Hesitation to engage in indoor air quality diagnostics increases health risks and task performance decline

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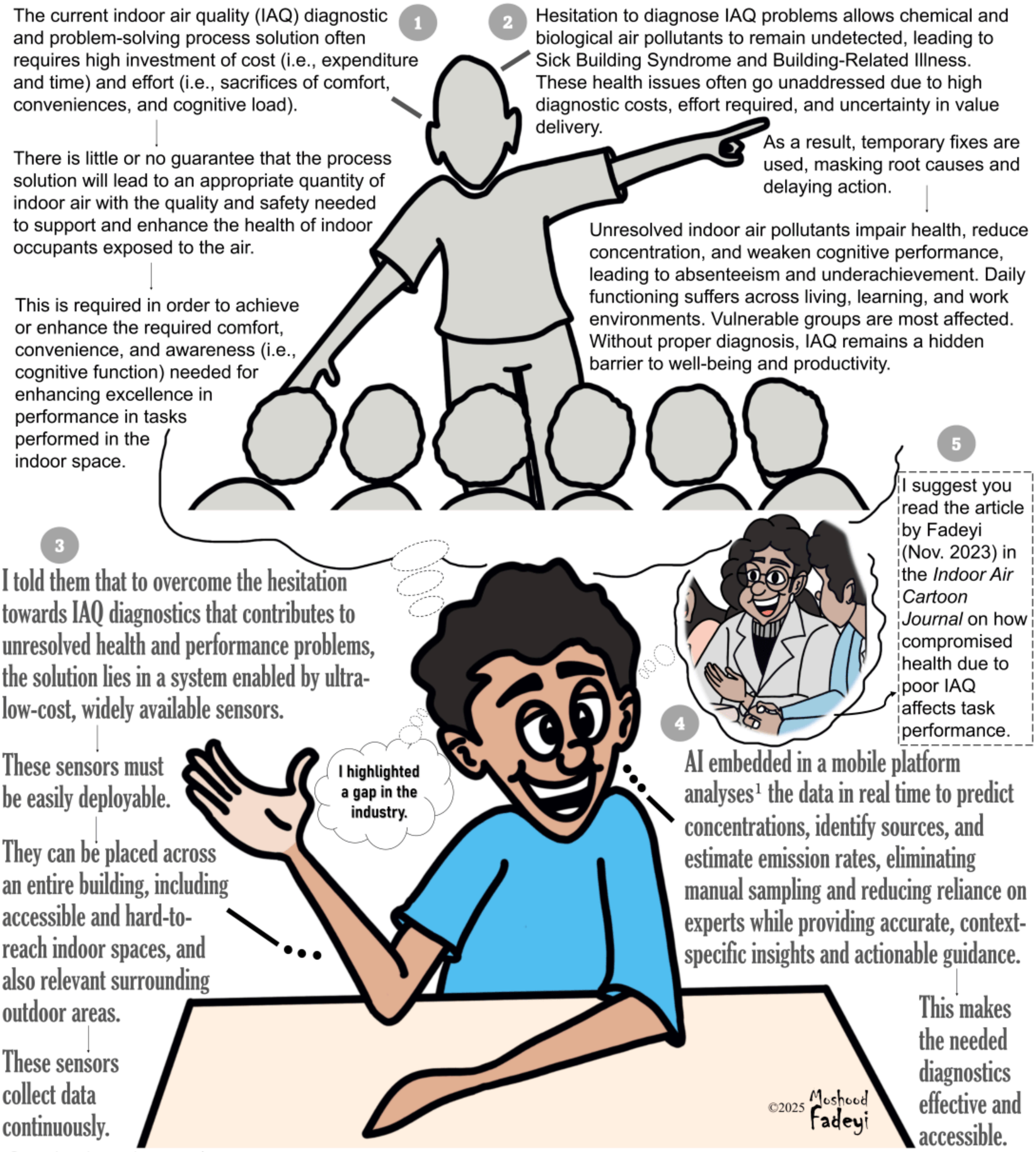
Artistic-Educational Research

HESITATION TO ENGAGE IN INDOOR AIR QUALITY DIAGNOSTICS INCREASES HEALTH RISKS AND TASK PERFORMANCE DECLINE



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[1]The system answers critical questions such as what, where, when, how often, who, which, how long, and whose.

