ using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.



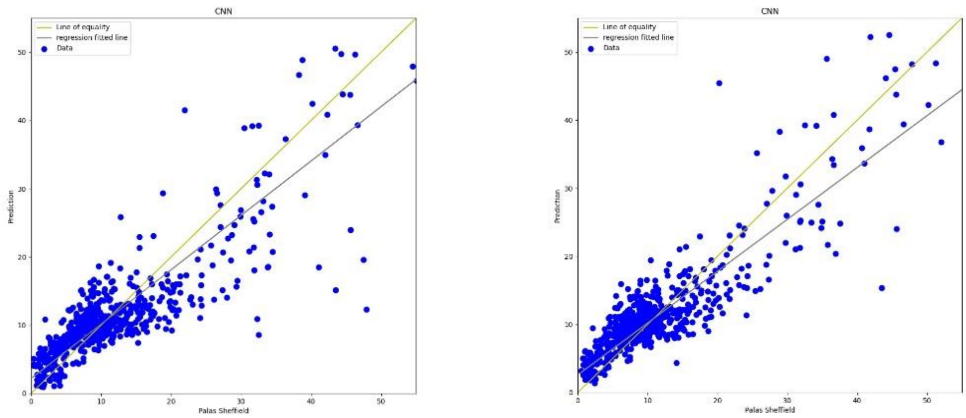
(a) (b)

Figure 16: (a) CNN calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using AH.; (b) CNN calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using RH.



(a) (b)

Figure 17: (a) CNN calibration plot for PM_{10} using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) CNN calibration plot for PM_{10} using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.

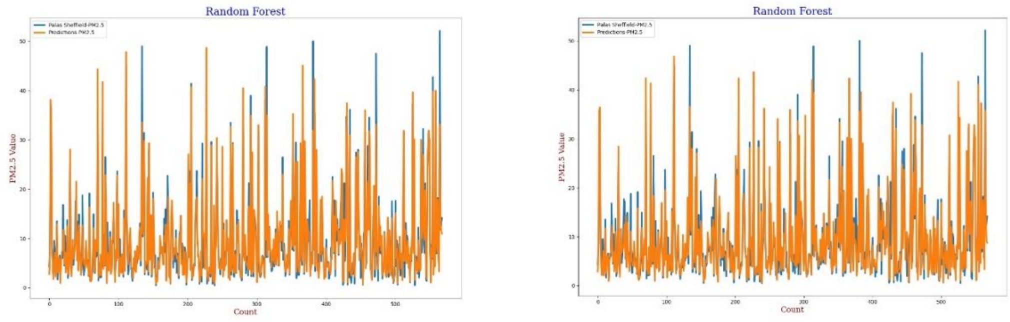


(a) (b)

Figure 18: (a) CNN calibration scatters plot for PM_{10} with the line of equality, regression fitted line and the calibrated data using AH.; (b) CNN calibration scatters plot for PM_{10} with the line of equality, regression fitted line and the calibrated data using RH.

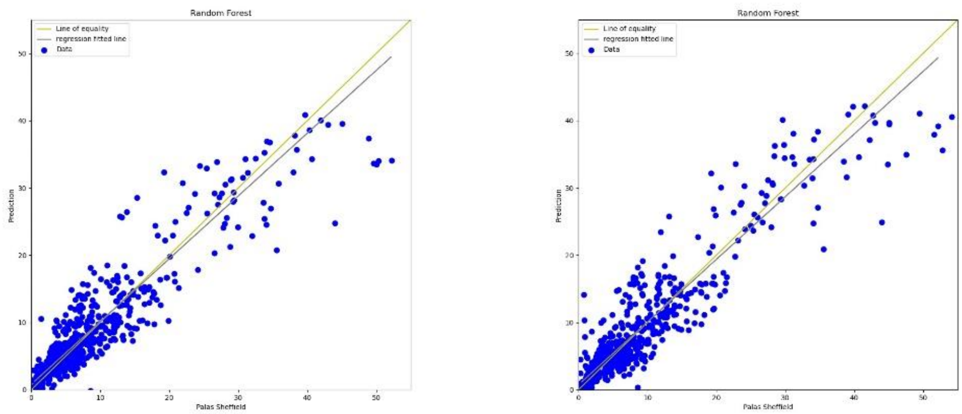
3.3.4 Random Forest

The Random Forest (RF) model is a machine-learning technique based on a combination of classification or regression trees introduced by Breiman in 2001 [257]. In this experiment, 20 trees were used in the forest for calibration by experimenting with different alternative tree sizes ranging from 10-25. The experimental results, lines and scatter plots have been analysed as the previous three models. Figures 19 – 22 show the lines and scatter plots obtained for AH and RH for both $PM_{2.5}$ and PM_{10}. The plot analysis shows similar results as the previous three models, supporting AH and performing better than RH for calibration.



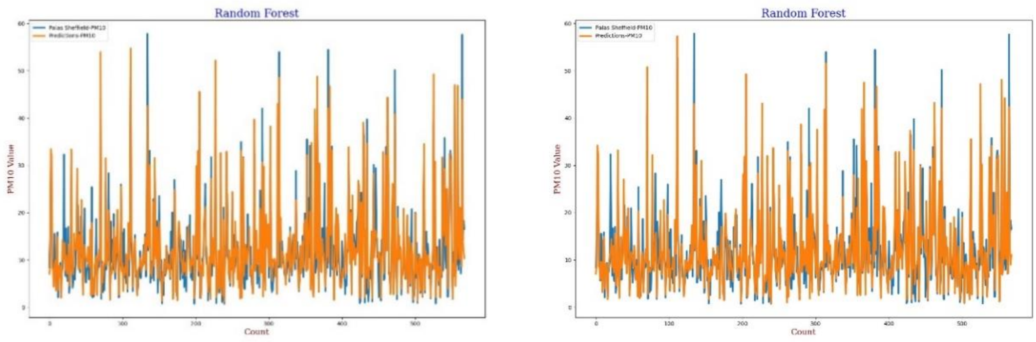
(**a**) (**b**)

Figure 19: (a) RF calibration plot for PM2.5 using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (b) RF calibration plot for PM2.5 using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.



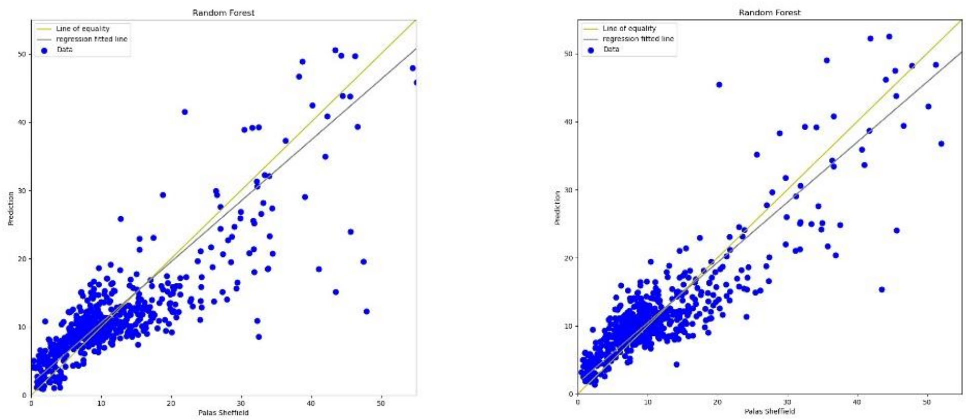
(**a**) (**b**)

Figure 20: (**a**) RF calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using AH.; (**b**) RF calibration scatters plot for $PM_{2.5}$ with the line of equality, regression fitted line and the calibrated data using RH.



(**a**) (**b**)

Figure 21: (**a**) RF calibration plot for PM_{10} using AH. Blue colour represents the reference data, and orange colour represents the calibrated data; (**b**) RF calibration plot for PM_{10} using RH. Blue colour represents the reference data, and orange colour represents the calibrated data.



(**a**) (**b**)

Figure 22: (a) RF calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using AH.; (b) RF calibration scatters plot for PM10 with the line of equality, regression fitted line and the calibrated data using RH.

3.4 Experimental Result Analysis

Four calibration models have experimented with the dataset of 1891 records for 1 month at the Sheffield data site. Among 1891 data, we have divided data into 70-30 ratios for training and testing data (number of training data = 1324 and number of testing data = 567) for all 4 models. For the comparative analysis, experimented results are summarized in Tables 7 and 8 for $PM_{2.5}$ and PM_{10}, respectively. In both the tables, five fields: R^2 (Coefficient of Determinations), RMSE (Root Mean Square Error) and MAE (Mean Absolute Error), Mean PMs' reading from the reference station and 4 calibration models. From Table 7, comparative analysis for $PM_{2.5}$, it can be observed that R^2 for the four calibration models have nearly the same values, ranging from 0.87 to 0.89 for the AH, whereas more variance in R^2 ranging from 0.84 to 0.88 when RH has been used. The RF model has the highest R^2 of both AH and RH cases among the four calibration models. The next parameters that have been compared are RMSE for both AH and RH. Analysing this, it has been noted that the RF model has the lowest RMSE for both AH and RH, which points out that it's able to fit the dataset the best out of the four calibration models. The next performance parameter that has been compared is MAE. Comparing MAE, the RF model has less error than other models. It has a nearly 47% improvement in errors in comparison with MAE for the MLR model.

The calibrated values from all four models are compared with the reference data. Mean values and standard deviations of reference data and calibrated models are compared. The comparative analysis has shown that the mean values of MLR and CNN calibration models are closer than the other two models, MLP and RF, to the reference mean when AH has been used. On the other hand, in MLP and RF models, mean values are closer than the MLR and CNN to the reference means when RH has been used. Comparing the standard deviation, it has been found that the RF model has the closest standard deviation values in both AH and RH cases to the reference standard deviation data. Similarly, in Table 8, all four models are compared with each other for PM_{10}. The comparative analysis reflected that there had been a wider variance among the measured performance measures' values for AH and RH for PM_{10} in comparison to $PM_{2.5}$. From Table 8, it can be analysed that the RF calibration model has fewer errors than the other three calibration models. It has also been observed that, for MAE, the RF model has a 25% improvement in MAE error measures than the other models. When comparing the mean readings, it has been noted that the MLR model is closer to the reference mean, and the MLP model is close to the reference standard deviation values. This comparative analysis of all these parameters shows that calibration models perform better when AH is used compared to RH. The results show that the RF calibration model (R^2 = 0.89, RMSE = 3.05 and MAE = 1.19) has appeared as the best calibration output compared with other models for $PM_{2.5}$. In the case of PM_{10}, there has been a variance in the performances of the different calibration models. R, the coefficient of determination of the RF (R^2 = 0.83) model, gives better results. However, it has also been observed that the CNN model gives a better result (R^2 = 0.81) with the use of RH for calibration, but RMSE and MAE are higher than RF, as shown in Table 8 for PM_{10}.

TABLE 7: Statistical performance measures analysis for $PM_{2.5}$

Model Name	**R^2**		**RMSE**		**MAE**		**Mean Reading (After Calibration) Reference Mean = 9.32 µg/m3**		**Standard Deviation (After Calibration) Reference Standard = 9.26 µg/m3**	
	AH	**RH**	**AH**	**RH**	**AH**	**RH**	**AH**	**RH**	**AH**	**RH**
MLR	0.87	0.84	3.32	3.65	2.19	2.58	9.36	9.86	8.72	9.13
MLP	0.88	0.85	3.20	3.48	2.13	2.18	9.60	8.10	9.08	7.94
CNN	0.89	0.88	3.07	3.65	2.01	2.30	9.26	10.29	8.32	9.50
RF	0.89	0.88	3.05	3.07	1.19	1.86	9.75	9.67	9.05	9.02

Table 8: Statistics for error calculation for PM_{10}

Model Name	**R^2**		**RMSE**		**MAE**		**Mean Reading (After Calibration) Reference Mean = 12.24 µg/m3**		**Standard Deviation (After Calibration) Reference Standard = 9.75 µg/m3**	
	AH	**RH**	**AH**	**RH**	**AH**	**RH**	**AH**	**RH**	**AH**	**RH**
MLR	0.79	0.75	5.28	4.95	3.69	3.53	12.39	12.52	9.10	8.81
MLP	0.81	0.78	4.43	4.68	3.13	3.26	12.64	12.35	9.55	9.01
CNN	0.80	0.81	4.42	4.71	3.04	3.19	12.45	12.10	9.15	9.09
RF	0.83	0.83	4.03	4.05	2.78	2.77	12.64	12.45	9.43	9.38

In this use case involving LCS-based AQ monitoring, the experimental setup and methodology used for sensor selection and calibration have the potential to be applied in similar applications across various domains. The methodology can be considered with its key success factors to create innovative LCS-based application device design solutions. This proposed methodology offers the opportunity to implement efficient and effective practices in LCS-based applications.

3.5 Chapter Summary

The study explores the potential of using LCS as an alternative to high-cost sensors for air quality monitoring. However, the selection process for LCS is challenging due to inconsistencies in standards, different measurement units, and diverse LCS available in the market with similar configurations. The study also reveals the impact of environmental factors such as temperature and humidity on the performance and reliability of LCS data. The study proposes a data-driven statistical approach for LCS selection and calibration to overcome these challenges. Calibration parameters are established using four widely used calibration models, and the best-suited model is identified. The proposed methodology is validated through experimental analysis, and the results are compared against high-cost monitoring station data. The study recommends defining acceptable uncertainty during measurements and conducting more extended observation and data analysis periods to enhance data quality and reduce uncertainty. In conclusion, the proposed methodology provides an efficient and effective approach for LCS-based applications, which can be transferable to other domains.

CHAPTER 4: CITIZEN ENGAGEMENT & BEHAVIOURAL CHANGE ANALYSIS

Changes in human lifestyle, urbanization, transportation, construction materials, and consumer products have significantly impacted indoor and outdoor air quality. These changes have transformed the composition and character of air pollutants over time [258]. These alterations have been accompanied by significant advancements in the scrutiny of air quality and the comprehension of the interplay among various factors influencing it [259]. Air quality is intrinsically linked to human health, as Bhatt et al. [260] have elucidated that chronic exposure to air pollutants can precipitate health complications, such as lung infections. Consequently, the monitoring of AQ and human activities is interconnected. In the context of Research Question 2, the investigation primarily concentrated on monitoring IAQ data and indoor human activities. The objective is to discern the correlation between IAQ and diverse parameters, including human indoor activities, socioeconomic status, and health conditions. Furthermore, the study explored how this information's availability increases citizens' awareness.

An IAQ monitoring experiment has been conceptualised to support RQ2 based on a use-case study. The Horton Park area, located within the Bradford Council, UK jurisdiction, has been selected as the site for conducting this study over two months. Throughout the study, measurements of indoor air pollutants have been taken concurrently with documenting daily human indoor activities and the participants' awareness. This approach facilitated a comprehensive understanding of the interrelationships between these variables and their collective impact on IAQ.

4.1 Design of Study

This study aimed to assess an IoT-based system for monitoring IAQ through experimentation. The study also determined if the visual presentation of IAQ data could improve awareness among participants. The research protocol underwent a thorough review and was approved by the University's Ethical Approval Panel, which falls under the Biomedical, Natural, Physical, and Health Sciences Research Ethics Panel. This study is a significant step towards making technological interfaces more user-friendly and intuitive, which can lead to a better understanding of IAQ data.

4.1.1 Horton Park Area and its Social Diversity

The study was geographically situated in the Horton Park area of Bradford, a city in the United Kingdom's northern region. The selection of study participants was meticulously carried out from this area. The Bradford Metropolitan District Council (BMDC), a collaborator in this research, was instrumental in bridging the gap between the researchers and the community group, thereby facilitating the establishment of initial points of contact. The participants were precisely chosen from a community group known as Friends of Horton Park. This group comprises active community members residing in and around Horton Park. The selection process was guided by the principle of coherence, ensuring that the participants were representative of the community's demographics and interests. The study's design and implementation were marked by a high degree of cohesion, with all elements working together to understand and enhance urban resilience and citizen engagement.

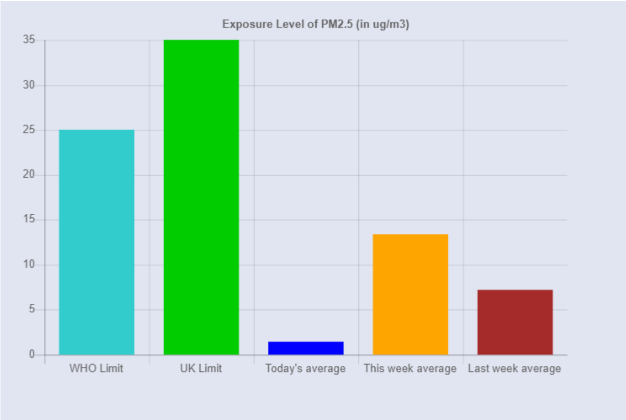
Moreover, the Bradford City Council has strategically chosen the Horton Park area as the focal point for this study due to its diverse socioeconomic landscape. As per the data provided by the Bradford Metropolitan District Council, this area exhibits a unique set of characteristics that make it an ideal case study for research. The Horton Park area is marked by a higher-than-average rate of overcrowded homes, with the figure standing at 8.9%. This is a significant deviation from the district average, indicating a unique housing situation in this area. Furthermore, the life expectancy of the male population in Horton Park is lower than the district average, while for women, it surpasses the district average. This disparity in life expectancy further underscores the area's socioeconomic diversity (https://ubd.bradford.gov.uk/district-profiles/ward-profiles-2021/, accessed on 15/04/2021). The housing structures in Horton Park are varied, with 44.4% terraced houses, 38.3% semi-detached, 9% detached, and 8.3% flats. This variety in housing types adds another layer of diversity to the area's socioeconomic profile. Notably, a significant portion of the UK's terraced houses, which constitute the majority in Horton Park, were built in the 19th and early 20th centuries. Often constructed inexpensively, these houses may present issues such as dampness, poor insulation, structural cracks, and roofing problems if not adequately maintained and modernised [261].

The social diversity, the mix of building types, and the presence of various ethnicities in the Horton Park Area make it an exemplary area for a use-case study. The unique combination of these factors provides a rich context for research, offering insights that may not be gleaned from a more homogenous area. Therefore, the selection of Horton Park as the research site is strategic and purposeful, aimed at generating a comprehensive understanding of diverse socioeconomic conditions.

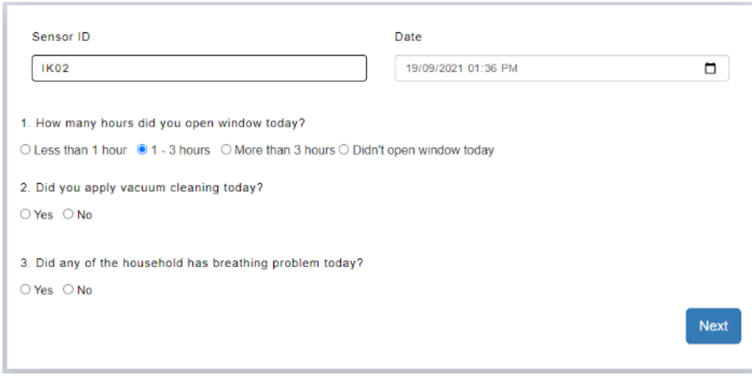
4.1.2 Study Instrument and Tools: IoT Device for IAQ monitoring, Visualisation Platform with Daily Digital Diary

In this preceding research, an IoT-based LCS device, discussed in the previous chapter, facilitated dependable IAQ monitoring. As delineated in Table 1, the calibrated device, equipped with an array of cost-effective sensors, enabled the tracking of air pollutants such as $PM_{2.5}$ and PM_{10} and meteorological parameters like temperature and humidity. It is important to note that these calibrated devices require a connection to the primary power supply and Wi-Fi for data transmission. The devices are programmed to collect and transmit IAQ data at 15-minute intervals to a secure cloud server for subsequent processing.

In this research, an innovative digital platform has been developed to facilitate the visualisation of IAQ data and the records of the daily indoor activities of the participants. This platform visually represents particulate matter data, specifically $PM_{2.5}$ and PM_{10}, through five distinct plots. These plots encompass the World Health Organization (WHO) limit, the UK limit, the average value for the current day, the average value for the current week, and the average value for the preceding week's indoor air pollutant data. The purpose of these five distinct plots is to empower participants by enabling them to compare their indoor air pollution readings with two established guidelines, namely those set forth by the WHO and the UK. This comparative analysis allows participants to understand better and manage their IAQ. Moreover, the platform incorporates a daily digital diary comprising nine interactive multiple-choice questions segmented into three stages. These questions relate to various indoor activities and conditions, including window ventilation, vacuum cleaning, respiratory issues, smoking, heating, and cooking. The design of these questions is grounded in the scholarly literature concerning socio-diversity and the health impacts associated with air quality [262-264]. This study has undergone rigorous health and safety approval processes, particularly emphasising adjustments related to the COVID-19 pandemic. This ensures that the study's procedures align with current health guidelines and best practices, safeguarding all participants' well-being.



(a)



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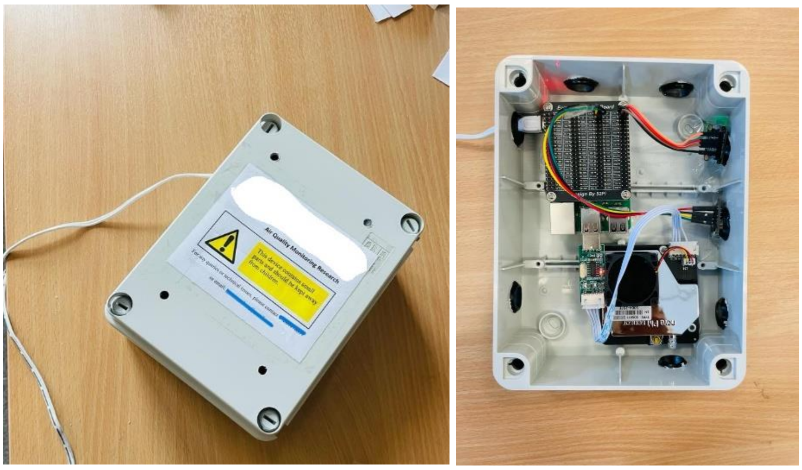


(c)

Figure 23: (a) IAQ data comparing with UK and WHO limits. (b) Digital daily activity log form. (c) LCS-based IoT assembled kit deployed at participant's house.

The research endeavour was executed over a period of two months, specifically from September to October 2021. The study spanned a total of eight weeks and involved a carefully selected sample of ten households. The selection criteria were designed to encapsulate a diverse range of socioeconomic and demographic variables, including geographical location, ethnic background, and the type of dwelling. Each participating household nominated a specific individual who was entrusted with the responsibility of accessing the IAQ data. This individual was also tasked with disseminating the data within the household and completing a daily digital diary on behalf of the household. Figure 23 (c) depicts that the IoT-enabled IAQ monitoring devices were strategically deployed within the participants' residences. Incorporating IoT technology into IAQ monitoring systems necessitates stringent security measures to ensure data confidentiality. Recognising this, our research implemented several key strategies to safeguard sensitive information. Data transmitted from IoT-enabled IAQ monitoring devices is encrypted using advanced protocols, ensuring that it remains secure in transit. Access to this data is tightly controlled, with robust authentication mechanisms in place to prevent unauthorised access. Furthermore, personal identifiers are anonymised prior to analysis, protecting participant privacy. These measures align with established best practices and regulatory standards, including GDPR compliance for research involving European Union participants. As IoT technology evolves, so too will the sophistication of security measures, underscoring the importance of continuous vigilance and adaptation to maintain the confidentiality and integrity of IAQ monitoring data.

After successfully installing the IAQ monitoring devices, an informative session was conducted with each household. These sessions aimed to educate the participants on using the IAQ visualisation platform and the process of filling out the daily digital diary. In order to uphold the privacy of the participants, all personal identifiers were anonymised. The linkage between participant IDs and the corresponding participants was also rendered anonymous. Throughout the duration of the study, regular contact with the participants was maintained, providing technical assistance as needed for accessing the platform or completing the diaries. This ensured a seamless flow of data collection and participant engagement throughout the research period.

4.1.3 Analysis of Initial Questionnaires

The commencement of the study necessitated the completion of an initial questionnaire by the participants (Appendix-A). This questionnaire was designed to elicit participants' subjective perspectives on the effects of substandard air quality. It also gathered data on various demographic factors, including ethnicity, level of education, combined household income, and proximity to the main road. Additionally, it collected information on the physical attributes of the participants' residences, such as the year of construction and type of house. Health-related queries were also included, focusing on the presence of any household members with asthma and the type of heating system employed.

The data analysis revealed a rich diversity in the ethnic backgrounds of the participants, with representation from Asian, Mixed, Arabic, and African ethnicities. This ethnic heterogeneity introduced a broad spectrum of variations into the study, encompassing differences in cooking styles, window opening habits, interior home configurations, and lifestyle patterns, which could influence IAQ monitoring. The ethnic breakdown of the participants was as follows: 40% identified as Asian or Asian British (specifically Pakistani), 20% as African, and 30% as other ethnic origins (including Arab and other Asian backgrounds). Further demographic details of the participants were analysed to enhance the diversity of the study, as illustrated in Table 9. The data also indicated a range in the participants' residential proximity to the main road. A significant 60% of the houses involved in the study were located within 0.1 km of the main road, while 30% were within 0.5 km. The types of residences varied as well, with one flat, two semi-detached houses, and seven terraced houses. The study also encompassed a mix of four electric and six gas cooker users. The heating systems in the participants' homes were diverse as well, with eight central heating systems, one electric, and one gas heating system. In summary, the initial questionnaire provided a comprehensive and diverse dataset, which is expected to contribute to a nuanced understanding of the impact of various factors on IAQ.

Table 9: Summary of initial questionnaire outcome of participant's demographic information.