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Fictional Case Story (Audio – available online) – Part 1

Fictional Case Story (Audio – available online) – Part 2

Fictional Case Story (Audio – available online) – Part 3

Fictional Case Story (Audio – available online) – Part 4

Fictional Case Story (Audio – available online) – Part 5

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There was a time in the industry when, despite advanced technologies in buildings, engagement with indoor air diagnostics remained low, hindered by hesitation, poor communication, and systems demanding high user expertise. Users often delayed action because alerts felt irrelevant, generic, or unclear, or because they lacked trust that their invested effort and cost would produce useful outcomes that exceeded the investment. This hesitation left indoor air pollutants to accumulate and health risks unresolved, leading to underperformance in comfort, convenience, and cognitive awareness crucial for well-being and productivity. Existing solutions rarely helped users develop cognitive pathways needed for achieving healthy indoor air. Instead, generic, context-independent alerts fostered doubt and inaction.

A young man who had long suffered from hesitation became emotionally connected with the ineffective, non-human-centric indoor air solutions that plagued the industry. His personal experience of delaying action, driven by uncertainty and fear of wasted effort, gave him a profound empathy for others facing similar doubts in managing indoor air quality. He understood intimately how daunting it felt to weigh the sacrificing cost and effort against uncertain outcomes, and how easily hesitation could take root when solutions seemed complex or untrustworthy. This emotional connection fuelled his determination to change the landscape of healthy indoor environments and help others avoid the consequences he once faced. This young man's journey is the subject of this fiction story.

1……………………………….

From early childhood, Ebuka Nwafor had always felt that his world moved faster than he could follow. He was a quiet boy growing up in the town of Osanle, where the red earth baked under the sun and children's laughter echoed through open courtyards. While other children responded instinctively to their surroundings, leaping into games, shouting over one another, solving disagreements in the dust, Ebuka remained on the margins, withdrawn but alert. His silence was not the result of disinterest. It was the outward expression of anxiety, a relentless undercurrent that shaped every experience without being visible to those around him.

Ebuka's anxiety was not explosive or disruptive. It was persistent and internal, a quiet turmoil that turned ordinary moments into mental obstacles. Whenever he considered speaking, acting, or even asking a question, his mind flooded with fears. What if he said the wrong thing? What if others laughed? What if he failed or disappointed someone? These thoughts came too quickly, piling on top of each other until no action seemed safe. His body would stiffen, his throat would tighten, and he would decide—without deciding—to wait.

To teachers, he seemed thoughtful. To his peers, he appeared hesitant. But what no one saw was the exhaustion that followed every moment of indecision. Ebuka was not slow to understand. In fact, he noticed more than most. He observed details, patterns, expressions. But his observations rarely became actions. Anxiety had trained him to rehearse rather than respond. Every choice became a calculation, every word a risk.

He did not yet have a name for what he felt. He only knew that he struggled to act while others moved easily. In truth, anxiety had become the lens through which he saw the world, and he carried it quietly, believing it was simply who he was.

In the primary school classroom, Ebuka's hesitation became a quiet yet persistent presence—one deeply rooted in anxiety. He often understood the lesson clearly and knew the correct answer before his classmates. But when the teacher asked a question, his hand would hover, suspended in mid-air, not because he doubted the answer itself, but because anxiety flooded his thoughts with warnings.

What if I am wrong? What if everyone laughs? What if I embarrass myself? These questions gripped him each time he considered speaking. Yet behind them was another fear, more subtle but just as paralysing—the fear that all his thinking, effort, and mental rehearsal might fail to yield anything of value. If he spoke and the answer was wrong, it would mean that everything he had invested—his concentration, his time, his careful preparation—had not produced something useful. That fear of wasted effort made every decision feel riskier than it was.

So, he hesitated. He waited for certainty, for the perfect moment where the risk of loss, embarrassment, or futility would be zero. But that moment never came. While he calculated every possible outcome, someone else would answer. The opportunity would vanish. When asked why he had not responded, he would reply, "I was still thinking." It was not untrue, but it concealed the deeper truth.

Ebuka's hesitation was not a matter of passivity. It was a behavioural response to anxiety—anxiety that magnified both the fear of visible failure and the fear of investing effort that yielded no tangible result. Each delayed action reinforced the message that it was safer to stay silent than to risk invalidating his own effort. In protecting himself from that imagined disappointment, he unknowingly began to cultivate a pattern of hesitation that would shape his learning, self-worth, and growing identity.