Sensor ID	House Location	Type of House	Type of Cooker	Type of Heating
IK01	Within 0.1 km from the main road.	Terraced	Electric	Central heating
IK02	Within 0.1 km from the main road.	Terraced	Gas	Central heating
IK03	Within 0.1 km from the main road.	Terraced	Gas	Central heating
IK04	Within 0.1 km from the main road.	Semi-detached	Gas	Central heating
IK05	Within 0.1 km from the main road.	Flat	Electric	Electric heating
IK06	More than 0.5 km from the main road	Terraced	Gas	Central heating
IK07	Within 0.1 km–0.5 km from the main road.	Terraced	Gas	Central heating
IK08	Within 0.1 km–0.5 km from the main road.	Terraced	Electric	Central heating
IK09	Within 0.1 km–0.5 km from the main road.	Semi-detached	Electric	Central heating
IK10	Within 0.1 km from the main road.	Terraced	Gas	Gas Heating

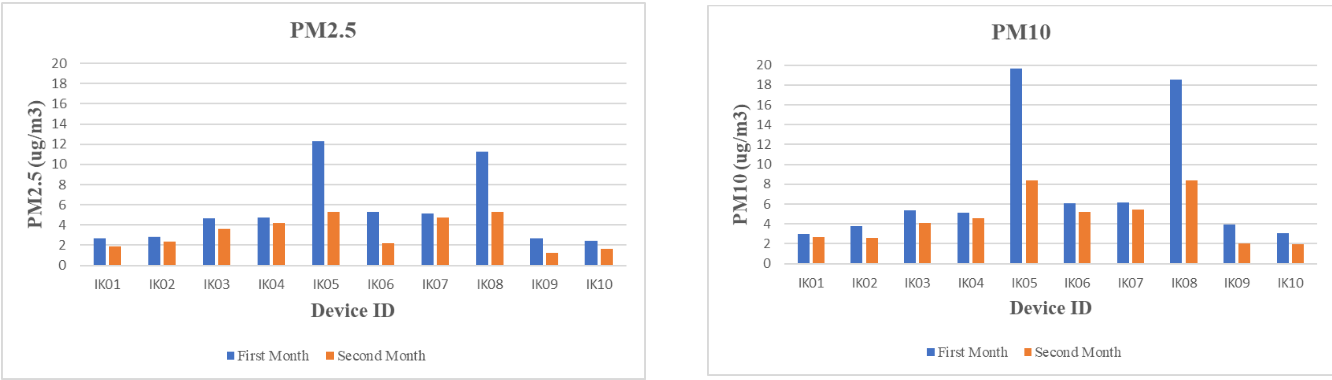
4.2 Data Analysis and Discussions

For the purpose of a comprehensive examination, the dataset has been bifurcated into two distinct monthly periods. This division facilitated a more granular analysis, enhancing the findings' accuracy. The final data evaluation has been systematically structured into three sequential stages. (i) IAQ Readings Analysis - This step is crucial as it provides an understanding of the air quality parameters within the indoor environment, thereby offering insights into potential health implications. (ii) Indoor activities analysis - This step is instrumental in identifying the correlation between human indoor activities and their impact on indoor air quality. It provides a comprehensive understanding of how everyday indoor activities can change the IAQ and potentially affect the health and well-being of the inhabitants. (iii) analysis of the increase in awareness - This step is pivotal in assessing the effectiveness of the measures implemented to enhance the understanding of IAQ among the participants. It provides a measure of the success of educational interferences and their impact on awareness levels related to indoor air quality.

4.2.1 IAQ Readings Analysis

An examination of the data presented in Figure 24 reveals a notable enhancement in indoor air quality during the second month of the study compared to the initial month. The primary objective of this analysis was to discern any significant changes in the levels of indoor air pollution. However, it is crucial to note that the observed improvements were inconsistent across all participating households. The data indicates a range of improvement, with the minimum enhancement recorded at 0.4 $\mu g/m^3$ and the maximum at 6.96 $\mu g/m^3$ for $PM_{2.5}$. For PM_{10}, the improvement ranged from a minimum of 0.26 $\mu g/m^3$ to a maximum of 11.2 $\mu g/m^3$. These findings are further illustrated in Figures 24 (a) and (b), which depict the indoor air pollution readings. Upon closer inspection of these figures, it becomes evident that the average indoor pollution level, represented by $PM_{2.5}$ and PM_{10}, experienced a significant reduction in the second month of the study. Specifically, the average $PM_{2.5}$ level decreased by 60%, while the PM_{10} level decreased by 80.43% among all participating households.

A t-test was conducted to validate these findings further. The results of this test confirmed that the average indoor pollution levels during the first month ($PM_{2.5}$: M = 5.41, SD = 3.54, and PM_{10}: M = 7.46, SD = 6.24) were indeed higher than those recorded during the second month ($PM_{2.5}$: M = 3.26, SD = 1.57, and PM_{10}: M = 4.54, SD =2.39). The parameters used in the t-test include the mean (M), standard deviation (SD), and sample size (n) for each group, along with the calculated t-value and p-value. This statistical approach allowed us to assess the significance of observed differences, ensuring that our findings are robust and reliable. This analysis demonstrated a significant improvement in IAQ, with $PM_{2.5}$: $t(9) = 2.82$, $p = 0.01$, and PM_{10}: $t(9) = 2.24$, $p = 0.026$, respectively. In conclusion, the data analysis provides compelling evidence of a significant improvement in indoor air quality throughout the two-month study. However, the degree of improvement varied among the participating households, indicating the need for further research to understand the factors contributing to these variations.



(a) (b)

Figure 24: (a,b): IAQ (PM2.5 and PM10) improvement patterns from all participant households, with blue plots showing the first-month readings and the orange plots showing the second-month readings.

4.2.2 Indoor Activities Analysis

The empirical data on indoor air pollution delineates a discernible enhancement in indoor air quality, as graphically represented in Figure 24. This study precisely examined the amelioration in air quality, correlating it with the diverse indoor activities recorded by the participants in their daily digital diaries over two distinct months. A salient indoor activity that was scrutinized in this context was the duration of the window opening. Participants were requested to document the length of time for which they kept their windows open in their daily digital diaries. A comparative analysis was conducted on the duration of window-opening across the first and second months by all participants, as presented in Figure 25. The findings from this analysis revealed a marked improvement in the duration of the window opening, with an increase ranging from 11% to 39%. Furthermore, the comparative study indicated a higher window opening frequency in the second month compared to the first month. Statistical analysis compared the average window opening duration in the first month ($M = 62.1$, $SD = 22.52$) with that in the second month ($M = 79.6$, $SD = 24.94$). The results significantly indicated an improvement in the duration of the window opening in the second month, $t\ (9) = -7.13$, $p = 0.000055$ (< 0.001). This statistical evidence underscores the enhancement in the window opening duration in the second month.

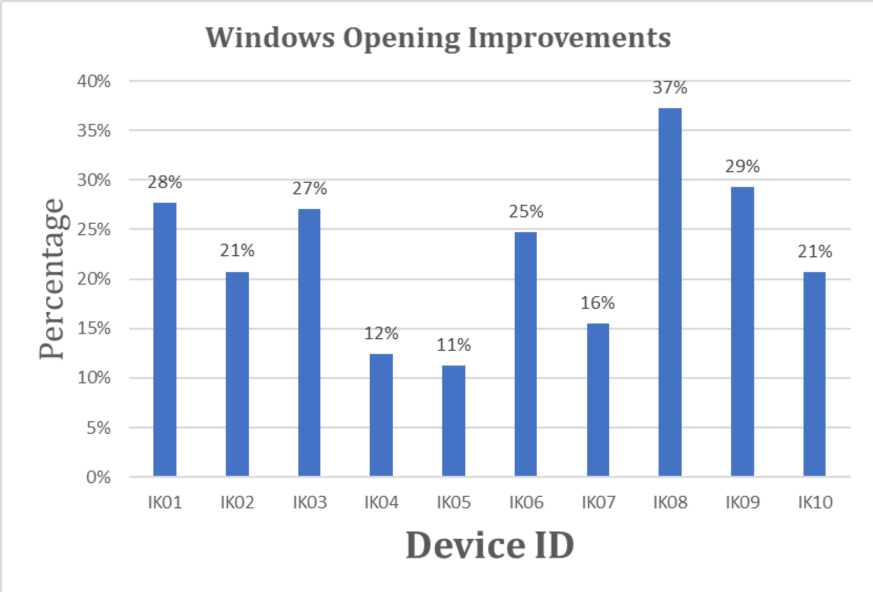


Figure 25: Shows improvement compared to the first month of deployment in the second month.

4.2.3 Measuring Awareness with Qualitative Analysis

After conducting a study, a semi-structured interview (Appendix B) was conducted to assess participant's understanding of IAQ after conducting a study. Due to the COVID-19 pandemic, the interviews were conducted online. The interviews aimed to explore four areas of awareness. The data collected was analysed to understand the participants' experiences and their level of awareness.

(i) IAQ Awareness

The WHO has underscored the substantial health implications of indoor air pollution on a global scale. A comprehensive understanding of AQ necessitates an awareness of the severity of indoor air pollutants, the health consequences of poor air quality, and the indoor activities that contribute to substandard air quality. In a study assessing IAQ awareness, half of the participants demonstrated a robust understanding of IAQ, two participants exhibited partial awareness coupled with concerns about IAQ, while the remaining three participants were conscious of outdoor air quality but lacked knowledge about indoor air quality. This initial level of awareness was taken into account during semi-structured interviews designed to gauge changes in awareness levels.

The interviews revealed that the strategy of presenting data on indoor air pollution and requiring participants to maintain a daily digital diary of indoor activities significantly enhanced their awareness, as evidenced in Figures 24 and 25. The interview discussions were structured to assess the participant's engagement with the study, alterations in their daily household indoor activities, and their observations on the correlation between their indoor activities and indoor pollution levels, taking into account the graphical data and daily digital diary. During the study, the participants noticed interesting patterns and expressed their concerns about their understanding of indoor activities.

For instance, participants frequently referred to products or sources that could potentially degrade their indoor air quality, expressing sentiments such as, *"We need to get more fresh air, we need to minimise the use of products that remove grease/grime and consider their effect on health."* They also made connections between the data and their reassurances or concerns about air quality, with comments like, *"I really want to ensure that we have good air quality", "If it is normal and not exceeding the WHO or UK threshold then I am ok with that"*, and *"That does help me in terms of bringing in awareness of maintaining the air quality by comparing with WHO guideline and will able to see you are comparing with previous and current readings level"*. Participants also exhibited a heightened consciousness about their indoor activities, as one participant noted, *"Making more aware of all the things we are doing inside the hous*e." These comments clearly indicate that the participants had developed an understanding and concern about IAQ, a finding that was further agreed when the devices were collected from the participants' residences.

(ii) Awareness through Indoor Activities: opening windows, cooking, and cleaning

The influence of indoor activities on IAQ is an area of increasing interest. Indoor activities such as the frequency and duration of window opening, cooking, and cleaning, including vacuuming, have significantly impacted IAQ. Despite the absence of explicit guidance linking these activities to IAQ, participants were merely asked to record these activities in a daily digital diary. This seemingly simple task led to a marked increase in awareness, as evidenced by their feedback. Participants' comments underscored this heightened awareness. One participant noted, *"When I vacuum, I think about air quality"*, indicating a newfound association between routine household tasks and IAQ. Another participant remarked, *"Prior to this, I never thought about window opening and air quality has relation"*, highlighting the transformative nature of the exercise in altering perceptions about the interconnectedness of indoor activities and air quality. Another participant echoed this sentiment, who stated, *"Definitely…I am always in the home recently because of the pandemic. I have noticed the change reflected upon me...obviously…this is great for the houses who need it the most"*. The quantitative results, as depicted in Figure 25, demonstrate an increase in window opening, a finding that is corroborated by the qualitative feedback. Participants shared comments such as, *"Before I cooked, I never open windows, but now I do after this,"* and *"When guests come* *over or partying and stuff and normally the last thing in my mind is to get fresh air in and open the window."* These statements indicate a shift in behaviour and an increased understanding of the importance of ventilation for IAQ.

This newfound awareness extended to cleaning practices as well. One participant shared, *"I like cleaning and I used to use bleach but Now I open windows when I use it,"* indicating a behaviour change prompted by an increased understanding of the impact of cleaning products on IAQ. This was further supplemented by a heightened awareness of the utility of exhaust fans, with one participant noting, *"Now after this, we start turning the gas fan on more frequently."* Participants also highlighted the role of visualization in enhancing this awareness. One participant shared, *"Since that device, it's a conscious act for me and what I am using and what I am doing,"* indicating the instrumental role of visual aids in fostering a deeper understanding of the impact of indoor activities on IAQ. Thus, it is evident that through simple daily activities, individuals can become more conscious of their indoor environment and take proactive steps to improve their IAQ.

(iii) Spreading Awareness

The analysis revealed a significant role played by the participants in disseminating awareness about indoor air quality within their social networks, including family and friends. This was evident in statements such as, *"It's been discussed a lot in the family since the device was deployed."* Participants often found themselves engaging in discussions about indoor air quality, especially when the topic of asthma was raised. They would then delve into the impact of household activities on indoor air quality. A recurring theme that emerged from these discussions was the recommendation to measure indoor pollution levels and identify activities that exacerbate it. This was reflected in statements such as, *"More concern about the indoor air quality and found my family and friends visiting us have a concern as well"* and *"I would recommend to others that it's a good idea to monitor your IAQ because it allows you to be conscious about what you do not see."* Furthermore, the presence of air quality monitoring devices in participants' homes sparked curiosity among visitors, leading to further discussions and interest in acquiring such devices. This was captured in comments like, *"My friend came to my house and asked about this device and I explain what is it doing and asked me how can she get such device for their house as well"* and *"I discussed this with my close friends and they asked for market availability."* In summary, the participants became more aware of indoor air quality issues and served as catalysts for spreading this awareness within their social circles, thereby contributing to a broader understanding of the importance of monitoring indoor air quality.

(iv) Role of technology in raising awareness

The role of technology in enhancing awareness, particularly in relation to air quality, has been explored in this study. Preliminary questionnaires were utilized to gauge the initial understanding of participants regarding the significance of air quality. Following the introduction of IAQ devices, a marked interest was noted among participants regarding the functioning of these devices. One participant expressed their comfort and familiarity with the device, stating, *"I was quite comfortable with the device and get familiar once I started to fill daily digital diary"*. Another participant provided feedback on the device's physical attributes, commenting, *"In terms of appearance, it's quite big and looks like a household appliance device"*. The device's user-friendly graphical display was commended for its informative nature, especially in relation to air quality standards. The study incorporated a daily activity log as a digital diary, which could be accessed via various devices such as iPads, mobile phones, or personal computers. This reflective tool was found to be instrumental in encouraging participants to delve deeper into the issue of indoor air pollution and subsequently raise their awareness. One participant shared, *"I already know what air quality means so I was excited to monitor it so that I will have an idea of the quality of air inside my house".* Another participant expressed their curiosity about the factors that influence air pollution, stating, *"Just concerned to know what activities trigger air pollution and how it changes on the dashboard"*. Informal confirmation of behavioural alterations was also evident, as exemplified by a participant's remark, *"We cook a lot, if I need to cut down something to make air quality better then I am happy to do that and I feel this study helps me to achieve that"*, accompanied by further observations of behavioural shifts such as, *"So much behaviour change in me as a mother", "I was talking with my mum regarding cooking methods",* and *"I forgot to use the cooking fan and now I have used to use it even for two min egg fry."*

Recommendations for enhancement encompassed diversifying the range of activities encapsulated within the daily digital diary, as indicated by one participant: *"need more activities in daily activity log with more options"*. Additional features, such as a *"note section to use to be recorded for yourself"* were suggested. The majority of participants desired a shift towards mobile-based applications from web-based tools, encapsulated in the remark, *"Mobile application is more convenient and cooler."*

4.3 Chapter Summary

The study focused on improving indoor air quality awareness through a digital visualization platform combined with a daily digital diary. Real-time IAQ data, including the seven-day average and metrics vis-à-vis WHO and UK governmental recommendations, were presented to the participants via the digital visualization platform. Concurrently, participants were prompted to record entries in a daily digital diary to foster self-understanding and reflection. Comprehensive analysis of participant data illuminated an upsurge in IAQ awareness, specifically linked to their household activities. The examination of the data revealed that access to IAQ data led to substantial enhancement in IAQ. Within the second month, a remarkable improvement of 60% was recorded for $PM_{2.5}$ concentrations, and an 80.43% reduction was observed for PM_{10}. Furthermore, the study indicated increments in the window opening duration ranging from 11% to 39% among the participants, suggesting that natural ventilation may have played a vital role in the observed improvements.

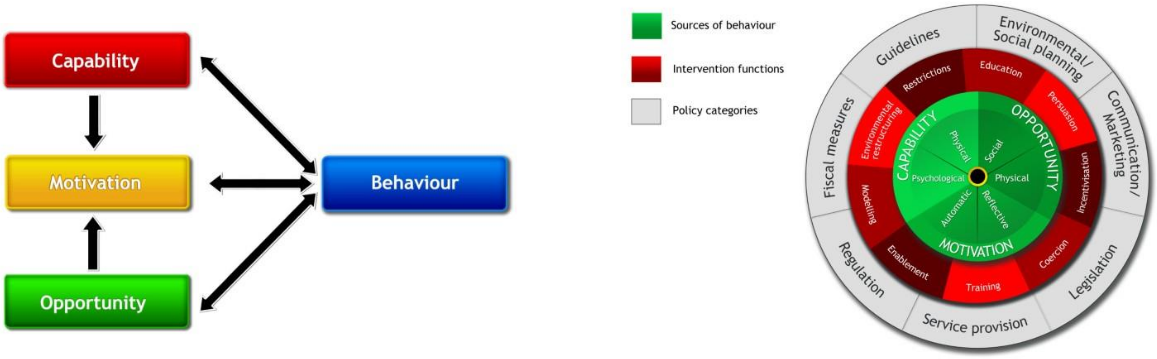
CHAPTER 5: EXPLORATION OF IAQ ADVANCEMENT VIA THE INTERSECTION OF IoT & COM-B MODEL

Despite the positive results presented in the previous chapter, the link between raising awareness and changing behaviour in terms of indoor activities may be coincidental. A subsequent study was conducted using the COM-B model, a well-established framework for understanding and designing behaviour change interventions to prove this correlation. The model was utilised to determine digital interventions' format, timing, and nature to measure behavioural change. Importantly, the outcomes of the study mentioned above, specifically the link between window opening hours and improved IAQ, influenced the design of the intervention. Through the use of a behavioural change framework, digital intervention protocols were carefully crafted to support the findings from the initial research. Therefore, this study provides valuable insights into how digital interventions can be used to increase awareness of IAQ, which can positively impact health and well-being.

The IoT has significantly changed Location-based Services (LBS) technologies, especially in monitoring IAQ and raising public awareness about air pollution. The COM-B model, which has three advantages, provides researchers and developers with deep insights into human behaviour, helps bridge knowledge gaps, and guides targeted interventions, thereby facilitating behavioural change. It has been widely used in public health interventions, including both digital and traditional methods, to achieve various health objectives. In the following chapter, the COM-B model has been used as a foundation to conceptualise digital interventions and assess behavioural changes using the capabilities of IoT technology. Analytical insights derived from prior research indicate a notable augmentation in window opening durations, with an increase spanning between 11% and 39%. This surge is exemplary of heightened self-awareness about IAQ. Within the purview of this chapter, it is evident that the digital interventions have profoundly influenced participants' behavioural patterns, reshaped indoor activities, and culminated in an enhanced IAQ. To the best of scholarly knowledge, this endeavour represents a pioneering effort in harnessing the behavioural psychology tenets of the COM-B model to design and implement digital interventions, thereby facilitating behavioural transformation in relation to IAQ.

5.1 Introduction to COM-B

The COM-B model is a prominent theoretical framework within social-cognitive models designed to underpin interventions to modify human behaviours [265, 266]. This model posits that an individual's willingness to initiate behavioural change is contingent upon their motivational levels, which are influenced by their beliefs regarding their ability to successfully execute the desired behaviour, provided they are given adequate opportunities. In applied behaviour analysis, the COM-B model acts as a critical tool for discerning the elements that need to be altered within an individual to ensure the effectiveness of a specific behavioural change intervention. The model, including the entities involved and a synopsis of their interactions, is depicted in Figure 26. Furthermore, the BCW, an integral component of the COM-B model, offers a practical framework for devising interventions targeting the components. The BCW thus acts as a tool for operationalising the theoretical constructs of the COM-B model, thereby facilitating the design of effective interventions for behavioural change.



(a) (b)

Figure 26: (a) The COM-B model [174]. (b) Behaviour Change Wheel (BCW) [174].

The concept of **physical capability** refers to an individual's inherent physical capacity, which is determined by their physique, to execute a particular activity. This capability is a fundamental aspect of human functionality, as it directly influences the range and extent of physical tasks an individual can perform. In contrast, **psychological capability** encompasses an individual's mental abilities, specifically their cognitive abilities such as comprehension and memory. This dimension of capability is critical as it underpins an individual's capacity to process information, make decisions, and engage in complex thought processes. The notion of **physical opportunity** primarily emphasises the external physical environment, including financial resources and material assets. These elements can either facilitate or hinder an individual's ability to engage in certain activities, thereby influencing their overall physical capability. **Social opportunity**, on the other hand, is primarily concerned with the social and cultural norms that govern interactions with others. These norms can shape an individual's behaviour and influence their social engagement and participation opportunities. **Automatic motivation** is a concept that focuses on the intrinsic desires and habits that naturally foster motivation in an individual. These automated processes often operate below the level of conscious awareness but play a crucial role in driving behaviour. **Reflective motivation**, in contrast, involves conscious thought processes. This type of motivation is characterised by deliberate reflection and conscious decision-making, often involving weighing the pros and cons before acting.

The BCW model incorporates these concepts and proposes nine distinct intervention functions: education, persuasion, incentivisation, coercion, training, enablement, modelling, environmental restructuring, and restrictions. These interventions, each with a unique role and purpose, are delineated in Table 11. They are strategic tools for influencing behaviour and promoting change in various contexts.

Table 10: The nine different types of intervention included in the BCW.

	Intervention Functions
Education	Increase knowledge or understanding
Persuasion	Using communication to induce positive or negative feelings to stimulate action
Incentivisation	Creating an expectation of reward
Coercion	Creating an expectation of punishment or cost
Restriction	Using rules to reduce the opportunity to engage in the behaviour (or to increase behaviour by reducing the opportunity to engage in the competing behaviours
Environmental restructuring	Changing the physical or social context
Modelling	Provide an example for people to aspire to or emulate
Enablement	Increasing means or reducing barriers to increase capability (beyond education or training) or opportunity (beyond environmental restructuring)
Education	Increase knowledge or understanding.

5.1.1 Implementing the COM-B Model to Investigate Behavioural Transformations: Evaluating Behavioural Change through Indoor Activities

In behavioural science, the COM-B model and the BCW have emerged as robust frameworks for designing digital interventions aimed at behavioural change. This study leverages these frameworks to address two pivotal aspects that enhance IAQ: (1) the use of domestic products and (2) the use of ventilation systems. The digital interventions are operationalised through a digital platform that acts as a platform for displaying data derived from IAQ monitoring sensors. This approach mirrors the methodology employed in a previous study. However, the current study extends beyond mere data presentation, offering actionable insights that are firmly grounded in the principles of the COM-B model and the BCW implementation framework. The COM-B model, which stands for 'Capability', 'Opportunity', and 'Motivation' leading to 'Behaviour', provides a comprehensive understanding of the factors influencing behaviour. By integrating this model with the BCW, the study aims to provide a more nuanced understanding of behavioural change, particularly in relation to IAQ. In summary, this study represents a significant step forward in applying the COM-B model and the BCW in designing digital interventions for behavioural change. Providing actionable insights based on robust behavioural science frameworks contributes to the broader goal of improving IAQ and, consequently, public health.

The first **intervention (Int 1)** entails the deployment of a pop-up message on the participant's screen each time they log in. As depicted in Figure 27 (a), this message is designed to be informative and supportive, with the content varying at each login. The primary aim of these messages is to boost the participants' psychological capability by providing them with new insights and information during each interaction. The recommendations for pop-up messages and suggestions are grounded in evidence-based guidelines from reputable organisations such as the Environmental Protection Agency (EPA) and the WHO, alongside findings from recent studies [267-269] in the field of behavioural science that highlight effective communication strategies for behaviour change. For instance, pop-up messages suggesting ventilation actions are based on EPA guidelines for reducing indoor pollutant levels, while advice on reducing the use of specific cleaning products references WHO recommendations on minimising exposure to VOCs.

Figure 27: (a) An interactive pop-up to provide instant information about IAQ improvement.

The second **intervention (Int 2)**, illustrated in Figure 27 (b), involves presenting comprehensive IAQ data from the participant's household. This intervention provides a dynamic view of indoor air pollution levels, enriched with pertinent information such as comparative analyses of daily and weekly averages. By comparing the current day's average pollution data with that of the current week and the preceding week, participants better understand the temporal progression of pollution levels. Furthermore, comparing these data with the air pollutant limits set by the WHO and the UK offers participants a benchmark to gauge their household's pollution levels. As an enhancement to the previous study, Figure 27 (c) presents additional contextual information to aid participants in comprehending the intricacies of indoor air pollution.

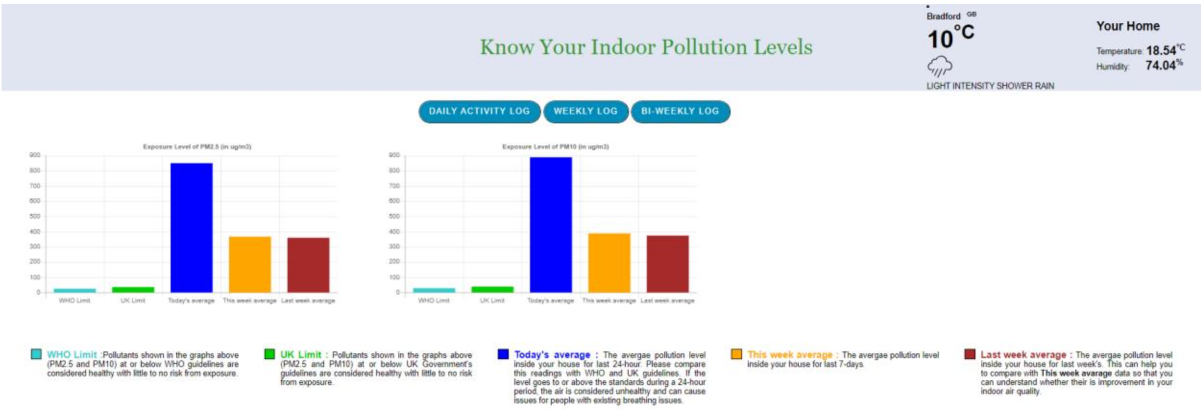


Figure 27: (b) An interactive digital visualisation platform to give access to participants' IAQ data with relevant information to provide context to this graphical presentation.

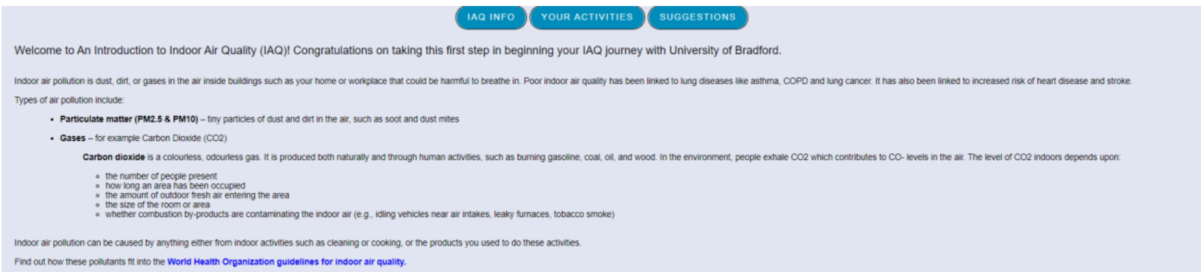


Figure 27 (c): The information regarding air pollutants helps the participant to get more knowledge.

The third **intervention (Int 3)** focuses on the participant's ventilation habits, specifically their window opening hours. Figure 27 (d), for instance, displays the participant's window opening hours for a given week, with a 'good' performance denoted by an average window opening duration of 16 to 21 hours. This intervention also recommends that participants elevate their performance to an 'excellent' rating.

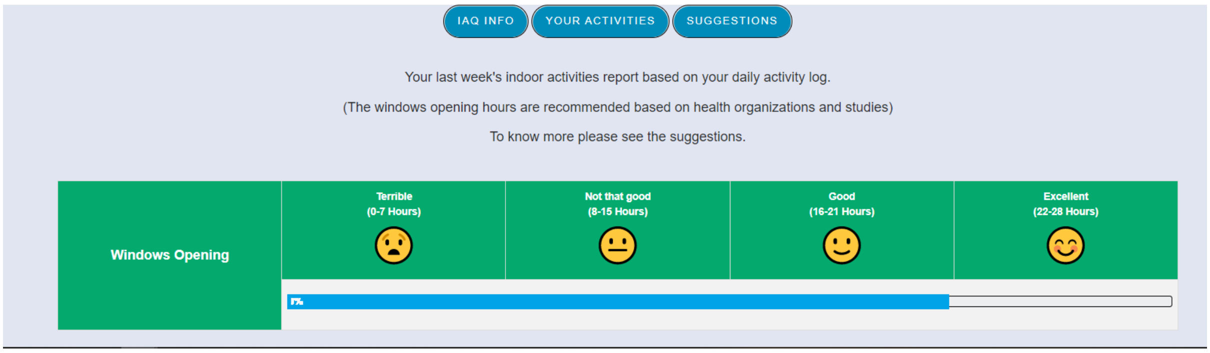


Figure 27: (d) Information about participants' indoor activity (window opening hours) coming from the participants referring to how better they are doing in reducing indoor air pollution on the meter.

The fourth **intervention (Int 4)** offers suggestions and provides various levels of contextual information. An example of this can be seen in Figure 27 (e), which provides comprehensive information on the role of ventilation in improving IAQ and the impact of consumer products on IAQ. This digital intervention is designed to equip participants with the knowledge necessary to make informed decisions regarding their indoor environment.

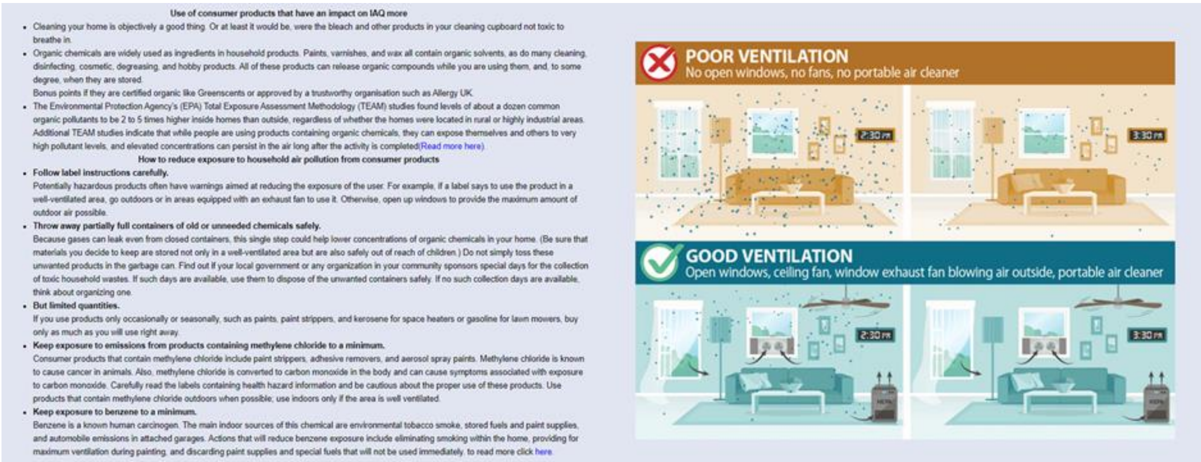


Figure 27: (e) Interactive intervention with detailed information for IAQ improvement.

The subsequent Tables 12 and 13 delineate how the BCW has been instrumental in formulating four digital interventions. These interventions have been designed to foster behavioural modifications about ventilation and product usage within residential settings. The BCW, a comprehensive framework for behaviour change, has been precisely employed to ensure that the interventions are effective and resonate with the target audience. The interventions have been crafted to enhance awareness and understanding of the importance of proper ventilation and sensible product usage in homes. It is imperative to note that the design of these interventions has been improved, ensuring that they are relatable, user-friendly, and easily understandable. This approach is anticipated to facilitate the seamless adoption and implementation of the suggested behavioural changes.

Table 11: COM-B model elements help design interventions for the domestic products that citizens use indoors.

	Intervention Functions			
	Education	**Persuasion**	**Modelling**	**Enablement**
Psychological Capability	**Int 1** and **Int 4** (These increase knowledge and understanding about the impact of product usage on indoor air quality)	**Int 2** and **Int3** (These provide relevant and contextualised information about product use and impact on air quality to simulate action)	-	**Int 2** and **Int 3** (The information increases the capacity to change by providing important insights)
Social Opportunity	**Int 1** and **Int 4** (These increase knowledge and understanding about the negative impact of product use that allows them to share with their social group)	**Int 2** and **Int 3** (These provide relevant and contextualised information on how the product usage change brought positive results to showcase their social group for simulating actions)	**Int 2** and **Int 3** (If they have seen a positive change in IAQ in their own home, then they act as an exemplar to their social group)	-

Table 12: COM-B model elements help to design interventions for indoor ventilation for IAQ improvement.

	Intervention Functions			
	Education	**Persuasion**	**Modelling**	**Enablement**
Psychological Capability	**Int 1** and **Int 4** (These increase knowledge and understanding about the impact of mechanical and natural ventilation on indoor air quality)	**Int 2** and **Int 3** (These provide relevant and contextualised information about ventilation use and impact on air quality to simulate action)	-	**Int 2** and **Int 3** (The information increases the capacity to change by providing important insights)

Social Opportunity	**Int 1** and **Int 4** (These increase knowledge and understanding about the negative impact of the lack of ventilation that allows them to share with their social group)	**Int 2** and **Int 3** (These provide relevant and contextualised information on how the increase in windows opening during certain activities brought positive results to showcase their social group for simulating actions)	**Int 2** and **Int 3** (If they have seen a positive change in IAQ in their own home, then they act as an exemplar to their social group)	-

5.2 Design of the Study

The research presented herein was executed sequentially, as depicted in Figure 28, over three weeks in May 2022. The study was conducted in Bradford, with a distinct set of participants from the preceding study. The primary objective of this research was to examine behavioural changes among the citizens when they were provided with digital interventions based on the COM-B model. These interventions were designed to enhance IAQ by adjusting window opening hours for ventilation and reducing the usage of household products. A total of eight households willingly participated in this study, which received ethical approval from the Chair of the Biomedical, Natural, Physical, and Health Sciences Research Ethics Panel. Online workshops were organised to provide a partial overview of the study's specifics. These workshops covered various aspects, including information about the device, maintaining a daily digital diary, and the deployment procedure. The participants' active engagement, as evidenced by their numerous queries about air quality, its significance, the benefits of IAQ monitoring, and other related topics, strengthened our confidence in the study. The workshop successfully stimulated the citizens' interest in participating in the study. Eight households were selected for the installation of the LCS-based IAQ monitoring device, considering various socioeconomic and demographic factors such as location, ethnicity, and type of dwelling, as illustrated in Table 14. Notably, none of the participants utilised dehumidifiers in their homes to manage indoor humidity. Individual sessions were scheduled with each participant, with the consent of the citizens who agreed to participate in the study.

Subsequent to the individual sessions, preparations were initiated for deploying the LCS-based IAQ monitoring device. The same equipment used in the previous study was used to monitor $PM_{2.5}$ and PM_{10} and deployed at each participant's home. Concurrently, the participants were requested to complete a pre-study initial questionnaire identical to the one used in the preceding study. Guidelines have been provided for maintaining the daily digital diary after the device deployment process. Beyond this, no additional information was disclosed to the participants. Each participant was given unique login credentials for the digital visualisation platform to ensure privacy. Any queries or concerns raised by the participants were addressed via telephone or email communication.

Table 13: Summary of initial questionnaire outcome of participant's demographic information.

Sensor ID	House Location	Type of House	Type of Cooker	Type of Heating
LIAQ1	Within 0.1 km from the main road.	Terraced	Gas and Electric	Central heating
LIAQ2	More than 0.5 km from the main road	Terraced	Electric	both central and electric
LIAQ3	Within 0.1 km–0.5 km from the main road.	back-to-back house	Gas	Central heating
LIAQ4	Within 0.1 km from the main road.	Semi-detached	Gas	both central and electric
LIAQ5	Within 0.1 km from the main road.	Semi-detached	Electric	Central heating
LIAQ6	Within 0.1 km from the main road.	Semi-detached	Gas	Gas Heating
LIAQ7	Within 0.1 km from the main road.	Semi-detached	Gas	Central heating
LIAQ8	Within 0.1 km from the main road.	Detached	Gas	Central heating

In the initial week of the study, participants did not have access to any IAQ data from their homes. They were only required to maintain a daily digital diary to record indoor activities. The IAQ data, along with all four interventions, were made available to the participants at the commencement of the second week via the digital visualisation platform. Upon the conclusion of the third week, an online meeting was scheduled to conduct interviews with the participants (Appendix-C), using pre-formulated questions at times that were convenient for them. By the end of the third week, the IAQ monitoring devices from the participants' homes had been retrieved.

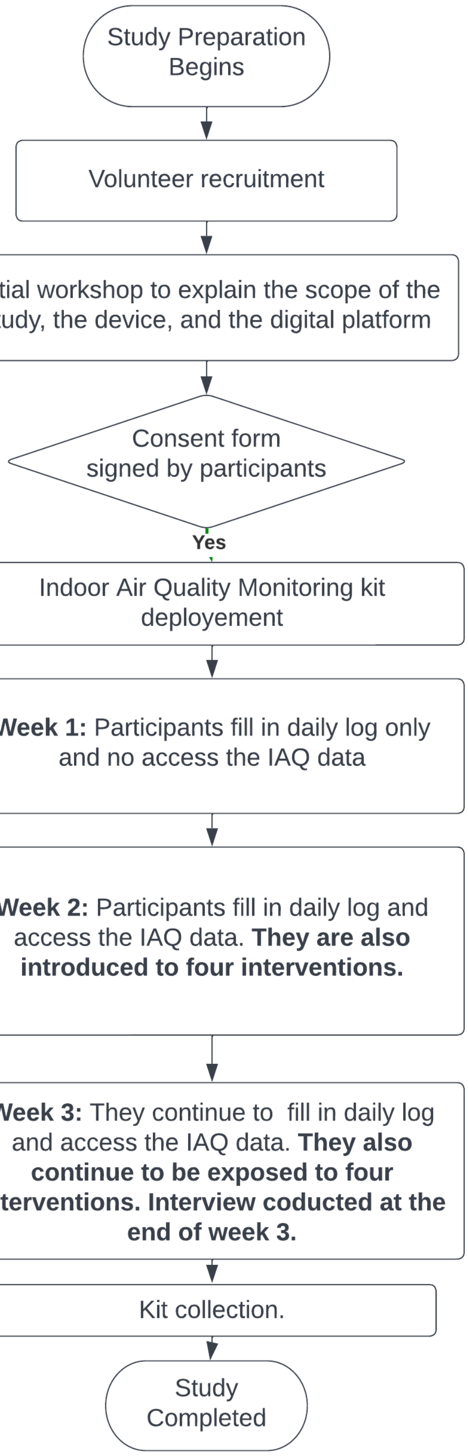


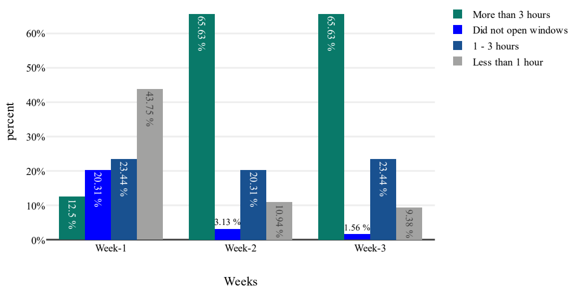
Figure 28: Study flow diagram for bringing intervention to raise awareness about IAQ.

5.3 Data Analysis and Discussion

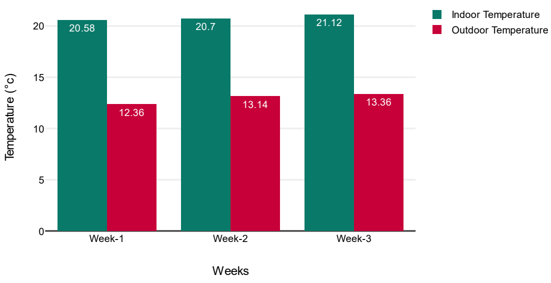
Over a period of three weeks, an extensive collection of data about IAQ and indoor activities was thoroughly gathered from the residences of all participants. This data was subsequently subjected to a comprehensive analysis. The process was conducted with the utmost attention to detail, ensuring the integrity and accuracy of the data collected. The objective was to gain a deeper understanding of the relationship between IAQ and indoor activities, thereby contributing to this field's broader body of knowledge. It is important to note that all data was collected and analysed in a manner that strictly adhered to ethical guidelines, ensuring the privacy and confidentiality of the participants. Furthermore, the analysis was conducted originally, ensuring that the findings are free from biases and contribute unique insights to the field.

5.3.1 Behaviour Changes Related to the Use of Ventilation

The analysis delineates a noteworthy trend commencing from the second week when participants were exposed to four distinct digital interventions via an interactive digital visualization platform. This period witnessed a discernible augmentation in ventilation practices, specifically windows opening, as depicted in Figure 29 (a).



(a)



(b)

Figure 29: (a) Changing pattern of week-wise window opening hours; (b) comparative temperature plot between indoor and outdoor from different weeks.

For the behaviour change activity in the form of encouraging people to keep their windows open longer (more than three hours), a statistically significant difference has been observed from week 1 to week 3. The frequency of window opening for periods exceeding three hours escalated from 12.5% to 65.63%, while the practice of not opening windows diminished from 20.31% to 3.13%. In addition to this behavioural change, the study also analysed average ambient and indoor temperatures over three weeks. This temperature analysis revealed no significant variation in indoor or outdoor temperatures that could potentially influence window opening practices, as illustrated in Figure 29 (b).

Furthermore, the study incorporated a qualitative analysis of data derived from interviews conducted after the study. This analysis facilitated the identification of correlations between the interventions and the observed behavioural changes. **Intervention 4 (Int 4)** offered advice on enhancing IAQ through improved ventilation and product usage, which was the most frequently cited intervention. This was followed by **Intervention 2 (Int 2)**, which presented participants with a dashboard displaying the IAQ within their residences; **Intervention 3 (Int 3)**, which provided feedback on their performance during the week; and finally, **Intervention 1 (Int 1)**, which provided information nuggets via pop-up notifications.

Intervention 4 (int 4): The consensus among participants indicates a recognition of the practical insights offered by this intervention. One participant expressed, *"The dashboard (visualisation platform) provides valuable insights on how proper ventilation can enhance air quality and how to regulate products that directly affect our indoor air quality."* Participants also shared changes in their behaviour influenced by the advice from Intervention 4. One participant shared, *"Indeed, our daily routines have altered. My spouse and I now clean our house together, and we have increased the frequency of opening windows compared to before. We have also reduced our use of bleach as a cleaning product, and when we do use it, we ensure to wear masks and open windows."*

Intervention 2 (Int 2): The dashboard emerged as a favoured tool for monitoring indoor pollution levels. One participant noted, *"It was intriguing and beneficial to view my house's pollution level graphically. I often find myself checking the pollution level on the dashboard while cooking, and if it indicates high levels, I ensure to open the windows and doors."* Another participant mentioned the positive impact of the intervention on their communication, *"I never used to inquire if my wife had turned on the exhaust while cooking, but now I always ask and check the dashboard to see the impact...and to my surprise, the pollution levels were low."* The information from other interventions further enhanced the utility of this intervention. For instance, one participant shared, *"One day, I noticed that I experienced breathing issues when I vacuumed while my mother was cooking, and the dashboard indicated high pollution levels. I revisited the information and realized that I wasn't opening windows. Since then, I have reduced vacuuming or ensured to open windows, even when my mother cooks."*

Intervention 3 (Int 3): Participants frequently referred to this intervention to gauge their performance. One participant stated, *"It provides updated data and informs you about the importance of opening a window and the levels of air pollution or humidity in your house. I believe it's beneficial as it is based on actual records."*

5.3.2 Behavioural Change Analysis—Use of Products in the House

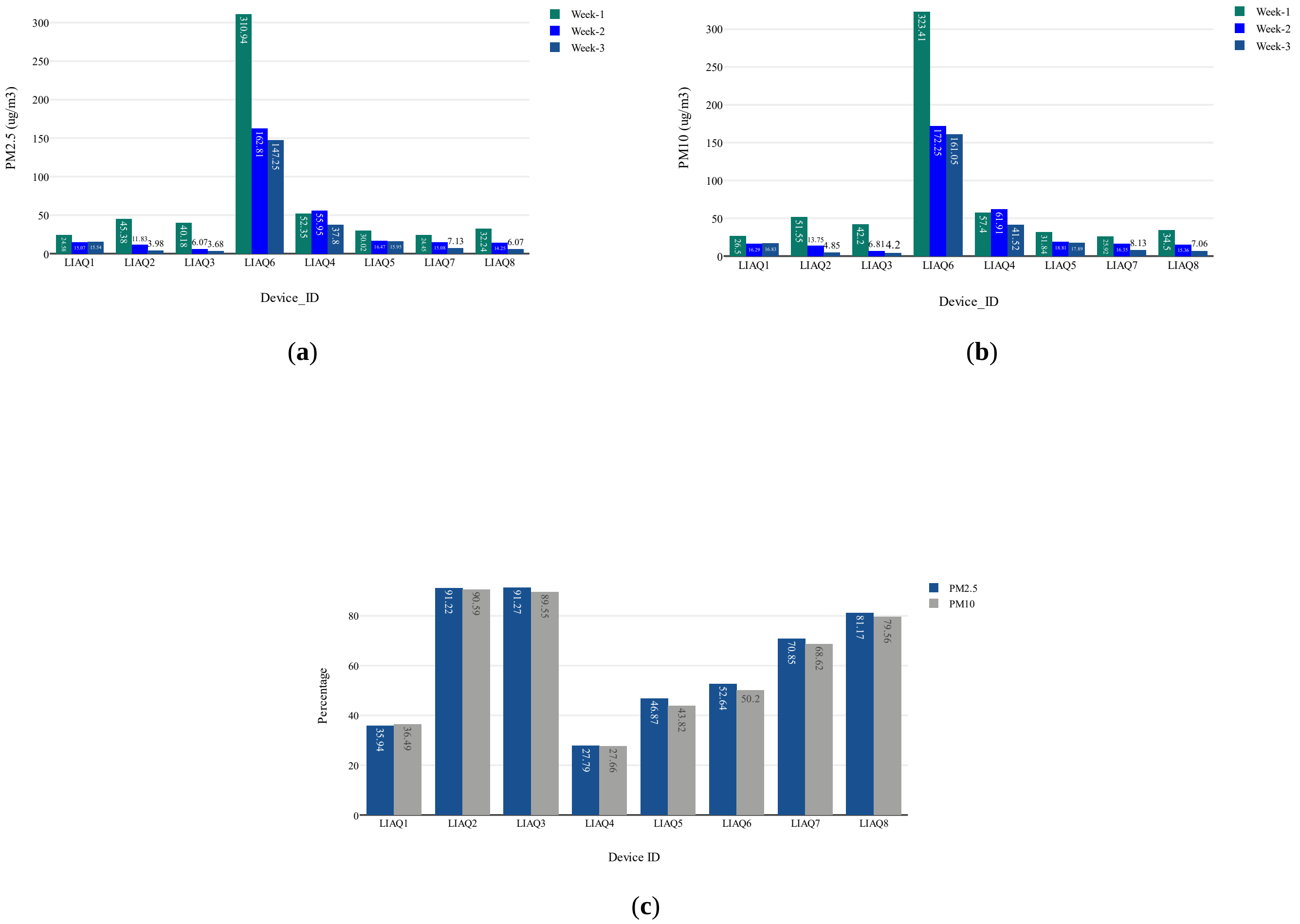
In this research, the post-study interview responses were meticulously examined with questions: "Did you change any of your regular day-to-day activities after seeing data on your IAQ level?". The analysis revealed a unanimous behavioural change across all households, specifically in relation to the use of products that could potentially influence IAQ. The participants' comments, which are detailed in Table 14, provide a comprehensive overview of their behavioural changes. Each household's unique response underscores the individualised nature of the intervention, demonstrating the diverse ways in which the participants adapted their daily routines in response to the data on their IAQ. It is important to note that these behavioural changes were not merely reactive, but rather, they represented a conscious decision by the participants to improve their indoor air quality. This personalised perspective of the intervention, which emphasises the active role of the participants in modifying their behaviour, is a critical aspect of our analysis.

Table 14: Answers to interview questions: "Did you change any of your regular day-to-day activities after seeing data on your IAQ level?

Household/ Device ID	**Comments**
LIAQ1	*"Even now I am checking the content of the cleaning products"* *"Yes, we are using less bleach or cleaner in the kitchen for cleaning"*
LIAQ2	*"Windows opening more and less use of candles in my house"*
LIAQ3	*"use water for cleaning unless cleaner is required"* *"less oil usage"*
LIAQ4	*"My wife and I clean the house together and whenever we do, we now open windows more compare to before and generally we use bleach as a cleaning product…now we are using less or whenever use it, we put the mask on and open windows"*
LIAQ5	*"Yes, I, as a mother and housewife, I love my house to smell nice all the time so I used a candle or Incense Sticks. Since I noticed that this raises the pollution high, I am using very less"* *"Even I practically checked with the dashboard, whenever I burn them, the pollution level looks high on the graph"*
LIAQ6	*"My wife loves cleaning, she always the tidy kitchen and keeps it clean. After I show what is written on the dashboard, she is now more concerned about using cleaning products"*
LIAQ7	*"Use less cleaning products or whenever use put gloves and mask on."*
LIAQ8	*"Me and my family are now more concern about bleach use"*

5.3.3 Behavioural Change Analysis—Improvement in IAQ

The impact of digital intervention on behavioural change among citizens concerning indoor air pollution levels was precisely examined. This was achieved using IoT-enabled LCS devices, as depicted in Figures 30 (a) and (b). A discernible pattern emerges from these figures, indicating a decrease in indoor air pollution levels across all participants' residences, specifically for particulate matter ($PM_{2.5}$ and PM_{10}). Furthermore, a comprehensive analysis was conducted to assess the overall percentage decrease in pollution levels from the first to the third week, as illustrated in Figure 30 (c). The data reveal a substantial reduction in pollution levels, ranging from 27.79% to 91.27% for $PM_{2.5}$ and 27.66% to 90.59% for PM_{10} across all households. These figures unequivocally demonstrate the efficacy of digital intervention in enhancing citizens' awareness and improving ventilation practices.



(a) (b) (c)

Figure 30: (a) Average $PM_{2.5}$ data from different households in week 1, week 2, and week 3; (b) average PM_{10} data from different households in week 1, week 2, and week 3; (c) percentage change in the indoor pollution level of $PM_{2.5}$ and PM_{10}.