This pattern followed Ebuka into secondary school, where expectations were higher and the consequences of silence became harder to ignore. One overcast afternoon, as he walked along the quiet corridor leading to the school's chemistry laboratory, he noticed something peculiar. A pipe above a stack of cardboard boxes was leaking steadily. Droplets of water were falling, darkening the topmost box marked *Paper*. Other boxes nearby were labelled *Cleaning Agents* and *Spill Cloths*. A faint chemical scent hung in the air.

Ebuka paused. A quiet alarm sounded within him. His instincts told him something was wrong. The idea of water collecting over a pile of absorbent materials, some of which might be chemically reactive, unsettled him. He imagined a situation in which heat, friction, or an unnoticed reaction might cause a spark. He imagined the smoke, the flames, the panic. The danger felt real. And yet, he did nothing.

As he stood there, preparing to speak, his thoughts began to twist into doubt. *What if this is normal? What if I report it and look foolish? What if the technician is already aware?* These internal questions grew louder than the situation itself. His heart began to beat faster. His throat tightened slightly. He told himself he would come back after class and raise it then, when no one was around. He even practised the words in his head.

But when he returned, the technician was already there, tightening a valve and wiping the pipe with an old cloth. The problem had been discovered and addressed. Nothing had happened. Yet as Ebuka walked away, he felt no relief. He could not shake the image of the worst-case scenario he had imagined. He had known something might go wrong, and once again, he had hesitated.

It was not the event itself that stayed with him, but the delay. The silence. The fact that he had recognised the risk and failed to act. He had seen the pattern before, but this time, it felt different. His knowledge had not translated into behaviour. This was not simply about being shy or quiet. It was something deeper, something internal, something rooted in fear.

He was not a psychologist, and he did not yet know the word *anxiety*, but a seed of awareness took root. He began to observe himself. He noticed that whenever a decision needed to be made, especially one that involved risk or responsibility, his mind would erupt with questions. He was not unsure of facts or logic. He was afraid of being wrong. He was afraid that all the time and effort he had invested would be wasted if the outcome was flawed. That fear paralysed him.

What troubled him most was the contradiction. He was praised for being observant and intelligent. His teachers trusted him. His classmates asked for his help. Yet when the moment came to speak, to act, he stalled. He waited for perfect certainty, which never came. As a result, others always moved first.

Months later, during the long holiday, a more serious incident unfolded at home. An exposed wire from a small generator began sparking near a bundle of dry palm fronds and unused timber stored behind the house. Ebuka saw the faint blue sparks and the twitching of heat. The fire had not yet started, but it would only take one gust of wind. He stood still, frozen by the same fear. *What if someone else already saw it? What if I raise a false alarm? What if I sound panicked?* He hesitated. Again.

Five minutes later, someone else noticed the smoke, shouted, and ran for help. By then, the flames had already spread to a wooden shed used for storage. It was too late to save it. The structure was reduced to ashes. Fortunately, no one was hurt, but valuable household items were lost, and the blackened wall behind the shed remained as a reminder of what could have been prevented.

This time, the guilt was sharper. For days, Ebuka barely spoke. He replayed the moment again and again, not the fire, but his pause. He realised then that hesitation was not just a personal quirk. It was a flaw. And it could lead to real harm.

That was when he began to think more seriously about his future. He did not want to continue carrying this flaw unexamined. He wanted to understand not only himself, but also the environments in which hesitation became costly. He wanted to learn how to build systems and safeguards that could respond even when people hesitated to act.

After much deliberation, he chose to study Environmental Engineering. He saw it as the field where technical systems met human vulnerability. It offered him a path to study building environments, safety systems, indoor air quality, and risk response frameworks. In this field, he could begin to understand how spaces and technologies could be designed not just for efficiency, but for protection—especially in those moments when hesitation created delay.

Ebuka's teachers supported his decision. He had always performed at the top of his class, especially in mathematics, physics, and chemistry. His national exam scores placed him in the top percentile in the country. He had also developed a science project on passive ventilation in overcrowded classrooms, which earned distinction at a regional student fair. His strong academic record and clear personal statement secured him admission to the University of Goldwood, the nation's most prestigious institution for engineering and applied sciences.

As he stood at the gates of the university, the red sandstone buildings glowing in the early morning sun, he carried his flaw with him still. But he also carried something else: clarity. He was no longer trying to outrun his hesitation. He was choosing to understand it, confront it, and use it as the foundation for a career that could help others act where he once could not.

When Ebuka secured admission to study Environmental Engineering at a university in the city, he felt hopeful. It marked the beginning of a new chapter, an opportunity to distance himself from the limitations of his past and apply himself to a discipline that offered both intellectual fulfilment and social value. He was particularly drawn to the study of ventilation, pollutant behaviour, and the hidden environmental factors that influenced human health. These were not abstract technical interests; for Ebuka, they represented tools for safety, resilience, and proactive problem-solving—areas where, deep inside, he still carried a sense of personal failure.