The integration of the IoT system with the COM-B model has evidently led to a significant improvement in indoor air quality. A week-by-week analysis further underscores this trend, revealing a consistent decrease in indoor air pollution levels from the first week to the second and subsequently from the second week to the third. This study thus provides compelling evidence of the transformative potential of digital intervention in fostering behavioural change and improving indoor environmental outcomes.

In the subsequent examination, the possible influence of humidity on PM values has been scrutinized, drawing on the evidence from previous research [270-272] that has demonstrated a correlation between PM values and relative humidity (RH). These prior studies have consistently indicated a decrease in PM values in response to a reduction in RH. Enlightened by these findings, PM concentrations in the context of RH have been evaluated. The results mirrored the pattern identified in previous research, with a decrease in PM values corresponding to a decrease in RH, as detailed in Table 15. However, it is essential to note that the changes in RH and PM values were not uniform across the board. This variability can be attributed to the diversity in housing types and the range of indoor activities conducted within these spaces.

Table 15: The weekly average reading of RH, $PM_{2.5}$, and PM_{10} from IAQ devices.

Device ID	**RH (%)**			**$PM_{2.5}$ (μg/m^3)**			**PM_{10} (μg/m^3)**		
	Week 1	**Week 2**	**Week 3**	**Week 1**	**Week 2**	**Week 3**	**Week 1**	**Week 2**	**Week 3**
LIAQ1	60.64	53.28	52.97	24.58	15.07	15.54	26.5	16.29	16.83
LIAQ2	67.65	57.81	58.01	45.38	11.83	3.98	51.55	13.75	4.85
LIAQ3	64.31	55.79	55.42	40.18	6.07	3.68	42.2	6.81	4.2
LIAQ4	61.82	63.29	55.27	52.35	55.95	37.8	57.4	61.91	41.52
LIAQ5	57.14	54.56	52.27	30.02	16.47	15.95	31.84	18.81	17.89
LIAQ6	74.95	69.14	68.65	310.94	162.81	147.25	323.41	172.25	161.05
LIAQ7	66.04	64.73	55.5	24.45	15.08	7.13	25.92	16.35	8.13
LIAQ8	57.93	54.16	52.33	32.24	14.25	6.07	34.5	15.36	7.06

The scholarly discourse suggests a correlation between the duration of window opening and indoor RH [155, 273-275]. In light of this, this study ventured to examine the influence of window opening duration (the intervention) on RH measurements, intending to discern any patterns indicative of a relationship between these two variables. Upon analysis of the window opening durations, it was observed that each participant augmented their window opening duration after implementing digital interventions, as depicted in Figure 29 (a). This change in window opening duration consequently affects the indoor RH value. Considering these two analyses, it can be hypothesized that the intervention designed to promote window opening also contributed to a reduction in RH values and, consequently, PM values, culminating in an enhancement of IAQ.

The weekly analysis reveals marginal to significant ameliorations in indoor air pollution across all households, which could potentially be a misleading indicator of improvement. Each household's daily percentage change in indoor air pollution was calculated to mitigate this factor, as delineated in Table 16 for PMs. The table reveals a daily fluctuation in indoor air pollution readings across all households. However, the readings for certain households, such as LIAQ1 and LIAQ4, do not exhibit a consistent improvement, as was observed in the weekly air quality improvement analysis. Conversely, some households, such as LIAQ3 and LIAQ6, demonstrate a more pronounced daily improvement, which is also mirrored in the weekly analysis. A scrutiny of these two tables reveals an enhancement in daily IAQ readings following the introduction of digital interventions.

Table 16: Daily percentage change in $PM_{2.5}$ and PM_{10} readings from all households.

	Device ID															
	LIAQ1		LIAQ2		LIAQ3		LIAQ4		LIAQ5		LIAQ6		LIAQ7`		LIAQ8	
Pollutants	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10
1	▼86.20%	▼83.97%	▲98.30%	▲95.39%	▲19.66%	▲28.22%	▲220.20%	▲240.77%	▼24.62%	▼25.80%	▲28.22%	▲220.20%	▼49.28%	▼44.85%	▲217.16%	▲217.12%
2	▲769.05%	▲674.95%	▼46.49%	▼50.56%	▼35.43%	▼40.39%	▲28.74%	▲30.48%	▼11.84%	▼13.75%	▼40.39%	▲28.74%	▼10.40%	▼14.16%	▼35.20%	▼38.28%
3	▼29.68%	▼32.13%	▲177.14%	▲209.04%	▲26.53%	▲28.96%	▼61.08%	▼61.96%	▲3.04%	▲2.35%	▲28.96%	▼61.08%	▲48.57%	▲49.85%	▼12.98%	▼16.82%
4	▲76.55%	▲79.43%	▼71.52%	▼74.36%	▼36.09%	▼36.43%	▲67.35%	▲70.39%	▲73.79%	▲69.61%	▼36.43%	▲67.35%	▼41.28%	▼40.19%	▼24.36%	▼18.68%
5	▲4.38%	▲8.01%	▼91.90%	▼83.19%	▲95.88%	▲94.41%	▼38.72%	▼42.41%	▼49.37%	▼46.49%	▲94.41%	▼38.72%	▼71.66%	▼68.67%	▼43.99%	▼40.15%
6	▼58.40%	▼56.71%	▲3769.80%	▲1913.52%	▼47.21%	▼43.58%	▼2.62%	▲1.14%	▲75.02%	▲68.13%	▼43.58%	▼2.62%	▲164.74%	▲131.27%	▲204.28%	▲169.71%
7	▲77.92%	▲83.09%	▼72.08%	▼74.83%	▼20.04%	▼21.52%	▲24.26%	▲23.19%	▼55.49%	▼53.06%	▼21.52%	▲24.26%	▼73.33%	▼71.33%	▼46.66%	▼44.32%
8	▼60.35%	▼62.72%	▼87.84%	▼85.12%	▼76.97%	▼75.45%	▲64.05%	▲66.16%	▲2.85%	▲2.23%	▼75.45%	▲64.05%	▲676.67%	▲623.02%	▲23.00%	▲18.69%
9	▲35.78%	▲36.26%	▲1743.59%	▲1478.48%	▼27.27%	▼23.75%	▼34.59%	▼35.40%	▲85.77%	▲97.10%	▼23.75%	▼34.59%	▼85.96%	▼83.68%	▲84.66%	▲93.26%
10	▼38.08%	▼37.57%	▼95.12%	▼94.55%	▼46.30%	▼40.00%	▲21.17%	▲26.64%	▼67.81%	▼65.57%	▼40.00%	▲21.17%	▲244.22%	▲196.85%	▼78.78%	▼79.18%
11	▲167.87%	▲151.40%	▲28.81%	▲46.15%	▲55.64%	▲35.48%	▼42.70%	▼46.62%	▼15.46%	▼16.93%	▲35.48%	▼42.70%	▲49.33%	▲52.13%	▼71.34%	▼63.10%
12	▼63.80%	▼60.87%	▼8.44%	▲25.67%	▲103.59%	▲96.64%	▲47.27%	▲53.98%	▲55.31%	▲40.76%	▲96.64%	▲47.27%	▼25.38%	▼23.40%	▲107.88%	▲61.69%
13	▼15.08%	▼15.33%	▲734.10%	▲386.81%	▼36.90%	▼35.96%	▼1.91%	▼0.60%	▲11.64%	▲16.46%	▼35.96%	▼1.91%	▼63.40%	▼62.12%	▼56.74%	▼56.59%
14	▲82.56%	▲80.75%	▼91.51%	▼85.93%	▲222.77%	▲191.65%	▲109.07%	▲113.04%	▲6.25%	▲8.86%	▲191.65%	▲109.07%	▼38.19%	▼34.63%	▲156.80%	▲160.64%
15	▲102.62%	▲96.03%	▲1.53%	▲1.30%	▼37.50%	▼32.28%	▼82.21%	▼82.76%	▼20.36%	▼29.28%	▼32.28%	▼82.21%	▲165.23%	▲147.90%	▼81.53%	▼76.76%
16	▼38.42%	▼39.02%	▲17.83%	▼14.53%	▼82.97%	▼79.22%	▲174.06%	▲178.07%	▲25.26%	▲22.39%	▼79.22%	▲174.06%	▼54.89%	▼52.68%	▲597.59%	▲446.14%
17	▼74.36%	▼62.65%	▲108.48%	▲80.08%	▲78.63%	▲55.58%	▼19.61%	▼20.28%	▼12.46%	▲14.59%	▲55.58%	▼19.61%	▲109.06%	▲128.18%	▲8.79%	▲13.22%
18	▲280.53%	▲166.86%	▼13.37%	▼15.10%	▲6.34%	▲4.91%	▼45.13%	▼49.63%	▼75.92%	▼76.77%	▲4.91%	▼45.13%	▼18.15%	▼29.46%	▼74.66%	▼74.48%
19	▼31.80%	▼29.84%	▼39.49%	▼35.77%	▲40.39%	▲38.89%	▲180.03%	▲209.85%	▲44.13%	▲39.18%	▲38.89%	▲180.03%	▼33.34%	▼26.64%	▲190.27%	▲185.21%
20	▼41.69%	▼44.60%	▲85.09%	▲130.09%	▲23.79%	▲14.97%	▼77.99%	▼79.79%	▲1361.36%	▲1163.39%	▲14.97%	▼77.99%	▲37.64%	▲30.02%	▼58.36%	▼46.12%
21	▲85.23%	▲88.66%	▼27.07%	▼44.57%	▲113.32%	▲108.68%	▲59.25%	▲67.50%	▼91.92%	▼91.47%	▲108.68%	▲59.25%	▼58.66%	▼57.17%	▲92.85%	▲64.08%

5.4 Chapter Summary

The study aims to enhance IAQ awareness using digital technologies, including the IoT. It also introduces the novel use of the COM-B behaviour psychology model as a digital intervention to facilitate behavioural change. Also, the study evaluates the efficacy of IoT-enabled LCS technology in visualising IAQ data and the reflective capacity of individuals when maintaining a daily digital diary. The results indicated an enhanced understanding of indoor air pollution among participants, leading to behavioural changes that improved IAQ. Four digital interventions were developed and implemented via the digital platform, each designed to bolster psychological capability and social opportunity. The data analysis revealed a significant enhancement in IAQ, with reductions in indoor air pollution levels ranging from 27.79% to 91.27% for $PM_{2.5}$ and 27.66% to 90.59% for PM_{10} across all participant households.

A general improvement in IAQ was observed as the week progressed, particularly following the introduction of interventions. In conclusion, the study's findings underscore the potential of an IoT-enabled IAQ monitoring system, combined with the COM-B model, to improve indoor air quality and foster self-awareness.

CHAPTER 6: HARNESSING DIGITAL VISUALIZATION PLATFORMS FOR IAQ AWARENESS, BEHAVIOURAL CHANGE AND ITS ACCEPTANCE

This chapter aimed to investigate which digital interventions have significantly impacted participants' behaviour to improve IAQ. Also, it will assess an IoT device's effectiveness and examine the role of a human-centred digital visualisation platform in raising participant awareness levels based on digital interventions. Previous work allowed the use of LCS-based IoT devices that reliably monitor IAQ [276, 277]. The digital platform has undergone significant improvements, focusing on delivering enhanced user experiences and catering to their specific needs and preferences. The platform has been designed with a user-centric approach, ensuring that users can easily navigate it and access the required features and functionalities. These enhancements have been implemented to provide users with a seamless and intuitive digital user experience, allowing them to achieve their goals efficiently and effectively. It is crucial to position this research within the context of User Experience (UX) research, highlighting the intersection of the findings with the principles of designing for optimal user interactions and experiences. This research contributes to the UX field by providing insights into how individuals interact with IAQ monitoring technologies and the resultant effects on their behaviour and perception of their living or working environments. Through the approach of mixed-methods research, combining quantitative analysis of sensor data with user feedback, key factors that influence user engagement and satisfaction with IAQ technologies have been identified. These factors include usability, the perceived accuracy of the information, and the motivational impact of real-time air quality feedback on user behaviour. By framing these research findings within the UX domain, we underscore the importance of user-centred design principles in developing effective IAQ monitoring and intervention strategies, ultimately aiming to enhance the overall user experience while promoting healthier indoor environments.

Moreover, the analysis focuses on participants' engagement and navigation behaviour on a digital visualisation platform. Time-series analysis revealed that while most participants' engagement remained consistent, participants L1 and L3 declined over time. A positive correlation was identified between time spent on the digital platform's IAQ Visualisation and Suggestions pages. Moreover, the document categorises users into personas such as "The Explorer," "The Focused," and "The Quick Visitor," each demonstrating distinct navigation patterns of the participants. Analytical results indicate that most participants complete a 6-step journey (42.86%), suggesting they find the required information by this step on the platform. The study underscores the importance of a multifaceted platform catering to diverse user preferences, emphasising users' inclination towards actionable insights for informed indoor environmental decisions. Furthermore, the TAM analysis of the digital visualisation platform reveals a positive trend in user acceptance; the digital visualisation platform showed a marked increase in user acceptance, with Perceived Usefulness (PU) having a t-statistic of -4.90 and a p-value of 0.00037 and Perceived Ease of Use (PEU) with a t-statistic of -2.83 and a p-value of 0.0152. However, the observed navigation patterns, where certain pages like "Suggestions" or "IAQ Info" were less frequented, highlight potential areas for user interface refinement, ensuring a more streamlined user experience.

6.1 Tool for participant's interaction analysis with the digital platform

For this study, a digital platform that has been designed for earlier studies has been modified to make it more interactive to visualise IAQ data and capture daily indoor activities by filling daily digital dairy. In parallel, the COM-B model and BCW framework from previous research have been used to design digital interventions [35]. These were realised with an interactive, human-centred digital platform that visualises IAQ data and records daily indoor activities, as shown in Figure 31 (b). This interactive digital platform, tailored specifically for the requirements of this study, acted as an instrumental tool in facilitating a more comprehensive understanding of IAQ dynamics among the users.

6.1.1 Designing of interventions for interactive Digital platform.

Intervention 1 (Int1 – Pop-up): A pop-up on the screen with a new informative message was designed to support two interventions whenever the participant logs in (see Figure 31 (a)). Each time the participant logs in, the pop-up message appears differently to support their psychological capability.

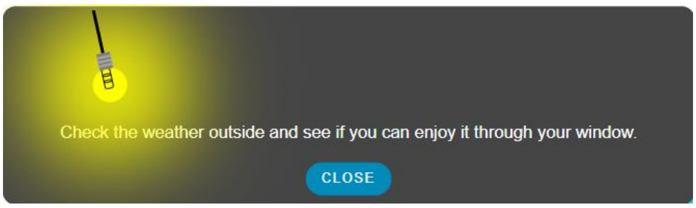


Figure 31: (a): Pop-up message whenever participant login to the platform.

Intervention 2 (Int2 - IAQ Visualisation): The visualisation displays of $PM_{2.5}$ and PM_{10} have been modified with different interactive appearance to see data across five different plots: WHO limit, UK limit, today's average value, this week's average value, and last week's average value as shown in Figure 31 (b).

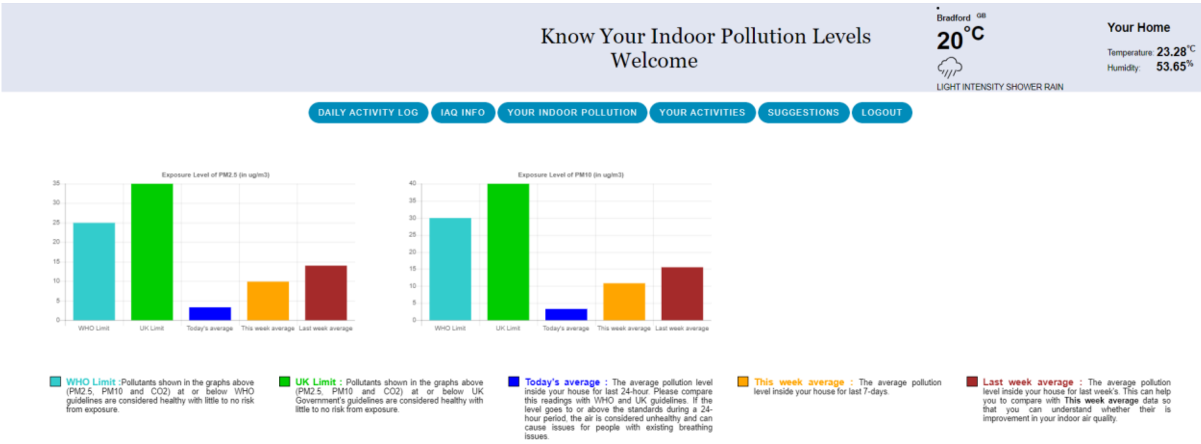


Figure 31: (b) Human-centred digital visualisation platform

Intervention (Int3 – IAQ Info): This digital intervention educates users about indoor air pollution, its sources, and its health impacts. It emphasises understanding pollutants in relation to World Health Organization guidelines for IAQ, as shown in Figure 31 (c).

Welcome to An Introduction to Indoor Air Quality (IAQ)! Congratulations on taking this first step in beginning your IAQ journey with University of Bradford.

Indoor air pollution is dust, dirt, or gases in the air inside buildings such as your home or workplace that could be harmful to breathe in. Poor indoor air quality has been linked to lung diseases like asthma, COPD and lung cancer. It has also been linked to increased risk of heart disease and stroke.

Types of air pollution include:

- **Particulate matter (PM2.5 & PM10)** – tiny particles of dust and dirt in the air, such as soot and dust mites
- **Gases** – for example Carbon Dioxide (CO2)

  Carbon dioxide is a colourless, odourless gas. It is produced both naturally and through human activities, such as burning gasoline, coal, oil, and wood. In the environment, people exhale CO2 which contributes to CO- levels in the air. The level of CO2 indoors depends upon:

  - the number of people present
  - how long an area has been occupied
  - the amount of outdoor fresh air entering the area
  - the size of the room or area
  - whether combustion by-products are contaminating the indoor air (e.g., idling vehicles near air intakes, leaky furnaces, tobacco smoke)

Indoor air pollution can be caused by anything either from indoor activities such as cleaning or cooking, or the products you used to do these activities.

Find out how these pollutants fit into the **World Health Organization guidelines for indoor air quality.**

Figure 31: (c) Providing the indoor air pollutants info.

Intervention (Int4 - Your Indoor Activity): How well the participants were doing in terms of opening windows to control ventilation. For example, Figure 31 (d) shows the participants' window opening hours in a particular week where 'good' performance is recorded when participants have average window opening hours between 16–21 hours. This also recommends what they need to do to move into an 'excellent' rating.

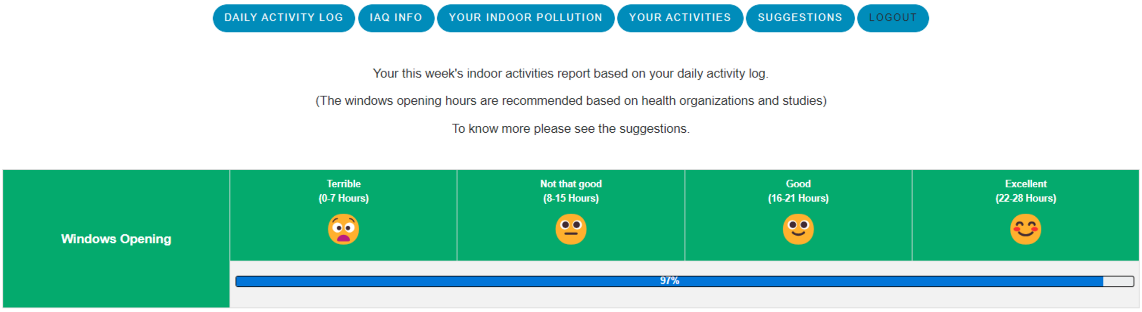


Figure 31: (d) Indoor activity – window control for ventilation

Intervention (Int5 - Suggestions): This digital intervention provides various levels of contextual information with additional messages to the earlier used to improve IAQ, and related health impacts were provided to help participants understand IAQ's importance better, as shown in Figure 31 (e).

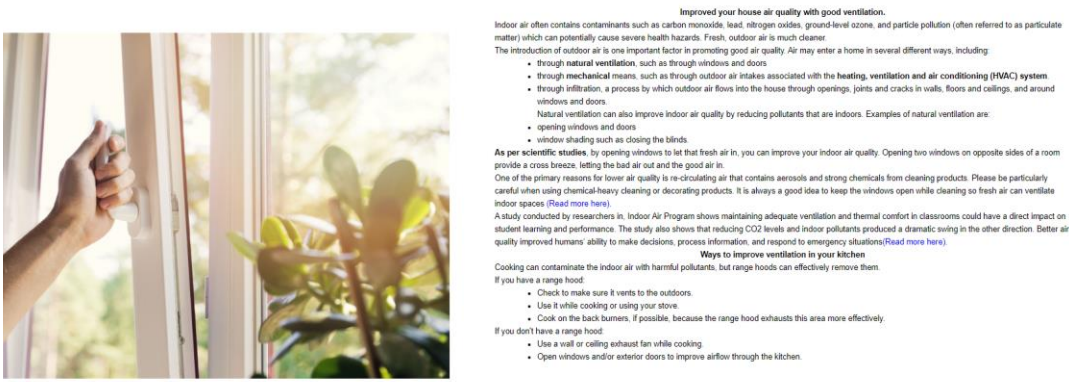


Figure 31: (e) Provide contextual information regarding IAQ and its improvement, including health impacts

Supplementary Intervention (Daily Indoor Activity log): The daily digital diary consists of eleven interactive multiple-choice questions (Appendix-E), structured in three steps: opening windows, vacuum cleaning, and noting any breathing problems, smoking, heating, and cooking activities as detailed in Figure 31 (f).

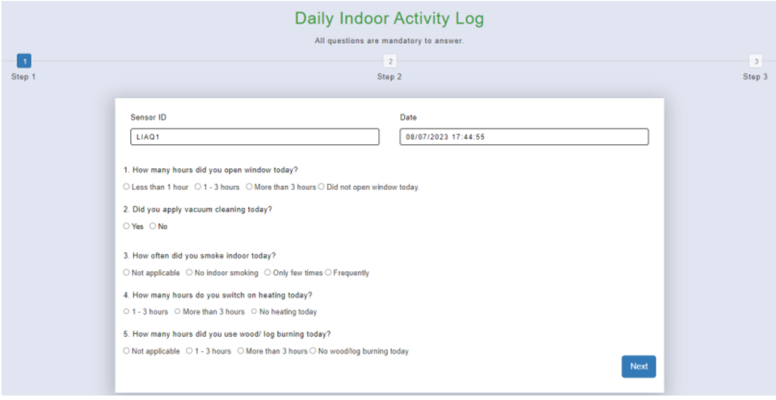


Figure 31: (f) The daily digital diary with multiple-choice questions related to indoor activities.

6.1.2 User tracking on digital visualisation platform.

In the prior study [35], digital interventions' influence on individual participants' behavioural patterns has been analysed, employing visualisation platforms as the primary tool. To understand the behaviour of users on the digital visualization platform, the methodology utilized by Google Analytics (GA) and Google Tag (GT) Manager technologies has been employed. These tools help comprehend user tendencies and enable the collection of comprehensive usage data across all digital platform sessions, as shown in Figure 31 (b).

The gathered data encompasses all digital platform sessions initiated from participants' devices, which are subsequently reported to the GA server. The GA system meticulously records the total count of unique events and time for each digital intervention tracked within the platform. This tracking spans the entire session, from the initiation at login to the termination at logout. The analysis extends to each webpage, where the GA tracking code and the GT Manager tracking code were tracked separately. This dual-layered analysis enables the study to ascertain the proportion of total sessions that engaged with each web-based digital intervention. In addition, the implementation of the GA IP anonymisation feature on the digital platform has been verified. This feature is crucial in obfuscating user tracking, thereby ensuring user privacy and data protection. The visualisation platform measures the following web-based digital interventions in the form of web pages: Pop-up, IAQ Visualisation, IAQ Info, Your Indoor Activity, and Suggestions. This tracking provides a comprehensive understanding of user behaviour and interaction with the platform, thereby contributing to the research on the impact of digital interventions.

6.1.3 Exploration of User Engagement Patterns through GA in Digital Environments

This study explores using GA to monitor consistent participants' activities. GA, a robust tool, can generate many reports, making it an ideal choice for this research endeavour due to its precise data granularity and relevance for the evolution of digital interventions. The user flow was the primary data source for digital user interactions on the digital platform. This resource facilitated in-depth analysis of participant behaviour, revealing the most frequented pages and the volume of user activities. The data generated offered comprehensive insights into participant engagement on the web platform, including page visits, duration of visits, and even the time spent on each page, quantified in seconds up to the point of logout.

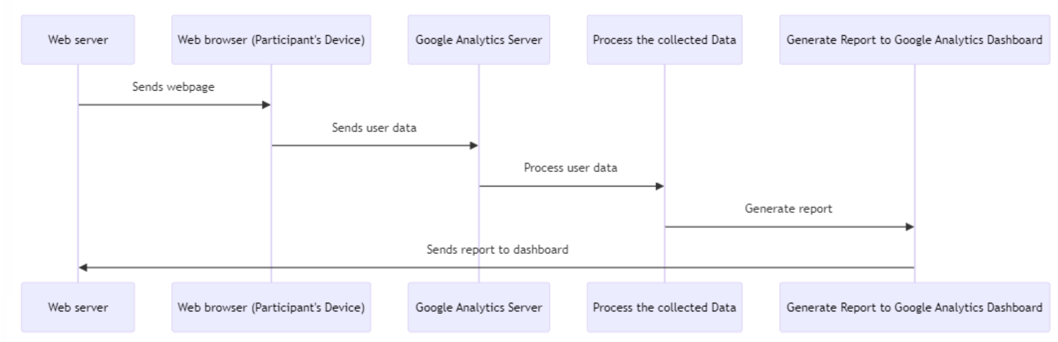


Figure 31: (g) Communication flow between participant's device and GA server

To ensure the distinct tracking of each participant, unique user IDs and passwords were assigned. This allowed GA to monitor individual login activities accurately across various browsers used to access the visualization platform. The data harvested from GA were securely stored, with each participant's activities coded to their unique ID for subsequent analysis. This approach underscores the potential of GA as a tool for tracking and understanding user behaviour in digital environments.

6.2 Study Setting, Participants, and Context

The study was carried out sequentially, as depicted in Figure 32, over three weeks in June 2023. The objective was to measure changes in participant behaviour when supported with COM-B-based digital interventions to improve IAQ, explicitly focusing on which digital intervention has more influence on changing their behaviour. Also, to measure which digital intervention has more impact on participants' behaviour. Seven households were selected for installing LCS-based IAQ monitoring devices based on various socioeconomic and demographic factors, including location, ethnicity, and type of dwelling. Before the study's commencement, participants completed an initial questionnaire (Appendix A) capturing their subjective views on the impact of poor air quality, as well as demographic information such as ethnicity, education level, combined household income, distance from the main road, and physical characteristics of their house (e.g., year of construction, type of house) as like previous study. The participant sample exhibited ethnic diversity, with individuals identifying as British and Asian. This ethnic diversity introduced variation into the study, particularly for cooking styles, window opening habits, interior home settings, and living patterns about IAQ monitoring. The participants' demographic information was further analysed to enhance the study's diversity, as shown in Table 17. It was observed that all households were at distances of 0.1 km from the main road. The study incorporated a variety of dwelling types, including three semi-detached, three terraced houses and one detached house with a mix of two electric and four gas cooker users. Additionally, all participants are using a central heating system.

Table 17: Summary of initial questionnaire outcome of participant's demographic information for the study

Sensor ID	House Location	Type of House	Type of Cooker	Type of Heating
L1	Within 0.1 km from the main road.	Semi-detached	Gas	Central heating
L2	Within 0.1 km from the main road.	Terraced	Gas	Central heating
L3	Within 0.1 km from the main road.	Detached	Electric	Central heating
L4	Within 0.1 km from the main road.	Terraced	Gas	Central heating
L5	Within 0.1 km from the main road.	Terraced	Electric	Central heating
L6	Within 0.1 km from the main road.	Semi-detached	Gas-Electric	Central heating
L7	Within 0.1 km from the main road.	Semi-detached	Gas	Central heating

During the study's first week, participants did not have access to IAQ data from their households like the previous study. This time, they were also not required to complete a daily digital diary to log daily indoor activities in the first week. IAQ data and all digital interventions through the visualisation platform were introduced at the beginning of the second week. Following this, an online meeting was arranged to interview participants using pre-prepared questions at convenient times towards the end of the third week. To protect participant privacy, participant IDs were anonymised to prevent linkage with specific individuals.

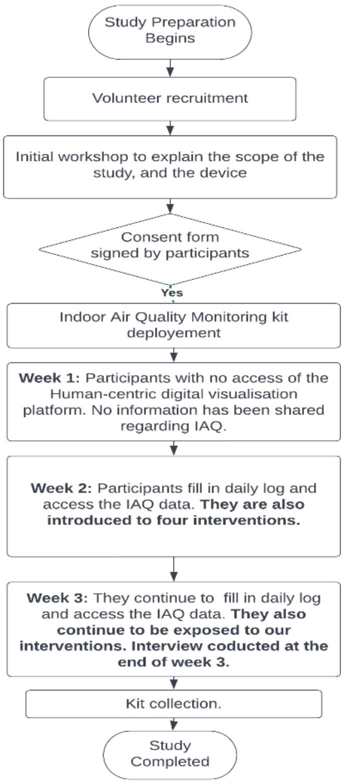


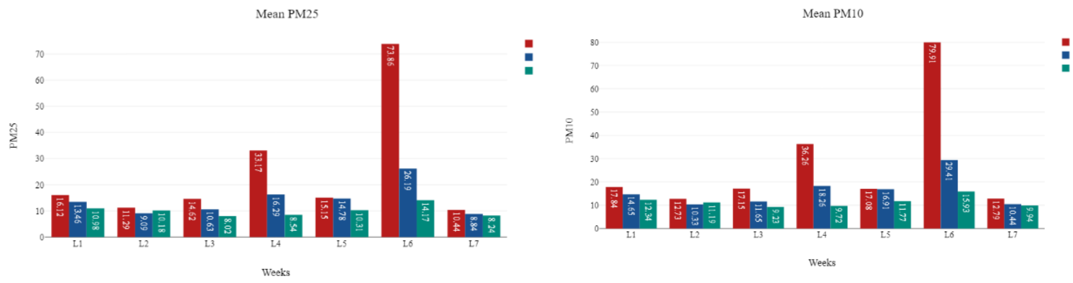
Figure 32: Study flow diagram.

6.3 Data Analysis and Discussion

Over three weeks, the data have been thoroughly gathered and analysed from study participants' homes and the digital visualisation platform. This absolute examination of the data has yielded valuable insights and information.

6.3.1 Behavioural Change Analysis—Improvement in IAQ

The analysis was conducted on IAQ data collected from a three-week study, where a human-centred digital visualisation platform based on the COM-B model and digital interventions were introduced from the second week onwards. The dataset contained measurements of $PM_{2.5}$ and PM_{10} levels from different devices over three weeks. The acquired IAQ data underwent a comprehensive analysis, employing various methods to elucidate the patterns and trends within the dataset. This analysis encompassed a temporal examination of the IAQ data spanning three weeks. Moreover, the study also incorporated an assessment of the duration of window opening, the usage of exhaust fans, and the hours spent cooking. These diverse analytical approaches facilitated a multifaceted understanding of the IAQ data, providing a robust foundation for subsequent interpretations and conclusions.



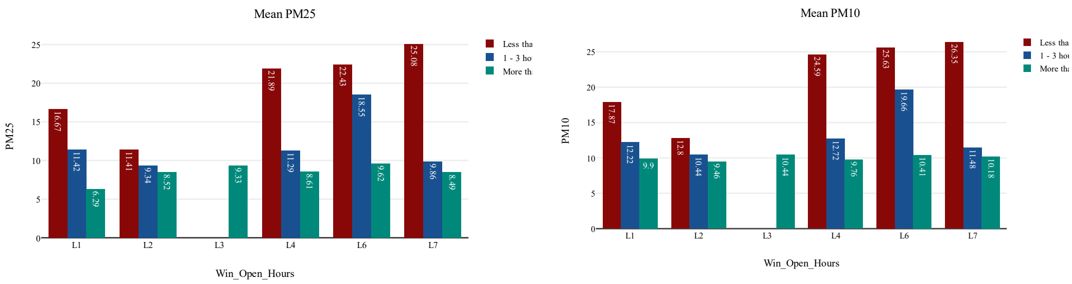
(a) (b)

Figure 33: (a) Average $PM_{2.5}$ data from multiple households over three consecutive weeks; (b) Average PM_{10} data from multiple households over three consecutive weeks

The data were visually analysed using bar graphs showing each device's average $PM_{2.5}$ and PM_{10} levels over the three weeks, as shown in Figure 33 (a) and (b). The graphs revealed a noticeable variation in $PM_{2.5}$ and PM_{10} levels across different households (L1-L7), suggesting differences in the environments where the devices were located. Furthermore, each household had fluctuations in $PM_{2.5}$ and PM_{10} levels from week to week, indicating changes in indoor environmental conditions, indoor activity patterns, or other factors affecting indoor air pollution levels. Despite these variations, a consistent pattern was observed across all devices: $PM_{2.5}$ and PM_{10} levels tended to be higher in the first weeks and lower in the second and final weeks. This suggested a common factor influencing indoor air pollution levels across all devices, such as window opening, cooking, cleaning and other indoor activities. With the introduction of the digital visualisation platform and digital interventions from the second week onwards, the visual analysis suggested a general decrease in indoor air pollution levels. This decrease was sustained over the third week, indicating that the impact of the digital visualisation platform and interventions were not just temporary but had a lasting effect over the duration of the study.

To provide statistical evidence supporting the visual analysis, independent two-sample t-tests were conducted to compare the means of $PM_{2.5}$ levels between different weeks. The results showed a statistically significant difference in the means of $PM_{2.5}$ levels between Week 1 and Week 2 (t-statistic: 4.20, p-value: 0.000027), between Week 2 and Week 3 (t-statistic: 2.85, p-value: 0.0044), and between Week 1 and Week 3 (t-statistic: 6.05, p-value: 0.00000000166). Similarly, the statistical analysis was conducted using independent two-sample t-tests to compare the means of PM_{10} levels between different weeks. The results showed a statistically significant difference in the means of PM_{10} levels between Week 1 and Week 2 (t-statistic: 4.17, p-value: 0.000032), between Week 2 and Week 3 (t-statistic: 2.81, p-value: 0.0050), and between Week 1 and Week 3 (t-statistic: 6.00, p-value: 0.00000000227). The p-values were less than 0.05, suggesting that the differences in PM levels between the weeks were not due to random chance but were likely due to the introduction of the digital visualisation platform and interventions. This provides statistical evidence that the interventions likely had a significant impact in reducing PM levels as well. In summary, both the visual and statistical analyses suggest that introducing the digital visualisation platform and digital interventions likely significantly reduced indoor air pollution levels with distinct participants, as appeared in the previous studies.

Furthermore, the analysis of the IAQ data revealed interesting patterns in $PM_{2.5}$ levels in relation to window open hours, as shown in Figure 34 (a). The visualisations showed variations in $PM_{2.5}$ levels across different devices and window open hours. The statistical analysis further supported these findings. Independent two-sample t-tests indicated statistically significant differences in $PM_{2.5}$ levels between different window open hours. Specifically, there were significant differences between "1 - 3 hours" and "More than 3 hours" (p-value: 0.0000616), and between "Less than 1 hour" and "More than 3 hours" (p-value: 0.0317). These results suggested that the number of window open hours significantly impacted $PM_{2.5}$ levels, with longer window open hours associated with lower $PM_{2.5}$ levels. This provides valuable insights for improving IAQ and can inform the development of effective interventions.

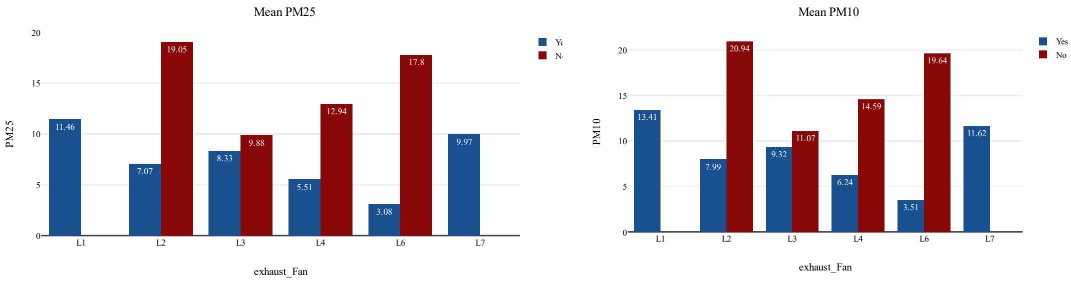


(a) (b)

Figure 34: (a) Relationship between average $PM_{2.5}$ and Window opening hours from different households. (b): Relationship between PM_{10} and Window opening hours from different households.

In addition, the statistical analysis, conducted using independent two-sample t-tests, revealed statistically significant differences in PM_{10} levels between different window open hours, as shown in Figure 34 (b). Specifically, there were significant differences between 'Less than 1 hour' and '1 - 3 hours' (t-statistic: 2.27, p-value: 0.028), between '1 - 3 hours' and 'More than 3 hours' (t-statistic: 2.08, p-value: 0.041), and between 'Less than 1 hour' and 'More than 3 hours' (t-statistic: 4.43, p-value: 0.000034). These results suggested that the differences in PM_{10} levels are likely due to the amount of outdoor air entering the room, as indicated by the window's open hours.

Moreover, the independent two-sample t-test comparing the means of $PM_{2.5}$ levels between different exhaust fan statuses (On or Off) returned a t-statistic of -2.43 and a p-value of 0.017, as shown in Figure 35 (a), similarly, for PM_{10} as shown in Figure 35 (b), a t-statistic of -2.44 and a p-value of 0.017. This p-value suggests that there is a statistically significant difference in $PM_{2.5}$ & PM_{10} levels depending on whether the exhaust fan is on or off. Specifically, the negative t-statistic indicates that the mean $PM_{2.5}$ & PM_{10} level is lower when the exhaust fan is “on” compared to when it is off.

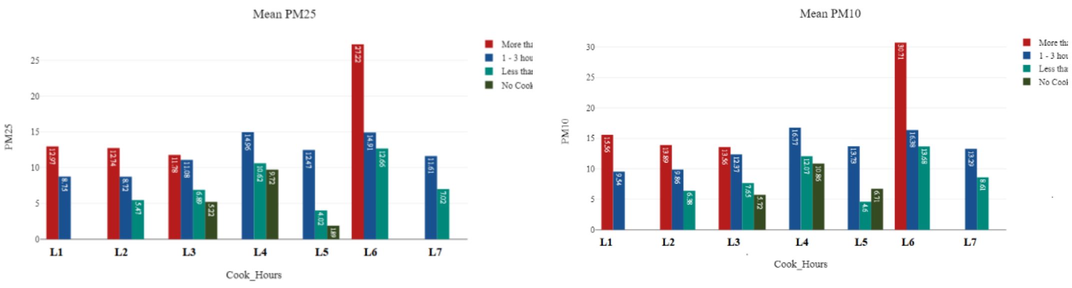


(a) (b)

Figure 35: (a) Impact of Exhaust fan usage on average $PM_{2.5}$. (b): Impact of Exhaust fan usage on average PM_{10}.

In summary, the visual analysis showed variations in $PM_{2.5}$ & PM_{10} levels across different devices and exhaust fan statuses. The subsequent statistical analysis confirmed that these variations are statistically significant, particularly in relation to the status of the exhaust fan. This suggests that the use of an exhaust fan can effectively reduce $PM_{2.5}$ & PM_{10} levels, contributing to improved IAQ.

In addition to the aforementioned analysis, a supplementary investigation was undertaken to explore the relationship between indoor air pollution levels and the duration of cooking activities within the household. This analysis aimed to elucidate the potential impact of cooking hours on the overall quality of indoor air, thereby providing a more comprehensive understanding of the factors influencing indoor air pollution. The visual and statistical analysis of $PM_{2.5}$ & PM_{10} levels in relation to cooking hours revealed significant variations, as shown in Figure 36 (a) & (b). The bar graph displayed differences in $PM_{2.5}$ & PM_{10} levels across devices and cooking hours. The independent two-sample t-tests further confirmed these differences for $PM_{2.5}$ (t-statistic: -2.22, p-value: 0.03) & PM_{10} (t-statistic: -2.36, p-value: 0.021). This suggests that indoor air pollution levels are significantly lower when cooking hours are less than 1 hour compared to more than 3 hours. Overall, the analysis indicates that longer cooking durations can increase indoor air pollution levels, affecting indoor air quality.



(a) (b)

Figure 36: (a) Relationship between average $PM_{2.5}$ and household cooking hours. (b): Relationship between average PM_{10} and cooking hours from different households.

6.3.2 Sequential Patterns, Behaviour and Persona Analysis

This sequence flow analytics provides insights into the typical navigation patterns among participants while browsing the digital visualisation platform. The analysis explores the patterns of interactions and the preferred sequences of actions each user performs. A two-phase analysis has been performed on the patterns. To begin with, individual interactions with the digital intervention pattern have been analysed for insights into participant behaviours. Further analysis has been applied to combine participants' data to generalise the pattern and behaviours. In addition, the study analysis employed cluster analysis and transition matrices to dissect user navigation patterns on a digital visualisation platform. Moreover, this research study has identified three distinct user personas: "The Explorer", "The Focused", and "The Quick Visitor". Each persona reflects a unique navigation sequence and platform engagement. Transition matrices elucidate the probabilistic journey of each persona. These insights can inform strategic platform design and content placement.

(i) Individual sequence analysis (for each Participant):

In this study, the user flow sequences for each participant have been analysed. Each Participant's most common sequences of actions have been identified while interacting with the digital visualisation platform. In the analysis, it was observed that **Participant L1** has a pronounced preference sequence: **Login -> Pop-up -> IAQ Visualization -> Your Indoor Activity -> Daily Activity Log -> Logout**, manifesting in 28.57% of their interactions. This trajectory underscores an engagement with the platform's pop-up intervention designed to bolster psychological capability, followed by an exploration of real-time IAQ data, an assessment of ventilation habits, and daily documentation of indoor activities. **Participant L2** exhibited a bifurcated pattern, with two sequences sharing equal prominence, **Login -> Pop-up -> IAQ Visualization -> Daily Activity Log -> Logout**, and **Login -> Pop-up -> IAQ**

Visualization -> Your Indoor Activity -> Daily Activity Log -> Logout, each occurring 14.29% of the time. Both sequences underscored the significance of the initial pop-up intervention, the real-time IAQ visualisation, and the daily activity documentation, with a variation in the emphasis on understanding ventilation habits. For **Participant L3**, a distinct pathway was noted: **Login -> Pop-up -> IAQ Visualization -> Your Indoor Activity -> Suggestions -> Daily Activity Log -> Logout**, observed in 28.57% of instances. This Participant's journey extends the engagement further by seeking recommendations to enhance indoor air quality after gauging their ventilation practices. Furthermore, **Participant L4** predominantly favoured the sequence: **Login -> Pop-up -> IAQ Visualization -> Daily Activity Log -> Suggestions -> Logout**, evident in 42.86% of their interactions. This pattern underscores an inclination towards pop-up interventions and real-time air quality metrics, followed by daily activity logging and then seeking suggestions. For **Participant L5**, a clear propensity was discerned towards **Login -> Pop-up -> IAQ Visualization -> Your Indoor Activity -> Daily Activity Log -> Logout**, accounting for a significant 71.43% of their interactions, resonates with the patterns of Participant L1, suggesting a possible alignment in their objectives and the value they derive from the platform. Both **Participant L6** and **Participant L7** exhibited preferences that amalgamate platform features, ranging from real-time visualisations to understanding their indoor activities and seeking interventions to enhance their indoor air quality. **Participant L6** exhibited a balanced pattern with two sequences, **Login -> Pop-up -> IAQ Visualisation -> Your Indoor Activity -> Daily Activity Log -> Logout" and "Login -> Pop-up -> IAQ Visualisation -> Daily Activity Log -> Suggestions -> Logout**, both manifested 21.43% of the time. Lastly, **Participant L7** showcased a preference for the sequence **Login -> Pop-up -> IAQ Visualisation -> Your Indoor Activity -> Daily Activity Log -> Logout**, evident in 42.86% of their interactions.

(ii) Overall sequence analysis (across all Participants):

The analysis reveals nuanced insights into participants' behaviour and their interactions with the digital platform's diverse features. With the highest visit frequency (31.30%), the "**IAQ Visualisation**" page emerges as a predominant focal point for participants. This is because of the real-time visualisation of IAQ metrics compared against established WHO and UK standards, also highlighted by the user during the interview session. This prominence suggests that participants were particularly keen on understanding their immediate indoor environment and evaluating it against recognised health benchmarks. The "**Daily Indoor Activity log**" approximately has equal visit frequency to the "IAQ Visualisation" with a frequency of 30.99%. This higher engagement is because of empowering the users to discern the direct implications of their actions on their living spaces via the interactive Daily digital diary. This also allows users to document their indoor activities potentially affecting IAQ. Further analysis shows that the "**Your Indoor Activity**" page clocks in with a moderate 20.14% visit rate. This indicates a substantial user interest in monitoring their ventilation habits and seeking guidance to enhance their performance. Conversely, the lesser frequented "**Suggestions**" (11.82%) and "**IAQ Info**" (5.75%) pages imply a potential user preference for real-time data and actionable feedback over contextual or educational content. These insights that these pages, once perused, don't compel revisits or perhaps aren't as intuitively accessible as the others.

The examination of the predominant user navigation patterns on the platform furnishes significant insights into participants' proclivities and interactive behaviours. 28.57% of users follow the main navigation path, which starts with logging in and is followed by the **Pop-up -> IAQ visualisation -> Your Indoor Activity -> Daily Activity Log**, and ends with **Logout**. This trajectory elucidates a comprehensive participant engagement sequence. The immediate transition to the IAQ Visualisation post the initial Pop-up accentuates the paramountcy of real-time indoor environmental data to the users. Subsequent navigation to the Your Indoor Activity page manifests an inclination towards comprehending ventilation practices and their accompanying performance. The ensuing transition to **Daily Activity Log** further underscores a propensity to chronicle activities potentially influencing the IAQ. The secondary prevalent path, adopted by 25.51% of participants' actions, comprises a more concise sequence: **Login -> Pop-up -> IAQ Visualisation -> Daily Activity Log**, and **Logout**. This streamlined path underscores a dual focus: an emphasis on real-time indoor environmental data visualisation and logging pertinent daily activities. The oversight of the **Your Indoor Activity** page in this sequence suggests that a considerable cohort prioritises immediate indoor environmental insights and the act of daily documentation over receiving feedback on their ventilation habits. The tertiary sequence, albeit less prevalent at 8.16%, is comprehensive, incorporating the **Suggestions** page into the pathway: **Login -> Pop-up -> IAQ Visualisation -> Your Indoor Activity -> Suggestions -> Daily Activity Log** and **Logout**. Based on the data, certain users seem more likely to want specific suggestions on improving the IAQ inside their homes after interacting with real-time data and feedback tools. Their subsequent navigation to the Daily Activity Log possibly indicates a tendency to either enact the provided suggestions or document associated indoor activities.

The **sequence pattern analysis** also reveals how many steps participants took in navigating before ending their session. The analytical result showed that most participants had 6 steps journey (42.86%) followed by 5 steps (25.51%), and fewer reached 7 (18.37%) or 8 steps (13.27%). This suggests users usually find what they need by step 6 and slowly lose interest after.

(iii) User Navigation Patterns Prediction Analysis

Several commonalities and dissimilarities among the participants have been observed in analysing user navigation patterns on this digital visualisation platform. All participants invariably started their journey with a '**Pop-up**' after logging in and subsequently transitioned to the '**IAQ Visualisation**' page, suggesting the significant draw of this feature, as discussed earlier. All participants except L4 ended their sessions with the '**Daily Activity Log'** page before **Logout**, indicating its importance in user interaction. However, there was a notable variation in the sequence of steps participants took post '**IAQ Visualisation**', with '**Your Indoor Activity**' being the most common for L1, L3, L5, and L7, and '**Daily Activity Log**' for L2 and L6. Notably, L4 deviated from this pattern, visiting '**Your Indoor Activity**' as their final step.

Moreover, in this analysis of platform navigation patterns, as listed in Table 18, it has been observed that none of the participants most frequently visited the "**Suggestions**" or "**IAQ Info**" pages as their third step in the sequence. This trend could be attributed to the length and complexity of the information on these pages, which might be perceived as time-consuming to process. As a result, participants preferred to visit these pages later or when needed in their navigation sequence, underscoring the importance of user-friendly digital intervention platform design and effectively organised content.

Table 18: Navigation patterns of all participants.

Participants	**Most Common Initial Step**	**Most Common Second Step**	**Most Common Third Step**	**Most Common Final Step**
L1	Pop-up	IAQ Visualisation	Your Indoor Activity (p=0.64)	Daily Activity Log (p=0.45)
L2	Pop-up	IAQ Visualisation	Daily Activity Log (p=0.43)	Daily Activity Log (p=0.71)
L3	Pop-up	IAQ Visualisation	Your Indoor Activity (p=0.75)	Daily Activity Log (p=0.71)
L4	Pop-up	IAQ Visualisation	Daily Activity Log (p=0.5)	Your Indoor Activity (p=0.75)
L5	Pop-up	IAQ Visualisation	Your Indoor Activity (p=1)	Daily Activity Log (p=0.79)

L6	Pop-up	IAQ Visualisation	Daily Activity Log (p=1)	Daily Activity Log (p=1)
L7	Pop-up	IAQ Visualisation	Your Indoor Activity (p=1)	Daily Activity Log (p=1)

(iv) User Engagement Duration Analysis

The analysis of participant engagement with pre-defined digital interventions on a human-centred digital visualisation platform reveals insightful patterns, as shown in Figure 37, and the data has been collected through GA. Participants spent the majority of their time (47.18%) during the second and third weeks of the study on the 'IAQ Visualisation' intervention, which provided visualisations of $PM_{2.5}$ and PM_{10} data, allowing them to compare their indoor air pollution levels with established guidelines from WHO and the UK government. This suggests a high level of interest and engagement in understanding personal indoor air pollution levels in relation to recognised standards. The 'Suggestions' intervention, offering contextual information to improve IAQ and highlighting related health impacts, also attracted significant attention, accounting for 29.32% of the total time. Conversely, 'Your Indoor Activity' and 'Pop-up' interventions, providing feedback on ventilation control practices and supportive pop-up messages, respectively, were less time-consuming for participants. These findings highlight the value of personalised, contextual information in digital interventions for improving IAQ. Future interventions can leverage these insights to better cater to participant needs and preferences.

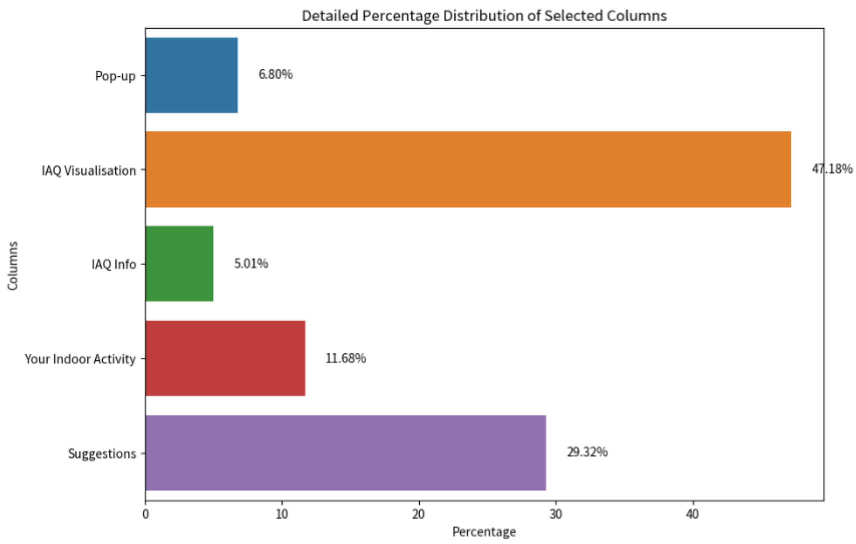


Figure 37: Insights from participant engagement with digital interventions on a human-centred digital visualisation platform.

In addition to the collective analysis, individual assessments were undertaken for each household concerning all digital interventions, as shown in Figure 38. This approach allowed for a more nuanced understanding of the impact and effectiveness of the interventions at a granular level, taking into account the unique characteristics and circumstances of each household. The analysis of engagement with digital interventions across different households reveals distinct patterns. Household L1 and L2 showed a strong interest in understanding individual air pollution levels and receiving actionable advice, spending 47.73% and 43.34% of their time, respectively, on 'IAQ Visualisation' intervention and 33.27% and 36.72% on 'Suggestions'. Households L3 and L4 demonstrated a higher engagement with 'IAQ Visualisation' (41.72% and 55.39%, respectively) and 'Pop-up' interventions (36.20% and 23.58%, respectively), suggesting the effectiveness of supportive pop-up messages for these users. Household L5 and L6 exhibited a more balanced interest across various aspects of Indoor Air Quality (IAQ) management, engaging with 'IAQ Visualisation' (50.87% and 49.42%, respectively), 'Pop-up' (7.59% and 11.57%, respectively), and 'Your Indoor Activity' interventions (23.99% and 12.07% respectively). Device L7 focused strongly on understanding pollution levels, spending most of the time on 'IAQ Visualisation' (59.16%) and 'Pop-up (16.30%). These findings underscore the importance of personalising digital interventions to cater to each user's unique needs and preferences, enhancing user engagement and effectiveness in promoting better IAQ practices.

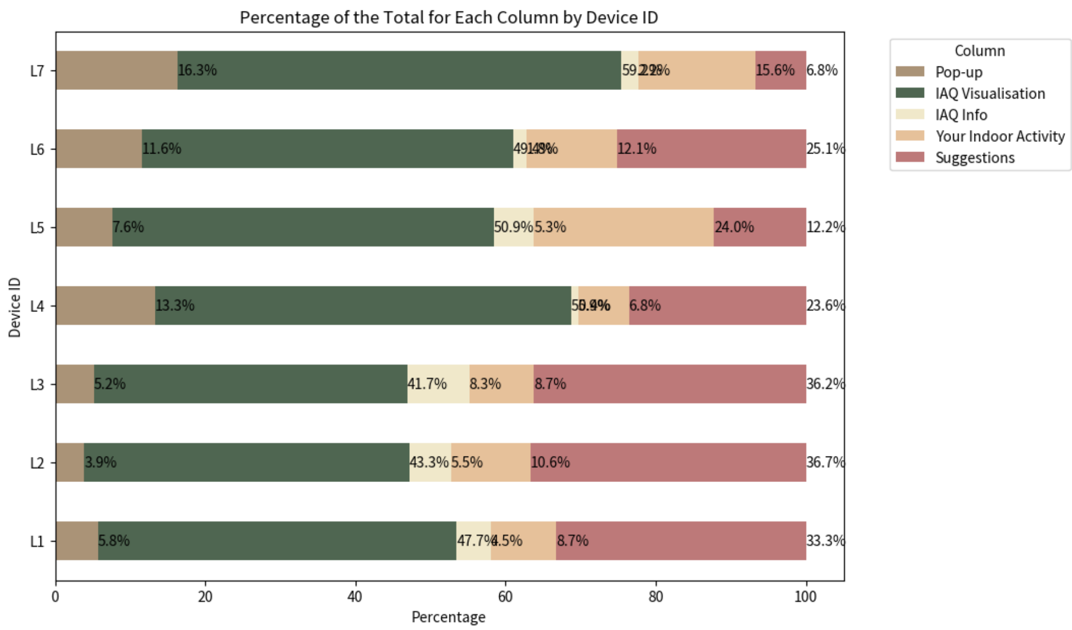


Figure 38: Individual assessment of digital interventions in household settings

Analysing participant engagement with various digital interventions provides valuable insights into user behaviour and preferences. The data reveals that users engage differently with each intervention, with the ‘IAQ Visualization’ digital intervention consistently attracting the most attention across all devices. This suggests a strong user interest in understanding personal pollution levels in relation to established guidelines. However, the second most engaged digital intervention varied across devices, indicating that different users value different types of information and support. For instance, some users showed a higher engagement with supportive pop-up messages (‘Pop-up), while others were more interested in actionable advice to improve IAQ (‘Suggestions’) or feedback on their ventilation control practices (‘Your Indoor Activity’). These findings highlight the importance of personalisation in digital interventions.

Moreover, the sequence analysis revealed that after initial common steps (**Login -> Pop-up -> IAQ Visualisation**), participants diverged in their paths, indicating varied interests and behaviours, as shown in Figure 39. Time-series analysis showed that most participants' total time spent on the webpage remained fairly constant over the observed days. However, participants L1 and L3 showed a decrease in total time spent over time. The correlation pattern analysis indicated a positive correlation between the time spent on the **IAQ Visualisation** and **Suggestions** pages with the total time spent on the platform. Finally, the distribution of total time spent on the webpage varied among participants, with L1 showing the highest median time. This analysis provides valuable insights into participants' engagement and navigation behaviour on the webpage.

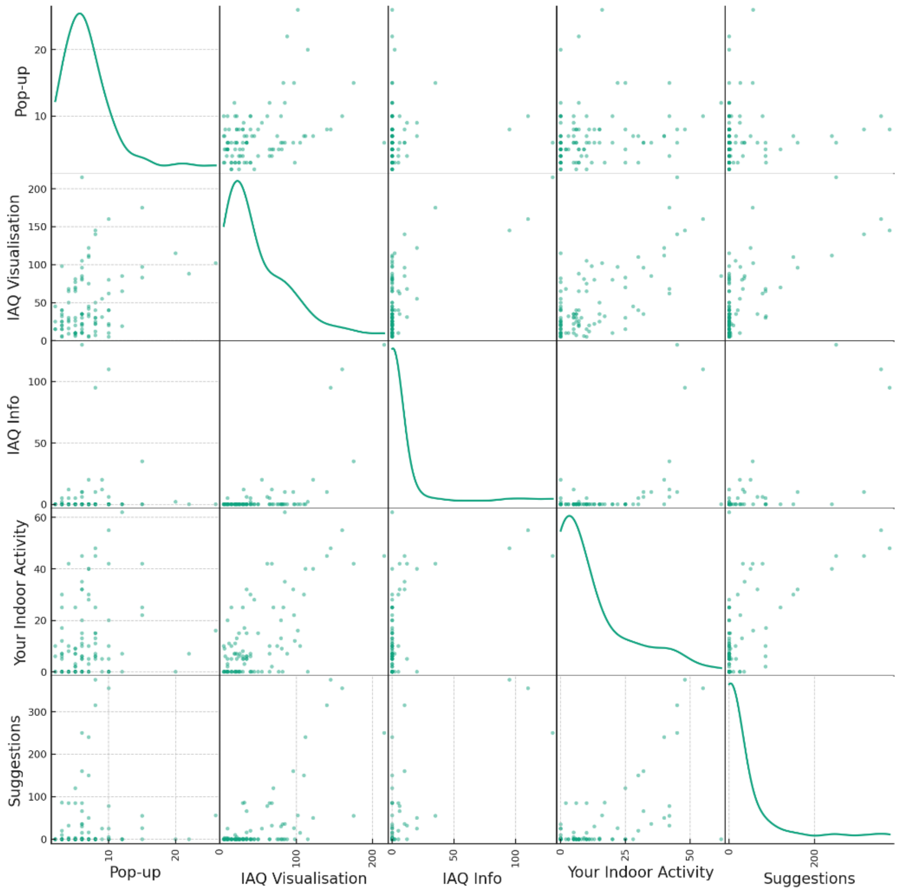


Figure 39: Participants diverged in their paths, which indicated varied interests and behaviours.

(v) User Personas Analysis

Personas are fictional characters that represent segments of the user base. They're often used in user-centred design and marketing to help teams understand users' needs, experiences, behaviours, and goals. Personas make empathising with users and considering their needs more accessible when making decisions. Each persona is usually given a name and a set of characteristics that reflect their segment. These characteristics include demographic information (like age, occupation, and location) and behavioural traits (like goals, motivations, and frustrations). The characteristics should be based on real data when possible [278-280].

In the context of cluster analysis within the study, each cluster of users has been represented by a persona. The high-level personas for each cluster have been created based on the collected data. However, the depth analysis and looking more closely at the transition between steps within each cluster reveal common paths that users take through the visualisation platform and help better define each persona's behaviours. For this, a **transition matrix** has been created for each cluster. A transition matrix shows the probability of moving from one state (in this case, a step) to another. This helped to identify each persona's most common paths through the platform. Based on the previous analyses, the following personas have been defined as illustrated in Table 19.

Table 19: Category of Persona by each participant.

Persona	**Most Common Participants**	**Common Sequence of Steps**	**Characteristics**
"The Explorer"	L3, L2, L1	Login -> Pop-up -> IAQ Visualisation -> Your Indoor Activity/Suggestions/IAQ Info -> Suggestions/Your Indoor Activity/IAQ Info -> Daily Activity Log/Suggestions/Your Indoor Activity -> Daily Activity Log/Logout -> Logout	These users are characterised by their exploratory behaviour, navigating through a variety of features on the platform. Following login, they are likely to engage with the 'IAQ Visualisation' feature, after which they explore 'Your Indoor Activity' (probability, p=0.5), 'Suggestions' (p=0.25), and 'IAQ Info' (p=0.17). Their session typically concludes with a visit to the 'Daily Activity Log' before logging out.
"The Focused"	L4, L6, L2	Login -> Pop-up -> IAQ Visualisation -> Daily Activity Log -> Logout/Your Indoor Activity/IAQ Info -> Logout/Suggestions/IAQ Info -> Your Indoor Activity/Logout/Suggestions -> Logout	These users exhibit a more streamlined approach to platform interaction. After login, they proceed directly from 'IAQ Visualisation' to 'Daily Activity Log'. Interestingly, these users frequently terminate their sessions midway (p=0.66), suggesting that they utilise the platform for shorter, more concentrated periods.

"The Quick Visitor"	L5, L1, L7	Login -> Pop-up -> IAQ Visualisation -> Your Indoor Activity/Suggestions/IAQ Info -> Daily Activity Log/Suggestions -> Logout/IAQ Info -> Logout	These users appear to engage with the platform for brief visits. They typically transition from 'IAQ Visualisation' to 'Your Indoor Activity' (p=0.83) or 'Suggestions' (p=0.83) and then proceed directly to 'Logout'. However, they do often visit the 'Daily Activity Log' (p=0.97).

(vi) Discussion on the findings

To summarise these analytical findings, it's evident that the digital platform is most effective when it provides participants with immediate insights on which they can take action. Although educational content is valuable, combining it with real-time data makes more sense to the participants. The findings also showed insights that the platform can empower users, enabling them to make a positive change in improving their indoor environment. In synthesising these findings, it becomes evident that a consistent user gravitation towards real-time data visualisation coupled with indoor activity data with variations in these predominant paths defining distinct user priorities and needs. The data underscores the imperative of a multifaceted platform that caters to a diverse spectrum of user preferences, underscoring the overarching theme of users seeking actionable insights and mechanisms that empower informed indoor environmental decisions.

Furthermore, if there's a particular action we want users to take or a page we want them to visit, it could be beneficial to place it along one of these common paths found in the analytics. There is also concern about designing a more extended sequence of digital interventions, which needs to simplify the user flow or offer more assistance in steps 7 and 8 so that any digital intervention could enhance the overall user experience. Doing so enhances user satisfaction, improves engagement, and ensures users can efficiently accomplish their objectives within the system or interface. Also, findings underscore the existence of common patterns and individual differences in user navigation, likely driven by differing user needs and interpretations of the platform's features. This information enhanced the user experience through tailored design improvements. In addition, persona analytics reveals that there are variations within each cluster with probabilistic interpretations. However, these analyses have been useful for understanding and predicting user behaviour within the same persona. In summary, while providing comprehensive and accurate information is crucial, understanding and catering to user preferences can significantly enhance the effectiveness of digital interventions.

6.3.3 A Qualitative Data Analysis Approach to Assess the Impact of Digital Visualisation Platform

In order to supplement the aforementioned quantitative analysis, a qualitative analysis has been implemented by conducting semi-structured interviews (Appendix-D) upon the study's conclusion. This approach allowed the study to discern the connections between the various digital interventions and the resultant behavioural changes as indicated by participant mentions. The intervention participants most frequently referenced was Intervention 2 (Int2), which provided participants with a dashboard displaying the IAQ data within their residences. This was followed in frequency by Intervention 5 (Int5), which offered advice on enhancing IAQ through strategies related to ventilation, product usage, and health-related information. Subsequently, Intervention 4 (Int4) was mentioned, which provided participants with a weekly assessment of their ventilation practices. Lastly, Intervention 1 (Int1) was referenced, which involved the use of pop-ups to deliver succinct informational content. This order of mention frequency suggests a potential hierarchy of impact and relevance among the interventions, with Int2 appearing to be the most influential in driving behavioural change.

Intervention 1 – Pop-up:

The Pop-up intervention was well-received by participants, who found it to be *"Helpful and Informative"* and appreciated its ability to provide *"quick information"*. As a result, they started to *"follow the pop-up suggestions and open windows now more frequently"*, indicating a change in their behaviour. While some participants admitted that the pop-ups could be *"sometimes irritating"*, they acknowledged that it was acceptable considering the benefits they received. One participant specifically mentioned that the *"daily activity logs and pop-ups were helpful"* in their efforts to improve indoor air quality. Overall, the quotes reflect the positive impact of the Pop-up intervention, with participants recognising its value in providing information and guiding their actions.

Intervention 2 – IAQ Visualization

The IAQ Visualization intervention elicited a range of reactions from participants. Some found the graphs and the wealth of information they provided to be *"Shocking"*, while others appreciated the clarity they brought to understanding indoor air pollutants and their impact on health. One participant noted, *"Indeed, help me to understand what indoor air pollutants and their impact are on our health."* The intervention led to proactive changes in behaviour, with one participant stating, *"Based on the data, I could do my best to change the air quality of the surroundings if the pollution was too high, then I would make sure that I turn on the exhaust while cooking or, you know, keep the windows open at least you know, when I'm cooking so that there is good ventilation around the house."* Another participant mentioned, *"I know the graphs fluctuate depending on what I am doing inside my house, so good to see every day. But, sometimes, my husband checks them."*

Intervention 3 – IAQ Info

The IAQ Info intervention was generally well-received by participants. They found the information provided to be helpful in understanding the graphs and gaining knowledge about air quality. One participant stated, *"Get used to it, and looks helpful."* Another participant noted, *"Of course, the information helped me to understand the graphs and all."* A third participant mentioned, *"I have read some of the information, not all. But it helps me to gain knowledge regarding air quality."*

Intervention 4 – Your Indoor Activity

The Your Indoor Activity intervention received positive feedback from participants who found it to be comfortable and beneficial for tracking their activities within the house, with one participant stating, *"It was comfortable and helped me to track my activities like what I am doing in the house."* Participants reported making changes in their behaviour, such as opening windows more frequently when dogs were present; as one participant mentioned, *"As he said, he opens windows more whenever dogs are in the house."* The intervention increased participants' awareness of ventilation and air quality, leading to adjustments in their routines; as another participant explained, *"The windows are definitely open more... you just made me more aware like that."* The interactive elements, including the use of emojis, were well-liked, and participants appreciated the daily activity log component, with one participant expressing, "*I like daily activity log."* The real-time feedback provided by the intervention motivated participants to maintain positive habits and prioritise good ventilation practices, as one participant noted, *"It showed me that today is... I have the windows up, and that the air quality was better, which was certainly good for me."* Overall, the Your Indoor Activity intervention effectively promoted awareness and encouraged behaviour changes for improved indoor air quality.

Intervention 5 – Suggestions

Participants expressed a strong appreciation for the suggestions provided by the intervention, recognising their helpfulness in improving indoor air quality. One participant mentioned, *"I really like the graphs and suggestions. They are really helpful to me. From suggestion, I can see what I can do to make the air better."* The suggestions not only resonated with the participants themselves but also with their family members, as another participant noted, *"Also, the suggestions, I like that one. Even my husband also read those things."* The suggestions served as a source of valuable information, prompting participants to consider their actions and make changes accordingly. For instance, one participant mentioned, *"Well, yes, I do. I just think, how can we? I mean, it's helped me, like, with the door opening, understanding that the vape is not healthy."* The suggestions also influenced participants' cleaning routines, with one participant explaining, *"If I'm honest, by vacuuming and cleaning in small space, I thought about air quality... So I start ventilating space, thanks to your suggestions on the platform."* These quotes highlight the positive impact of the suggestions provided by the intervention, empowering participants to take proactive measures to improve indoor air quality based on the guidance they received.

In summary, the digital interventions significantly impacted participants' behaviour. The Pop-up intervention provided helpful and informative information, leading to increased window opening and behaviour change. The IAQ Visualization intervention shocked participants with its graphs and extensive information, empowering them to make changes for better air quality. The IAQ Info intervention offered valuable insights into air quality, while the Your Indoor Activity intervention facilitated tracking and resulted in increased ventilation. The Suggestions intervention guided participants with actionable suggestions for improving air quality. Overall, these interventions positively influenced participants to take proactive steps towards healthier indoor environments.

Behaviour Change Evidence

Participants reported various behaviour changes as a result of their engagement with the human-centred digital visualisation platform. One participant mentioned, *"After reading the information on the platform, we stop using bleach now. Use warm water."* This highlights a shift towards using less harmful cleaning products. Opening windows for ventilation was a common practice among participants, regardless of the outside temperature; as one participant stated, *"I open windows no matter what temperature outside."* Participants also emphasised the importance of opening windows and doors while vacuuming, as it helped improve air circulation, and advised their spouse to turn on the exhaust while cooking. The platform provided valuable knowledge and learning experiences, with participants expressing, *"It was* *a good experience; I learned a lot."* Cooking habits were also influenced, with participants now turning on the exhaust fan and opening windows to ensure better ventilation. Participants mentioned increased awareness of ventilation while using appliances like air fryers and a conscious effort to reduce oil usage in cooking. Additionally, participants recognised the benefits of having more plants in their homes, as they contribute to improved air quality. One participant mentioned that the platform played a role in quitting harmful habits: *"Now I quit vaping because of the information I got from the dashboard."* Participants acknowledged the importance of opening windows and doors while cooking to enhance air circulation. They expressed a sense of responsibility in making small changes to improve air quality, such as quitting smoking and creating a well-ventilated environment at home. Overall, the platform fostered behaviour changes that focused on reducing exposure to harmful substances, improving ventilation practices, and creating a healthier indoor environment.

Sharing Information with Family and Friends

Participants reported engaging in conversations and sharing information with their family, friends, and neighbours based on their experiences with the digital visualisation platform. One participant mentioned how the platform sparked discussions within their household, saying, *"Me and my wife started a conversation when we saw the platform. We never ever worried about indoor air, but now we are more conscious, especially for our kids."* Participants also extended their sharing beyond their immediate family, with one participant sharing the study and showing the graphs to their neighbour, who expressed interest in having a similar device in their own house. Another participant noted that their partner initially showed little interest but later became engaged in conversations about the platform. The topic of indoor air quality and the importance of opening windows for ventilation became a recurring subject of conversation among friends, as one participant mentioned, *"So obviously, the group of friends... we were just talking about it. You know, we need to open your windows, you know, definitely was a topic of conversation."* Participants acknowledged the significance of discussing indoor air quality with their friends and family, with one participant stating, *"It's something I've particularly discussed, like with friends or family."* Sharing information about the platform and its capabilities also piqued the curiosity of others, as one participant explained, *"Yeah, they (Husband) did ask me about the device. They found it very fancy. So they did ask me what is this about... they did not know about something like this. Like there can be a device, which can monitor their quality."*

The context of sharing information with family and friends revolves around participants' experiences discussing the platform, its features, and the importance of indoor air quality. Participants actively engaged in conversations with their partners, neighbours, and friends, highlighting the platform's impact on their awareness and concerns regarding indoor air quality. Sharing the graphs and information from the platform generated curiosity and interest among those they interacted with, leading to discussions and recognising the need for improved ventilation practices. Participants found value in sharing information about the platform, as it raised awareness and sparked conversations about the importance of indoor air quality among their social circles. The platform's ability to generate interest and promote conversations about indoor air quality highlights its potential as a tool for creating awareness and encouraging positive changes in behaviour.

Suggestions and Thoughts from Participants

Participants provided valuable suggestions and thoughts regarding the IAQ monitoring platform. One participant suggested the implementation of a reminder system for daily logs, stating, *"Reminder system could be helpful for daily logs."* Another participant highlighted the importance of receiving alerts on their mobile devices, emphasising that it would enable quick access to information, stating, *"If we can get an alert on our mobile, this might help us to get quick information."* Participants also expressed the need for the platform to be accessible across different operating systems, similar to a mobile app, to enhance usability and convenience. As one participant mentioned, *"The platform should be accessible to any operating system like the mobile app."* Additionally, participants suggested having more IAQ monitoring devices in a single household to provide comprehensive coverage and accurate data. Overall, these suggestions reflect participants' desire for enhanced functionality, accessibility, and usability of the IAQ monitoring platform, highlighting opportunities for improvement and addressing user needs.

This feedback is centred on participants' thoughts and ideas for improving the IAQ monitoring platform. They suggested implementing a reminder system to facilitate daily logs, recognising its potential to enhance consistency in data recording. Participants also emphasised the importance of receiving mobile alerts, indicating their preference for real-time information and the convenience of accessing it on their mobile devices. They expressed the desire for the platform to be accessible across different operating systems, reflecting the need for compatibility and flexibility. Furthermore, participants mentioned the importance of having multiple IAQ monitoring devices within a household to ensure comprehensive monitoring and accurate data representation. These suggestions highlight participants' engagement with the platform and their proactive approach to optimising their indoor air quality monitoring experience.

6.4 Role of the Technology for Interventions Using Digital Platforms

Another objective of this research study is to examine users' acceptance of digital visualisation platforms to enhance their understanding and management of IAQ in their households. In addition, the study incorporates the Technology Acceptance Model (TAM) [180, 281]. According to the TAM, user acceptance of such digital platforms is influenced by several key factors, including perceived usefulness (PU), perceived ease of use (PEU), attitude intention (AI), and behavioural intention (BI) towards technology adoption.

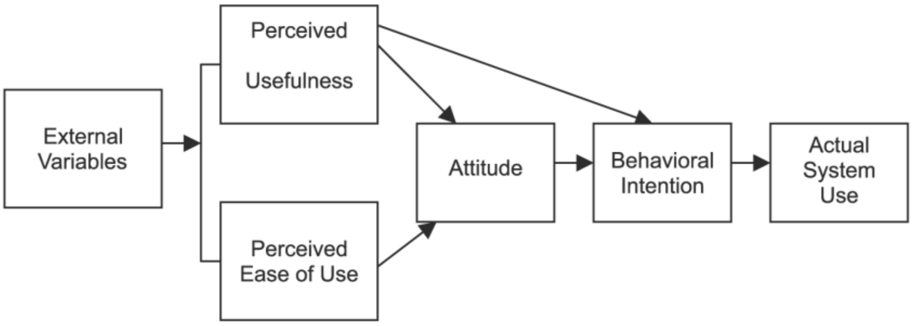


Figure 40: Technology Acceptance Model [281]

The TAM provides a theoretical framework for understanding users' attitudes and behaviours when it comes to adopting and utilising new technologies. In the context of this study, perceived usefulness refers to users' perception of how the digital visualisation platform can effectively contribute to improving their understanding and management of their household IAQ. The perceived ease of use pertains to the user's perception of the platform's simplicity and usability. These two factors, perceived usefulness and perceived ease of use, are crucial in determining users' attitudes and intentions towards the digital platform.

Moreover, attitude intention represents users' overall evaluation and subjective judgment towards the digital visualisation platform. It reflected their general attitude and inclination towards adopting and using the technology in question. Finally, behavioural intention denotes users' willingness and readiness to engage in specific behaviours related to the technology, such as actively utilising the platform for IAQ monitoring and making informed decisions based on the provided data. By incorporating the TAM model and examining the relationships between PU, PEU, AI, and BI, this study aims to gain insights into users' acceptance of the human-centred digital visualisation platform. The findings will shed light on the factors influencing users' attitudes, intentions, and behaviours towards adopting and utilising the platform to enhance their understanding and management of IAQ in their households.

After introducing the digital visualisation platform, the TAM questionnaire (Appendix-F) was administered to individual households twice, once at the beginning of the second week and again at the end of the study, as described in Table 20. This longitudinal approach aimed to capture any changes in participants' acceptance and intention to use the platform over time. By comparing participants' initial impressions and expectations with their experiences and attitudes towards the platform at the study's conclusion, it was easy to gain insights into the effectiveness and impact of the technology. The repeated administration of the TAM questionnaire provided a comprehensive analysis of participants' evolving acceptance and intention, enhancing the study's understanding of the platform's influence on household IAQ management.

Table 20: A longitudinal study questionnaire using the TAM.

Components	What are we measuring?
Perceived Usefulness (**PU**)	**PU1:** How useful do you find the indoor air quality data and information provided on our platform? **PU2:** Which indoor air quality improvement suggestion did you find most helpful to you? **PU3:** Did you find our platform's indoor activity tracking feature helpful? **PU4:** How accurate do you find the indoor air quality data provided on our platform?
Perceived Ease of Use (**PEU**)	**PEU1:** How easy was it to navigate the indoor air quality platform? **PEU2:** How easy was it to track your indoor activity on our platform (Windows opening)? **PEU3:** Did you encounter any difficulties in using our web platform?
Attitude (**AT**)	**AT1:** How positively or negatively do you feel about using our indoor air quality platform regularly in the future?
Behavioural Intention (**BI**)	**BI1:** How likely are you to use our indoor air quality platform again tomorrow to improve indoor air based on the information available?

6.4.1 TAM data analysis: Quantitative approach based on the questionnaire.

The t-tests conducted below provide a comparison of the means of the first and second responses for each component (Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Towards Use (AT), and Behavioural Intention (BI)).

a) **Perceived Usefulness (PU):** The negative t-statistic and the p-value less than 0.05 indicate a statistically significant increase in perceived usefulness from the first to the second response (t-statistic is -4.90, and the p-value is 0.00037). This suggests that participants found the human-centred digital visualisation platform more useful over time.

b) **Perceived Ease of Use (PEU):** The t-statistic is -2.83, and the p-value is 0.0152. This indicates that there is a statistically significant increase in perceived ease of use from the second week of introduction to the end of the study.

c) **Attitude Towards Use (AT):** The t-statistic is -6.97, and the p-value is 0.0000149. This indicates that there is a statistically significant increase in attitude towards use over time. Therefore, this result suggests that participants' attitudes towards the technology became more positive over time.

d) **Behavioural Intention (BI):** The t-statistic is -3.24, and the p-value is 0.00708. This indicates that there is a statistically significant increase in behavioural intention from the start of the second week to the third week. Therefore, this result suggests that participants' intentions to use the technology increased over time.

Overall, these results suggest that while the technology's perceived usefulness and ease of use increased over time, the user's attitude and intention to use it also increased.

6.4.2 To support TAM analysis using Semi-structured Interview questions: Qualitative approach.

Based on the responses provided by the participants, it is evident that the use of technology, specifically the human-centred digital visualisation platform for raising awareness regarding IAQ, has been positively received. The participants expressed a high level of confidence in the technology and acknowledged its role in raising awareness about IAQ at the household level. Here are the key findings from the qualitative analysis:

1. Affirmative Response to Technology: All participants responded affirmatively to the role of technology in AQ monitoring at the household level. This is evident in quotes such as *"I would say big Yes"* and *"Well, yes, I do."* This suggests a high level of technology acceptance, aligning with the TAM principle of Perceived Usefulness.

2. Increased Awareness and Understanding: The participants indicated that the platform helped them understand their household situation and how to improve it. This is reflected in statements like, *"This helps me a lot to understand my house situation and what I can do to improve it, thanks to the platform."* This suggests that the platform successfully raised awareness and provided actionable insights, which is a key goal of the study.

3. Confidence in the Technology: Participants expressed confidence in the AQ monitoring technology. Quotes such as *"To be honest. I like the study, so I can say that I have enough confidence"* and *"Yes, I have confidence. This platform helps me so much to understand about my house's air quality"* indicate a high level of trust in the technology's capabilities. This aligns with the TAM principle of Perceived Ease of Use.

4. Sharing with Social Circle: Some participants shared their experience and knowledge gained from the study with their friends and family, as indicated by the quote, *"I did tell my friends about the device like how it measures the quality of the house and based on that how we can take preventive actions, you know, in order to improve the overall air quality of the house."* This suggests that the platform not only influenced the participants but also extended its impact to their social circles.

5. Behavioural Changes: One participant mentioned making changes in their behaviour (i.e., understanding that vaping is not healthy) based on the information provided by the platform. This suggests that the platform successfully influenced behavioural changes, which is a key objective of using the COM-B model and Behaviour Change Wheel (BCW) framework supported by the technology.

In conclusion, the participants' responses suggest a high level of acceptance and confidence in the IAQ monitoring technology and the use of digital interventions. The platform successfully raised awareness, provided actionable insights, influenced behavioural changes, and extended its impact beyond the participants to their social circles. These findings affirm the effectiveness of the human-centred digital visualisation platform and its potential for wider application in IAQ monitoring and improvement.

6.5 Chapter Summary

This chapter comprehensively explores user navigation patterns on a digital visualization platform focused on IAQ. The prominence of the "IAQ Visualisation" page among participants underscores the modern user's inclination towards real-time data. This suggests that in the age of instant gratification, users are not just content with static information; they seek dynamic insights that evolve with their environment. Therefore, the effectiveness of such platforms hinges not just on the accuracy of the data but also on its presentation and real-time relevance. However, while the "IAQ Visualisation" page was frequently visited, other pages like "Suggestions" and "IAQ Info" had a lesser engagement. This disparity raises questions about the platform's holistic utility. Is the platform becoming a one-trick pony, or are users genuinely not finding value in the other features? For instance, the lesser engagement with educational content might indicate a potential information overload or lack of intuitive design that makes such content easily digestible and actionable. Furthermore, the study's findings on user personas, such as "The Explorer" and "The Focused", provide a window into the diverse ways users interact with the platform. This diversity is both a challenge and an opportunity. While it means that a one-size-fits-all approach might not be effective, it also opens avenues for personalised user experiences, which can be a significant differentiator in the digital age. Moving forward, there's a pressing need to address the underutilised sections of the platform. Future iterations should consider a more intuitive design, perhaps integrating AI-driven suggestions that evolve with user interactions. There's also a potential goldmine in the form of user-generated data from the "Daily Indoor Activity log". Analysing this data can offer insights into user behaviour, which can feed into refining platform features. Moreover, the study hints at the platform's potential to drive behavioural change, especially with features like pop-up interventions. However, the challenge lies in ensuring these interventions are not perceived as intrusive. In summary, while the platform shows promise, especially with its real-time IAQ visualisations, there's ample room for improvement. The findings show that the focus should be on a more holistic user experience, leveraging underutilised data and ensuring that the platform remains a dynamic tool that evolves with its users rather than just another static digital interface. Furthermore, the study utilised the TAM to evaluate users' acceptance of a digital platform for IAQ monitoring. Quantitative and qualitative analyses revealed a significant increase in users' perceived usefulness (p-value 0.00037) and intention to use (p-value 0.00708) the platform over time. The platform successfully enhanced IAQ understanding, influenced behavioural changes, and garnered widespread user confidence. In addition, the limitation of small sample sizes highlights the need for caution when interpreting the study's findings. It underscores the importance of replicating similar studies with larger, more diverse populations to validate and potentially generalise the results. Future research should aim to include a broader demographic to capture a wider range of behaviours and interactions with IAQ monitoring technologies. Also, the timing of the experiments during a particular season could indeed influence the outcomes, especially considering that citizen behaviour and indoor air quality can vary significantly with the external temperature and other seasonal factors. Conducting the study in one season limits the ability to account for these variations and their potential impact on the study's findings.

CHAPTER 7: PERSISTENT ANALYSIS OF BEHAVIORAL CHANGE

Indoor environmental research is advancing rapidly, and IAQ has emerged as a crucial focal point. This is because of its significant impact on human health and well-being. Given the intricate relationship between IAQ and human health, it is essential to devise effective strategies for improving IAQ. A year ago, an influential study was conducted in this area, as discussed in Chapter 5. It combined state-of-the-art technological tools, such as LCS-based IAQ monitoring devices and digital platforms, with the COM-B model. The research aimed to bring about subtle changes in participants' behaviour towards IAQ and monitor them closely. The preliminary results showed improvements in IAQ and the participants' behavioural patterns over three weeks. However, it is essential to note that in behavioural science, initiating positive changes is only the first step. The real challenge lies in adhering to these newly inculcated behaviours over an extended period. A year after the initial intervention, a subsequent study examines the resilience and persistence of these behavioural changes. It will also determine the participants' lasting commitment and engagement towards enhancing IAQ and safeguarding their indoor environment.

7.1 Design of the Study

In order to further explore this research, a longitudinal study has been conducted and invited the same participants from our previous study, as discussed in Chapter 5, to participate once again [35]. The enthusiasm of the participants to persist with the research was noteworthy. Their readiness to partake once more contributes significantly to the depth and continuity of the findings. Utilising this methodology facilitates monitoring developments and progressions over an extended duration. Such an analytical technique allows for a thorough understanding of the subject matter, including subtle trends and patterns often disregarded in a broader perspective. Ultimately, it yields a comprehensive and exhaustive understanding of the study. The Transtheoretical Model (TTM) is a preferable choice compared to other behavioural science models for this study because it uniquely combines the concept of stages of change, making it well-suited for assessing the resilience and persistence of behavioural changes related to IAQ over time. TTM's five stages (pre-contemplation, contemplation, preparation, action, and maintenance) provide a clear and structured framework for tracking participants' progress in their IAQ-related behaviour change journey, which is essential for this research objective. While other models like the Health Belief Model [282] or Theory of Planned Behaviour [283] are valuable in understanding initial behaviour change motivations, TTM focuses explicitly on how individuals maintain these changes over an extended period, aligning precisely with the study's goal of evaluating long-term commitment and engagement in enhancing IAQ. Moreover, TTM's flexibility in modifying interventions based on individuals' stages of change enhances its applicability and effectiveness in promoting sustained IAQ-related behaviours, and its established practical support reinforces its suitability for this research.

To fully understand this process's intricacies, 20 questionnaires (Appendix-E) have been crafted based on the Stages of Change Questionnaire (SOCQ). These questionnaires elicit detailed responses regarding participants' current behaviours, motivations, and perceived barriers to maintaining improved IAQ practices. The choice of these questions is justified by the need to tailor the assessment of readiness to change IAQ-related behaviours within the TTM to the research's specific objectives and context. Standardized questions may not fully capture the diversity of IAQ behaviours or the nuanced stages of change that participants may be in. It can gather more precise and relevant data by carefully selecting or designing questions that align with the unique research goals and the IAQ behaviours under examination. These custom questions also ensure that the assessment accurately reflects this study's specific population, setting, and context, enhancing the validity and reliability of the research findings within the TTM framework. For instance, the question "I do not consider indoor air quality as a priority" evaluates participants' awareness of IAQ's importance, distinguishing those in pre-contemplation from those recognizing the need for change. Similarly, "I am not currently considering changing my habits to improve indoor air quality" gauges active contemplation, distinguishing those who haven't yet considered change from those contemplating it. "I need more information on how my daily activities can impact indoor air quality" addresses the readiness to seek knowledge, reflecting contemplation. "I have committed to regularly maintaining my ventilation system" assesses concrete action, aligning with action or maintenance stages, while "I am confident I can maintain the changes I've made" evaluates self-efficacy and maintenance. These questions offer a nuanced understanding of participants' readiness to change IAQ-related behaviours, enabling tailored interventions and strategies to promote lasting improvements within the TTM framework. This follow-up study is designed to answer critical questions regarding the maintenance phase of the behaviour change process. It examines whether the initial indoor activities and routine changes have been persistent. Additionally, the research assesses the consistency of participants' IAQ concerns and awareness.

7.2 Data Collection

A mixed-methods approach was employed to comprehensively understand the participants' behaviour maintenance, integrating both quantitative and qualitative data. This approach allowed the gathering of numerical data as well as personal insights and experiences from the participants, providing a more holistic view of their behaviour patterns and habits. Utilizing both methods facilitated a comprehensive and precise analysis of the individual's actions and the underlying influencing factors. A Google form with 20 pre-designed questionnaires based on the SOCQ was developed for the quantitative aspect. Participants were invited to complete the questionnaires, offering critical insights into their current behaviour stages, motivations, and possible barriers to improving IAQ. The digital format of these questionnaires facilitated seamless data collection and management, enhancing the efficiency of the process. Simultaneously, semi-structured interviews captured qualitative data, providing an open platform for participants to share their experiences, learnings, and insights from the past year. Also, the interview questions were asked based on the given feedback answers during the interview. Unlike traditional structured interviews, this approach did not rely on predefined questions; instead, it allowed participants to drive the conversation and encouraged a more candid, reflexive discussion about their behavioural changes and their impact on IAQ.

The interviews were held online and recorded for subsequent analysis. This interview style enriches the collected data by offering a deeper understanding of the participants' narratives and personal experiences. This integrative data collection strategy ensures a holistic perspective on the behavioural changes made and their persistence. The combination of structured questionnaires and open-ended interviews allows for both breadth and depth in the data, providing a robust foundation for the subsequent analysis and interpretations.

7.3 Data Analysis

The questionnaire responses were examined according to the stages of the TTM, a behaviour change model delineating five stages of change: pre-contemplation, contemplation, preparation, action, and maintenance. Each question in the questionnaire was assigned to one of these stages, and the participant's responses to these questions were used to compute an average score for each stage, as illustrated in Table 21. The stages were operationalised as follows:

1. Pre-contemplation (questions 1,2,3,4): These questionnaires assess the participants' recognition of a problem and their consideration to change their behaviour.

2. Contemplation (questions 5,6,7,8): These questionnaires gauge whether the participant is thinking about change and understanding its benefits.

3. Preparation (questions 9, 10, 11, 12): These questionnaires assess whether the participant plans to take action soon and make small changes.

4. Action (questions 13, 14, 15, 16): These questionnaires gauge whether the participant has made observable modifications to their behaviour.

5. Maintenance (questions 17, 18, 19, 20): These questionnaires measure whether the participant is working to prevent relapse and consolidate the gains obtained during the action.

For each participant, an average score was computed for each stage by summing the participant's responses to the questions within that stage and dividing by the number of questions within the stage. The results are presented in Table 21. For example, there are four questions for the "Pre-contemplation" stage, and Participant P1 scores a total of 11 for these questions; their average score for this stage would be:

$$\text{Average score} = \frac{Total\ score\ for\ Pre-contemplation}{Number\ of\ questions\ for\ Pre-contemplation} = \frac{2+2+3+4}{4}$$

$$= \frac{11}{4} = 2.75$$

Table 21: Average score of each stage of TTM

Participant	**Pre-contemplation**	**Contemplation**	**Preparation**	**Action**	**Maintenance**
P1	2.75	3.5	3.5	4.5	4.25
P2	3.0	3.5	3.0	4.25	4.5
P3	2.75	4.25	3.75	3.5	3.0

Each participant's stage of change was determined as the stage for which they had the highest average score. These results provide a snapshot of each participant's readiness to change their behaviour or that they have already changed in relation to IAQ.

Participant P1:

Having previously demonstrated an improvement in IAQ, Participant P1's scores in the TTM suggest a continued journey of realisation and proactive action. Their moderate score in pre-contemplation (2.75) might hint at initial reservations or lack of awareness before the study began. This initial phase of unawareness is subtly hinted at in their reflection, *"It took me a while to realise how crucial indoor air quality is, but now I'm all in. I just wish I had started sooner."* As they progressed, their growing awareness (Contemplation – 3.5) is evident in the statement, "The more I learn, the more I see the value in prioritising indoor air quality." Their proactive measures vividly portray their commitment to action (4.5) and maintenance (4.25): *"I've been pretty good at keeping up with the changes I made for better air quality. Using houseplants has been a game-changer, and I've made it a point not to smoke indoors for over six months now."* Their journey of transformation is further emphasised by, *"I never thought I'd be the type to research air purifiers, but here I am, seeing the difference it makes,"* and *"Looking back, I can't believe I used to be so casual about the air I breathe indoors. It's become such a focal point for me now."*

Participant P2:

Participant P2, having shown positive changes during the study, presents a balanced approach in the TTM stages. Their notable inclination towards preparation (3.0) and a strong score in maintenance (4.5) suggest that while they are strategising ways to enhance indoor air quality further, they are also keen on ensuring the longevity of these changes. Their preparatory mindset post-study is encapsulated in, *"I'm getting ready to make some big changes for the air quality in my home. I've been doing my research and planning things out,"* and *"I've bookmarked so many articles on indoor air quality lately. It's high time I put that knowledge into action."* Transitioning from planning to execution post-study seems to pose challenges for P2, as they candidly admit, *"I've got all these plans to improve the air in my home, but putting them into action and sticking to them has been a bit tough,"* and *"Sometimes, it's a bit overwhelming thinking about all the changes I want to make, but I remind myself it's for the better."* Their dedication to long-term improvement remains unwavering, as highlighted by, *"I've started noticing the air quality in other places too, not just my home. It's become something I'm genuinely passionate about."*

Participant P3:

Participant P3, having previously shown improvements in IAQ, exhibits a contemplative nature in the TTM with a score of 4.25 in the contemplation stage. This suggests deep introspection and consideration of indoor air quality post-study, as evident in, *"I've been reading up on indoor air quality, and it's got me thinking. I know I need to make some changes,"* and *"Every now and then, I stumble upon a new tip or trick to improve indoor air. It's a continuous learning process for me."* However, while they exhibit a strong inclination to improve, their score in the maintenance stage (3.0) suggests potential challenges in sustaining these improvements over the long term. Their struggles with consistency post-study are candidly expressed in, *“I’ve tried a few things to improve the air in my home, but sticking to them long-term? That’s been a challenge,”* and *“I’ve made some strides in improving the air quality, but consistency is where I need to focus more.”* Their sentiment is further echoed in their reflection on their journey’s broader impact: *“I often discuss indoor air quality with my friends now. It’s interesting to see how many are also on this journey of improvement.”*

7.3.1 Challenges while maintaining behavioural change.

Participant P1:

A transformative realisation of the importance of IAQ has marked Participant P1’s journey. However, this journey hasn’t been without its challenges. As P1 reflects, *“While I’ve come to value indoor air quality, it’s been a challenge to unlearn some of my old habits and replace them with healthier ones.”* This sentiment is further emphasised by their acknowledgement of the ongoing nature of their journey: *“Every time I think I’ve got a handle on improving the air quality, there’s a new challenge that pops up, reminding me this is a continuous journey.”* Despite their progress, moments of doubt have crept in, with P1 admitting, *“I’ve faced moments of doubt, wondering if all these changes are worth the effort, especially when life gets busy.”*

Participant P2:

Participant P2’s balanced approach in the TTM stages showcases their commitment to improving indoor air quality. Yet, this commitment is tested by the challenges they encounter. P2 candidly shares, *“The journey to better indoor air quality isn’t without its hurdles. Just when I think I’m making progress, I find another area I need to address.”* The gap between planning and execution has been a particular challenge for P2, as they note, *“It’s one thing to plan and another to execute. Sometimes, the gap between the two is filled with challenges I didn’t anticipate.”* Their journey has also been marked by introspection, with P2 reflecting, *“I’ve had days where I questioned my commitment, especially when it felt like I was taking two steps back for every step forward.”*

Participant P3:

Participant P3’s contemplative nature in the TTM is evident in their deep introspection about indoor air quality. They recognise the complexities involved, stating, *“The more I learn about indoor air quality, the more I realise the complexities and challenges involved in maintaining it.”* Their journey has been marked by efforts to maintain consistency, but as P3 admits, *consistency has been my biggest challenge. It’s easy to start, but sustaining these changes requires a different kind of effort.”* The vast amount of information and the continuous evolution in the domain of indoor air quality can sometimes be overwhelming for P3, as they share, *"Every article or tip I come across is a reminder that there's always more to do, and sometimes, it feels overwhelming."*

Overall, each participant, having shown improvements during the study, has demonstrated varying degrees of readiness and commitment to maintaining these positive changes. Participant P1's transformative journey underscores the importance of continuous learning and adaptation. Participant P2's balanced approach highlights the challenges that lie in the transition from planning to execution, emphasising the need for perseverance and resilience. Meanwhile, Participant P3's contemplative nature acted as a reminder that the journey towards better IAQ is multifaceted, requiring both knowledge acquisition and consistent application. The challenge-related quotes further enrich our understanding, shedding light on the obstacles and reflections each participant has faced or is currently facing. These challenges, ranging from unlearning old habits to navigating the vast amount of information, underscore the complexities of behavioural change. However, they also highlight the participants' resilience, commitment, and evolving understanding of the significance of IAQ. While each participant's journey is unique, they collectively underscore the multifaceted nature of behavioural change. Their experiences testify to the importance of continuous learning, adaptation, and resilience in pursuing healthier indoor environments. The journey towards improved IAQ is not linear but filled with challenges, understandings, and moments of introspection, making each step forward more valuable.

All three participants appear to be at different stages in the behaviour change process, suggesting the importance of individualised interventions. Although the participants understand the importance of IAQ, there seems to be difficulty in consistently implementing and maintaining these changes, pointing to a potential gap in the transition from contemplation to action and maintenance. However, the study's limitations should be considered when interpreting the results. The reliance on self-reported data may introduce potential bias or inaccuracies in the results, and the limited response scale may not fully capture the nuances of the participants' experiences. A larger, more diverse sample could provide more generalisable insights. Additionally, using qualitative methods could provide a deeper understanding of the participants' perceptions and challenges related to improving IAQ. Nevertheless, it is important to interpret these results within the complexity of behaviour change. Although the TTM provides a valuable framework, behaviour change is not always a linear process and can involve fluctuation between stages. Furthermore, the nuances in perceptions and behaviours may not be fully captured by the limited scale of the questionnaire.

7.4 Chapter Summary

The study's longitudinal design, which involved reconnecting with previous participants, suggested a unique opportunity to track and evaluate the continuity and progression of behavioural changes. Using the TTM framework, the study assessed participants' readiness and stages of change through a structured lens. With a mixed-methods approach to data collection, incorporating both quantitative questionnaires and qualitative, semi-structured interviews, the study gained a holistic understanding of participants' experiences and behaviours. Analytical results revealed varying degrees of readiness and commitment among participants. While some underwent transformative journeys, others experienced challenges transitioning from planning to execution. The contemplative nature of some participants highlighted the multifaceted nature of behavioural change, emphasising the importance of continuous learning and adaptation. Despite participants struggling with unlearning old habits and navigating vast amounts of information, their resilience, commitment, and evolving understanding of IAQ's significance shone through. Their collective experiences emphasised the multifaceted nature of behavioural change, underscoring the importance of individualised interventions and the non-linear nature of the behaviour change process. Moreover, the experiments conducted as part of this study indeed involved relatively small sample sizes, which is a common limitation in specialised, context-specific research. Small sample sizes can limit the statistical power of the findings. This means that while the study may have identified significant trends or effects, the ability to generalise these findings to a broader population is constrained. The small sample sizes were primarily due to the resource-intensive nature of the experiments and the challenge of recruiting participants after an extended period.

In conclusion, the study highlights the intricate relationship between IAQ and human behaviour. While technological tools and models like the COM-B provide valuable insights, the human element remains central. Behavioural change, especially in the context of IAQ, is a complex journey marked by challenges, understandings, and moments of introspection. The findings of this study underscore the need for continuous engagement, individualised interventions, and a deeper understanding of the nuances of behaviour change. As the field of indoor environmental research continues to evolve, the insights gleaned from this study will undoubtedly act as a foundation for future endeavours to enhance IAQ and promote healthier indoor environments.

CHAPTER 8: CONCLUSION & FUTURE RESEARCH DIRECTIONS

8.1 Summary

The issue of ambient air pollution is gaining increasing attention worldwide. However, the issue of indoor air pollution, a fundamental aspect of our health and well-being, has yet to receive the same level of attention. This is especially critical given that we spend an average of 90% of our time indoors. Human indoor activities, from using various products to cooking, cleaning, and ventilation, significantly impact IAQ. Furthermore, IAQ directly affects human behaviour, performance, and productivity, particularly for those whose work primarily involves being indoors. For example, activities such as cooking and cleaning and how frequently and long windows are opened while cooking can significantly influence IAQ. Thus, human behaviour plays a crucial role in determining IAQ. Factors such as human attitudes and beliefs, socioeconomic status, and education level are critical in shaping an individual's behaviours towards air quality awareness. As discussed in the literature review, several studies have employed sensor technologies to monitor IAQ and raise citizen awareness. However, there remains an open subject of exploration regarding methodological approaches that utilise well-known behaviour models to influence behaviours with the help of sensor data visualisation using digital platforms.

LCS offer an affordable and convenient solution for environmental monitoring and data acquisition, but several factors complicate their deployment. The lack of standardised protocols and a variety of options available for measuring identical components make sensor selection challenging. Furthermore, temperature and humidity can significantly affect sensor performance, and calibration procedures must be thoroughly designed to account for these variables. To address these challenges, a data-driven methodology has been proposed and tested through a comprehensive experiment. The methodology can help to build LCS-based devices from the sensor selection process and their calibration. The calibration parameters have been established through precise testing using a high-cost reference station placed at pre-defined locations for optimum results. These parameters are then carefully transferred to other sensors and reference stations, taking into consideration their unique type and application. From the analysis, it was observed that AH performs better than RH in sensor calibration. The RF model is the best for calibrating LCS among the four AI-based calibration models. However, it's essential to explore various techniques and methodologies for recalibration to enhance the accuracy of the data collected by these systems. By adhering to such thorough procedures, LCS-based monitoring systems can remain invaluable tools for diverse research applications.

Initial two studies were conducted in Bradford, UK, to test the effectiveness and usefulness of IoT-enabled LCS technology in monitoring IAQ. The study aimed to increase citizen awareness and assess the relationship between indoor activities and IAQ. The first study provided households with calibrated IoT devices to monitor indoor air pollutants such as PM and other meteorological parameters. Participants also maintained daily digital diaries to record qualitative data on indoor activities using digital platforms. The results showed that increased awareness of IAQ led to changes in indoor activities, such as opening windows more often, ultimately improving IAQ. The second study introduced the COM-B behaviour psychology model to support behavioural change. Four digital interventions based on this model were implemented, influencing the participant's behaviour and significantly reducing indoor air pollution levels. In summary, IoT-enabled LCS technology effectively improved IAQ and fostered self-awareness. Integrating the COM-B model with digital interventions further amplified these positive outcomes, highlighting the potential for technology-driven behavioural change interventions in IAQ management.

In addition, another study focused on creating a human-centred digital platform to enhance IAQ by influencing human behaviour using improved digital interventions. Key features were identified to enhance the effectiveness of a digital platform. Citizen engagement was found to be directly related to the acceptance of digital interventions to improve IAQ. By analysing user interactions and preferences, the study provided recommendations for designing user-centric platforms that encourage behavioural changes leading to improved IAQ. The study also emphasised the importance of real-time indoor air quality data visualisation in raising citizen awareness. Furthermore, employing the TTM and the SOCQ can help understand and evaluate digital interventions' long-term impact. The study utilised a longitudinal design to observe changes in behaviour among previously engaged participants, using the TTM framework as a guide. A thorough understanding of participants' experiences and behaviours was achieved using quantitative questionnaires and qualitative semi-structured interviews. Findings revealed varying readiness levels among participants, with some struggling to move from planning to action. Challenges like unlearning ingrained habits and sorting through vast information were apparent. However, participants consistently recognised the importance of IAQ. These results highlight the complex process of behavioural change and the need for customised interventions.

Furthermore, in recognizing the broader applicability of the insights and methodologies derived from these studies, this thesis explores potential application domains beyond the primary focus on IAQ monitoring and intervention strategies. As demonstrated in the IAQ improvement efforts, integrating AI and IoT technologies holds significant promise for several other domains. Among these are **smart city initiatives**, where these approaches can contribute to more effective environmental monitoring and management, enhancing urban sustainability and resident well-being. Similarly, in the **healthcare sector**, these findings can inform the design of hospital and clinical environments to support patient health through better air quality management. Additionally, the principles outlined in this research can be applied to **smart home technologies**, offering insights into creating more adaptive and responsive living environments that actively promote the well-being of occupants. By identifying these additional application domains, this thesis not only underscores the versatility and potential impact of the research findings but also opens avenues for future exploration and interdisciplinary collaboration to tackle broader environmental and public health challenges.

8.2 Research Contribution Summary

8.2.1. Data-driven approaches for LCS Selection and Calibration for AQ monitoring.

This thesis has contributed effective data-driven methods for selecting and calibrating LCS for IAQ monitoring using IoT technology. Accurate and reliable IAQ monitoring is of paramount importance in giving confidence to authorities and citizens who rely on it. By exploring various statistical and AI-based calibration models, the research has compared their efficacy in terms of accuracy, reliability, and ease of implementation. The findings from this exploration have the potential to revolutionise the way IAQ monitoring systems are designed, making them more accessible to the citizens and more reliable for researchers and policymakers. This contribution lays the technological foundation for subsequent exploration in the domain of IAQ.

8.2.2. Enhanced citizen engagement and awareness through real-time monitoring

The advent of the IoT has brought about a paradigm shift in how we perceive and interact with our indoor environment. This research has tapped into this potential by assessing the impact of real-time IAQ data, facilitated by IoT devices, on citizen engagement and awareness. By examining how real-time data influences citizens' understanding of IAQ, their engagement with monitoring platforms, and any subsequent changes in their indoor activities, the research provides invaluable insights into the effectiveness of IoT-based IAQ monitoring systems. As highlighted by the research, the potential for increased citizen awareness and engagement can pave the way for more informed citizen health interventions and policies.

8.2.3. COM-B Model-Based Digital Interventions for behavioural change to improve IAQ.

Behavioural change is a complex process influenced by a myriad of factors. The COM-B model is an excellent and constructive framework for understanding behaviour change, providing innovative and timely insights that can be applied to various situations. However, a significant research challenge exists in operationalising such a theoretical model as part of a digital platform. As far as we know, this thesis represents the first and early work on using the COM-B model for building a digital platform targeting activities that impact IAQ. The research delves deep into the intricacies of IAQ-related behaviours by evaluating the effectiveness of digital interventions designed using this model. The findings of this study highlight the usefulness of the COM-B model as a tool for designing interventions. By examining the effectiveness of interventions based on this model to succeed in achieving sustained behavioural changes and whether these changes lead to improvements in IAQ, the research contributes to the broader discourse on behavioural science and its implications for citizen health.

8.2.4. Designing and evaluating digital interventions using Human-Centred Digital Platforms

Information presentation is as crucial as the information itself in today's digital age. With this in mind, this research has endeavoured to identify the elements that make a digital visualisation platform effective. After a thorough investigation, it was discovered that a platform's user-centric qualities and the way users engage with it are critical to its success. The study highlighted that user interactions with these platforms play a pivotal role in determining the acceptance and significance of initiatives to improve IAQ. Furthermore, it emphasised the importance of presenting real-time IAQ data in an understandable and captivating way, as it significantly contributes to raising awareness among citizens. By combining insights from user experience, real-time data visualisation, and behavioural science, this research has laid out a plan for designing future digital platforms. When developed with a human-centric approach, these platforms have the potential to inform and influence behavioural changes, ultimately leading to tangible improvements in IAQ.

8.2.5. Measuring Persistent Behaviour Influenced by Technology

Any intervention must be effective over the long term. This research recognises this fact and investigates digital interventions' long-term sustainability and efficiency in improving IAQ. By conducting a longitudinal study, participants from an earlier study have been invited to evaluate persistent behavioural change. The research adopted the TTM to track the evolution and persistence of IAQ-related behavioural changes over time. The study used 20 custom-designed questionnaires rooted in the SOCQ to gather nuanced data. These questionnaires were tailored to capture specific nuances of behaviours, motivations, and perceived barriers, ensuring a comprehensive understanding of the participant's journey. To our knowledge, this thesis is one of the early works that uses TTM to evaluate sustained behaviour change using digital platforms. The primary objective of the research was to observe initial behavioural changes and critically assess the long-term maintenance of these changes, especially in the context of participants' consistent concerns and awareness about IAQ. This research bridges the gap between short-term behavioural changes and long-term behavioural maintenance in IAQ, presenting a significant contribution to indoor environmental research.

8.3 Future Research Directions

The thesis has some limitations that provide opportunities for future research directions.

8.3.1. LCS Re-calibration

Building on the pivotal contributions made in data-driven methods for LCS selection and calibration for IAQ monitoring, a compelling direction for future research would be the development of dynamic re-calibration frameworks for LCS using real-time feedback loops. As environmental conditions, sensor degradation, and other external factors can influence the accuracy of LCS over time, it is crucial to ensure that these systems remain precise throughout their operational lifespan. Integrating continuous data collection with advanced machine learning algorithms allows the system to identify drifts or anomalies in sensor readings, triggering an automatic re-calibration process. This self-correcting mechanism would not only maintain the reliability of the LCS but also reduce the need for manual re-calibrations, making the system more efficient and cost-effective. Additionally, leveraging cloud-based analytics can facilitate data aggregation from multiple LCS units across various locations, enabling a collective learning approach. This would allow individual units to benefit from the calibration experiences of other units, further enhancing the robustness and accuracy of the entire network. Such a proactive and interconnected re-calibration framework would set a new standard in IAQ monitoring, ensuring consistent and trustworthy data for citizens and decision-makers.

8.3.2. Adaptive Personalized Digital Platforms for IAQ Improvement:

Building upon the research on human-centred digital platforms and the long-term behavioural influence of technology, a promising avenue for future exploration is the development of adaptive digital platforms that offer personalised user experiences based on individual preferences, behaviours, and IAQ needs. As the digital age progresses, personalisation has emerged as a critical factor in enhancing user engagement and ensuring the effectiveness of digital interventions. By integrating real-time IAQ data with user behavioural patterns, the platform can dynamically adjust its information presentation, recommendations, and interventions to cater to individual users. This personalisation can be achieved through advanced machine learning algorithms that learn from user interactions and feedback. Moreover, understanding the cultural, demographic, or socio-economic factors influencing user engagement can further refine the platform's adaptability. Such a personalised approach not only ensures that the information is relevant and actionable for each user but also addresses the challenge of sustaining long-term behavioural changes by continuously aligning with the evolving needs and preferences of the user. This research direction, rooted in the intersection of user experience design, real-time data visualisation, and behavioural science, has the potential to revolutionise the way digital platforms influence and sustain positive behavioural changes related to IAQ.

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APPENDICES

Appendix-A: IAQ Awareness Questionnaires (Google Form)

IAQ Questionnaire

Thanks for taking part in this study. Please answer the following questions as best as you can.

* Required

1. Is poor outdoor air quality a concern for you? If so, why? *

   ____

2. is poor indoor air quality (air quality inside your home) a concern for you? *

   Mark only one oval.

   - ◯ Yes - very concerned
   - ◯ Yes - mildly concerned
   - ◯ Yes - somehow concerned
   - ◯ No -
   - ◯ Other: ____

3. 3. What is your residency status? *

Check all that apply.

- [ ] Born and raised here
- [ ] Migrated (First Generation)
- [ ] Migrated (Second generation)
- [ ] Migrated (Third Generation)
- [ ] Prefer not to say

Other: [ ] ______________________

4. 4. What is the ethnicity of the household? *

Check all that apply.

- [ ] White- English, Welsh, Scottish, Northern Irish or British
- [ ] White - Irish
- [ ] White - Gypsy or Irish Traveller
- [ ] White - Any other White background
- [ ] White and Black Caribbean
- [ ] White and Black African
- [ ] White and Asian
- [ ] Any other Mixed or Multiple ethnic background
- [ ] Asian or Asian British - Indian
- [ ] Asian or Asian British - Pakistani
- [ ] Asian or Asian British - Bangladeshi
- [ ] Asian or Asian British - Chinese
- [ ] Asian or Asian British - Any other Asian background
- [ ] African
- [ ] Caribbean
- [ ] Any other Black, African or Caribbean background
- [ ] Arab
- [ ] Any other ethnic group

5. 5. What is the highest education of the household? *

Mark only one oval.

- Entry Level.
- GCSE.
- A level.
- HND.
- Bachelor's Degrees.
- Master's Degree.
- Doctoral Degree.
- Other: ______

6. 6. Are there any children in your household? *

Mark only one oval.

- Yes.
- No.

7. 7. Are there anyone living over 60 in the house? *

Mark only one oval.

- Yes.
- No.

8. 8. What is the combined annual income of the household? *

Mark only one oval.

- Less than £19,200.
- More than £19,200.
- Prefer not to say

9. 9. Where is your house located? *

Mark only one oval.

- Within 0.1km from the main road.
- Within 0.1km -0.5km from the main road.
- More than 0.5km from the main road.
- Other: ______

10. 10. How old is the building you are living in? *

Mark only one oval.

- Built before 1955.
- Built between 1955 to 1985.
- Built after 1985.
- I don't know.

11. 11. What type correctly describes your house? *

Mark only one oval.

- Terraced.
- Semi- detached.
- Detached.
- Flat.
- Other: ______________________

12. 12. Is any of the member of the family surfing from Asthma or COPD? *

Mark only one oval.

- Yes (Asthma).
- Yes (COPD).
- Both.
- No.
- Prefer Not to Say

13. 13. Is there any smoker in the house, if yes then how often do they smoke (select frequency of smoking from below)? *

Mark only one oval.

- Yes (2- 3 times a day).
- Yes (More than three times a day).
- No.

14. 14. How Frequently do you open windows in the house per day? *

Mark only one oval.

- Less than one hour a day.
- One hour or more.

15. 15. How Frequently do you vacuum the house? *

Mark only one oval.

- None/ Rare.
- Once a week.
- More than once a week.
- Other: ____________________

16. 16. Do you have (wood/log stove/burner)? *

Mark only one oval.

- Yes.
- No.

17. 17. If you answered yes to previous question, how frequently do you refill your wood/log burner/stove? *

Mark only one oval.

- Once during single usage.
- More than once during single usage.

18. 18. How frequently do you cook per week? *

Mark only one oval.

- Once.
- Twice.
- More than twice.

19. 19. Do you have ventilation in kitchen? *

Mark only one oval.

- Exhaust fan.
- Cooker hood.
- Windows that open.
- No
- Other: ____________________

20. 20. What type of cooker do you use? *

Mark only one oval.

- Gas.
- Electric.

21. 21. What types of cooking do you practice? *

Check all that apply.

- [ ] Deep-frying.
- [ ] Pan-frying.
- [ ] Stir-frying.
- [ ] Boiling.

Other: [ ] ____________________

22. 22. Do you have any pets? *

Mark only one oval.

- Yes.
- No.

23. 23. What type of heating system do have in your house? *

Mark only one oval.

- Central heating.
- Electric heating.
- Wood/ log burning.
- Other: ____________________

Appendix-B: Interview Questions:

Sensor ID:

Interview Method (Online/In-Person):

Serial	Main	Follow-up	Answers
01	What do you think when you see the IAQ monitoring device inside your house?	Share your first impression.	
02	How comfortable are you to fill online daily activity log?	Do you ever feel uncomfortable about feeling these questions? (As they are directly linked with your personal household activity?)	
03	We are storing data to our secure cloud-based server, is this gives you enough confidence regarding security and privacy concerns.	If you have any concerns that please elaborate.	
04	What do you think of the dashboard that showed your house's PM values -daily average, last week and the week before average?	what comes to your mind when you see these readings on the dashboard?	
05	What effect (04) it had if any?		
06	Do you think the visualisation platform help you to monitor your IAQ?	Is this help you to raise awareness levels in your family?	
07	When you do any indoor activity such as cooking, cleaning, vacuuming, do you think about the IAQ?	Does it force you to think about opening doors/windows or turning on the exhaust?	
08	What would you feel when you sense poor AQ (bad/ dirty smell, smoke) inside your house?	Does it lead you to think about IAQ and check your pollution level on the dashboard?	
09	Would you discuss anything/anytime about IAQ or your indoor daily activity which is rising indoor air pollution?		
10	Did you change any of your regular day-to-day activities after seeing data on your IAQ level?	Any Specific changes you want to point out.	
11	Do you refer others to use AQ monitoring devices at their house?		
12	Do you think technology can play a role in AQ monitoring at the	How much confidence do you have in AQ monitoring technology?	

	household level and raising awareness?		
13	Any other experience of this study you want to share with us?	Any suggestions? Any trouble you face during this study?	
14	Any negative experience to report on?		

Appendix-C: Interview Question

Sensor ID:

Interview Method (Online/In-Person):

No.	Main	Follow-up	Answers
01	What do you think when you see the IAQ monitoring device inside your house?	Share your first impression.	
02	How comfortable are you filling online daily activity logs throughout the study?	Do you ever feel uncomfortable about feeling these questions? (As they are directly linked with your personal household activity?)	
03	We are storing data to our secure cloud-based server, which gives you enough confidence regarding security and privacy concerns?	If you have any concerns that please elaborate.	
04	What do you think of the dashboard that showed your house’s PM values -daily average, last week and the week before average after the first week of the study?	What comes to your mind when you see these readings on the dashboard first time from the second week of study?	
05	What effect (04) it had if any?		
06	Do you think the visualisation platform and information available on the dashboard help you to understand and monitor your IAQ?	Is this help you to raise awareness levels in your family?	
07	When you do any indoor activity such as cooking, cleaning or cleaning product usage, or vacuuming, do you think about the IAQ?	Does it force you to think about opening doors/windows or turning on the exhaust?	
08	What would you feel when you sense poor AQ (bad/ dirty smell, smoke) inside your house?	Does it lead you to think about IAQ and check your pollution level on the dashboard from the second week of the study?	
09	Would you discuss anything/anytime about IAQ or		

	your indoor daily activity which is rising indoor air pollution?		
10	Did you change any of your regular day-to-day activities after seeing data on your IAQ level?	Any Specific changes you want to point out? Any change in the use of domestic products?	
11	Do you refer others to use AQ monitoring devices at their house?		
12	Do you think technology can play a role in AQ monitoring at the household level and raising awareness?	How much confidence do you have in AQ monitoring technology?	
13	Any other experience of this study you want to share with us?	Any suggestions? Any trouble you face during this study?	
14	Any negative experience to report on?		

Appendix-D: Interview Questions - Daily activities log design with Questionnaires.

Sensor ID:

Interview Method (Online/In-Person):

Serial	**Main**	**Follow-up**	**Answers**
01	What do you think when you see the IAQ monitoring device inside your house? (How has your impression changed since the first time you saw it)	when you first encountered this device, what did you think of it?	
02	We are storing data in our secure cloud-based server. Does this give you enough confidence regarding security and privacy concerns?	If you have any concerns - please elaborate.	
03	What do you think of the dashboard that showed your house's PM values -daily average, last week and the week before average?	What comes to your mind when you see these readings on the dashboard first time?	

04	How comfortable are you with filling online daily activity logs?	Do you ever feel uncomfortable about feeling these questions? (As they are directly linked with your personal household activity?)	
05	What effect (04) it had, if any?		
06	Do you think the visualisation platform helps you to monitor your IAQ?	Is this help you to raise awareness levels in your family?	
07	When you do any indoor activity, such as cooking, cleaning, or vacuuming, do you think about the IAQ?	Does it (at times) make you think about opening doors/windows or turning on the exhaust?	
08	Did you change any of your behaviours related to product usage or indoor air quality as a result of participating in the study?		
09	What would you feel when you sense poor AQ (bad/ dirty smell, smoke) inside your house?	Does it lead you to think about IAQ and check your pollution level on the dashboard?	
10	Did the study provide helpful information about how to improve indoor air quality?	If yes, what did you like the most?	
11	Would you discuss anything/anytime about IAQ during the study or your daily indoor activity with your family, which is rising indoor air pollution?		
12	Did you change any of your regular day-to-day activities after seeing data on your IAQ level?	Any Specific changes you want to point out?	
13	Would you recommend others to use AQ devices?	if yes, would you recommend using our AQ monitoring device? For our device (if answer is no) - could you tell us why this IAQ device falls short of your expectations?	
14	Do you think technology can play a role in AQ monitoring at the household level and raising awareness?	How much confidence do you have in AQ monitoring technology?	

15	Any other experience of this study you want to share with us?	Any suggestions? Any trouble you face during this study?	
16	Any negative experience to report on?		

Appendix-E: Modified Daily Digital Diary

All questions are mandatory to answer.

* Indicates a required question

1. **How many hours did you open window today? ***

Mark only one oval.

- Less than 1 hour
- 1 - 3 hours
- More than 3 hours
- Did not open window today.

2. **Did you apply vacuum cleaning today? ***

- Yes
- No

3. **How often did you smoke indoor today? ***

- Not applicable
- No indoor smoking
- Only few times
- Frequently

4. **How many hours do you switch on heating today? ***

- 1 - 3 hours
- More than 3 hours
- No heating today

5. **How many hours did you use wood/ log burning today? ***

- Not applicable
- 1 - 3 hours
- More than 3 hours
- No wood/log burning today

6. **How many hours did you cook today? ***

- Less than 1 hour
- 1 to 3 hours
- More than 3 hours
- No cooking today

7. What type of cooking was done today? (Choose more than 1 options, if * applicable)

Check all that apply.

- [ ] Pan Frying
- [ ] Deep Frying
- [ ] Stir Frying
- [ ] Microwave
- [ ] Air Fryer
- [ ] Other ______________

8. Did you turn on exhaust fan or open window while cooking? *

- ( ) Yes
- ( ) No

9. During what time did you cook today? (Choose more than one option, if applicable) *

Check all that apply.

- [ ] 8 am - 11 am
- [ ] 11 am - 2 pm
- [ ] 2 pm - 5 pm
- [ ] 5 pm - 8 pm
- [ ] 8 pm - 11 pm
- [ ] 11 pm - 8 am

10. During what time did you open the windows during the day? (Choose more than one option, if applicable) *

Check all that apply.

- [ ] 8 am - 11 am
- [ ] 11 am - 2 pm
- [ ] 2 pm - 5 pm
- [ ] 5 pm - 8 pm
- [ ] 8 pm - 11 pm
- [ ] 11 pm - 8 am

11. What household products did you use at home today for any purpose? *

(Choose more than one option, if applicable)

Check all that apply.

- [ ] Air fresheners/ Aerosol sprays (e.g. deodorants, hairsprays)
- [ ] Cleaning sprays and solutions (e.g. bleach, ammonia, disinfectants)
- [ ] Paints and varnishes
- [ ] Candles and incense
- [ ] All of the above
- [ ] None of the above

Appendix-F: Technology Acceptance Model (TAM) Questionnaire

* Indicates a required question

1. Perceived usefulness: On a scale of 1 to 5, how useful do you find the indoor air quality data and information provided on our platform today? (1 = not useful, 5 = very useful) *

Mark only one oval.

- 1 = Not useful at all
- 2 = Slightly useful
- 3 = Moderately useful
- 4 = Very useful
- 5 = Extremely useful

2. Perceived ease of use: On a scale of 1 to 5, how easy was it to navigate the indoor air quality platform today? (1 = very difficult, 5 = very easy) *

Mark only one oval.

- 1 = Very difficult
- 2 = Somewhat difficult
- 3 = Neutral
- 4 = Somewhat easy
- 5 = Very easy

3. Attitude towards use: How positively or negatively do you feel about using our indoor air quality platform regularly in the future? (Select one) *

Mark only one oval.

- a) Very positive
- b) Somewhat positive
- c) Neutral
- d) Somewhat negative
- e) Very negative

4. Behavioural intention: How likely are you to use our indoor air quality platform again tomorrow to improve indoor air based on the information available? (Select one) *

Mark only one oval.

- f) Very likely
- g) Somewhat likely
- h) Neutral
- i) Somewhat unlikely
- j) Very unlikely

5. Perceived usefulness: Which indoor air quality improvement suggestion did you find most helpful today? *

Mark only one oval.

- Checking indoor air pollution data (PM2.5, PM10 and CO2 graphs)
- Pop-up for providing information.
- Information regarding use of domestic product
- Keep temperature and humidity levels in check.
- Other: ______________________

6. Perceived ease of use: On a scale of 1 to 5, how easy was it to track your indoor activity on our platform today (Windows opening) ? (1 = very difficult, 5 = very easy) *

Mark only one oval.

- 1 = Very difficult
- 2 = Somewhat difficult
- 3 = Neutral
- 4 = Somewhat easy
- 5 = Very easy

7. Perceived usefulness: Did you find the indoor activity tracking feature on our platform today to be helpful? *

Mark only one oval.

- k) Yes, very helpful
- l) Yes, somewhat helpful
- m) No, not helpful

8. Perceived usefulness: How accurate do you find the indoor air quality data provided on our platform today? (Select one) *

Mark only one oval.

- n) Very accurate
- o) Somewhat accurate
- p) Neutral
- q) Somewhat inaccurate
- r) Very inaccurate

If you chose d) or e), could you briefly explain why do you feel the air quality data is inaccurate: *

9. Perceived ease of use: Did you encounter any difficulties in using our web platform today? (Select one) *

Mark only one oval.

- s) Yes, several difficulties
- t) Yes, a few difficulties
- u) No difficulties

If you chose a) or b), could you briefly explain (in a few words) what were the issues: *

Appendix-G: Persistent Analysis of Behavioural Change Analysis

* Indicates required question

Email *

1. I do not consider indoor air quality as a priority. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree:
- 4: Agree
- 5: Strongly agree

2. I am not currently considering changing my habits to improve indoor air quality. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree
- 4: Agree
- 5: Strongly agree

3. Indoor air quality does not significantly impact my health. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree 4:
- Agree
- 5: Strongly agree

4. I don't think I need more information on how my daily activities can impact indoor air quality. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree 4:
- Agree
- 5: Strongly agree

5. I sometimes think about reducing the use of chemical cleaners to improve indoor air quality. *

- 1: Strongly disagree
- 2: Disagree

6. I am considering buying an indoor air quality monitor. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree 4:
- Agree
- 5: Strongly agree

7. I am contemplating the use of natural cleaning products in the near future. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree 4:
- Agree
- 5: Strongly agree

8. I need more information on how my daily activities can impact indoor air quality. *

- 1: Strongly disagree
- 2: Disagree
- 3: Neither agree nor disagree
- 4: Agree
- 5: Strongly agree

9. I plan to start using air purifiers shortly. *

1: Strongly disagree

2: Disagree

3: Neither agree nor

disagree 4: Agree

5: Strongly agree

10. I have a specific plan to reduce the use of aerosols to improve indoor air quality. *

1: Strongly disagree

2: Disagree

3: Neither agree nor

disagree 4: Agree

5: Strongly agree

11. I am planning to start using natural cleaning products in the near future. *

1: Strongly disagree

2: Disagree

3: Neither agree nor disagree

12. I am interested in learning more about indoor air quality. *

1: Strongly disagree

2: Disagree

3: Neither agree nor

disagree 4:Agree

5: Strongly agree

13. I have already started using low-VOC (less air pollutants emitting) products * to improve indoor air quality.

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4: Agree
5: Strongly agree

14. I have committed to regularly maintaining my ventilation system (opening windows or doors) to improve indoor air quality. *

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4:Agree
5: Strongly agree

15. I have changed my cooking habits to reduce indoor air pollution.

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4: Agree
5: Strongly agree

16. I have committed to minimizing using air fresheners and aerosols in my home. *

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4:Agree
5: Strongly agree

17. I regularly ventilate my living spaces to improve indoor air quality. *

1: Strongly disagree
2: Disagree

3: Neither agree nor
disagree 4: Agree
5: Strongly agree

18. I have used houseplants to improve indoor air quality over six months. *

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4: Agree
5: Strongly agree

19. I am confident I can maintain the changes I've made to improve indoor air quality. *

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4: Agree
5: Strongly agree

20. I have been avoiding/ never smoking indoors for more than six months. *

1: Strongly disagree
2: Disagree
3: Neither agree nor
disagree 4: Agree
5: Strongly agree