But even in this promising new environment, his hesitation followed him. It manifested quietly but persistently, especially during group discussions and collaborative assignments. He would spend hours reading ahead of class, gathering insights, checking calculations, and writing notes. Yet, when the group gathered to make decisions, he often remained silent. A tension would rise in his chest, and he would begin calculating the potential outcome of speaking. What if his suggestion derailed the discussion? What if he challenged an idea that others were confident in, only to be wrong himself? What if his contribution consumed his mental energy but led to no meaningful change?

This anxiety, though silent, was powerful. It came not just from the fear of being incorrect, but from the fear that the emotional and cognitive energy needed to speak up—sacrificing comfort and taking a social risk—might result in no usefulness. He feared investing effort without return. That fear kept him quiet, even when his understanding told him otherwise.

This conflict came to a head during a course on indoor air quality (IAQ) modelling. The group had made an assumption about ventilation effectiveness in a naturally ventilated classroom, but something about it did not sit right with Ebuka. He double-checked the equation. Then checked it again. He found an error. The value used did not account for seasonal wind variability, which would significantly affect pollutant dispersion and make the model less accurate. For two nights, he agonised over it. But in the end, he said nothing.

When the group presented their work, the flaw was noted by the lecturer. The feedback was firm. The assumption had oversimplified key variables, and this undermined the model's reliability. The group received a lower mark than expected. There was disappointment all around—disappointment Ebuka knew he could have prevented.

While his teammates speculated about where things went wrong, Ebuka blamed himself in silence. His chest ached with guilt. He had seen the error. He had known what was at stake. But his anxiety had convinced him that speaking up would cost him more than keeping quiet. And now, everyone had paid the price for his silence. This time, the consequences were not just personal. They were shared. And that made the weight of his hesitation even heavier.

When Ebuka began his third-year internship at Healthy Air Champ (HAC), a public health engineering company widely recognised for its work in IAQ diagnostics, he carried with him a quiet determination to learn, contribute, and validate the academic journey he had undertaken. The company's projects focused on deploying environmental sensors across high-rise residential buildings to monitor airborne pollutants such as $PM_{2.5}$, $PM_{0.1}$, volatile organic compounds (VOCs), formaldehyde, ozone, carbon dioxide, and other critical IAQ indicators.

Ebuka had followed their work long before he was selected, and the opportunity to be part of their field operations felt like a dream earned through persistence, especially considering his silent, often reluctant journey to speak up and take initiative in earlier years.

The internship started with a flurry of activity. He was assigned to a team tasked with deploying sensor networks in a cluster of residential towers known for poor ventilation and high occupant density. These buildings were located in a densely populated neighbourhood on the city's eastern fringe.

The sensors were designed to continuously monitor indoor air pollutant concentrations and trigger alerts through a mobile interface accessible to building occupants. In theory, the system offered an ideal platform for early detection and intervention, helping occupants respond quickly to health risks and enabling building managers to oversee environmental performance in real time.

Initially, Ebuka was focused on technical tasks—configuring sensor nodes, mapping indoor airflow paths, calibrating the mobile alert systems, and maintaining digital logs. However, within the first few weeks, he began to notice something that deeply unsettled him. Despite the accuracy and efficiency of the sensor system, the occupants of the buildings rarely engaged with the alerts being sent.

Many mobile app notifications were left unopened. Some residents, when interviewed during follow-up visits, admitted that they did not understand what the numbers meant or why they mattered. Others dismissed the alerts entirely, insisting that they had lived in the same air conditions for years without problems. A few even expressed distrust toward the system, describing it as another burdensome technology imposed without their input or consent.

As Ebuka observed these behaviours, he began to feel a growing discomfort. He found himself revisiting the apartment blocks after official hours, reviewing sensor trends, examining alert response logs, and reading resident feedback. In Building 17C, for instance, $PM_{2.5}$ concentrations peaked consistently during the evening hours—likely due to cooking emissions combined with poor natural ventilation.

In several units located near the rubbish chutes and stairwells, formaldehyde levels remained elevated throughout the day. Alerts were triggered repeatedly, but no follow-up action was taken. Residents had not opened windows or adjusted fans, and no mitigation strategies had been adopted. The data told a clear story, yet the human response was virtually absent.

At first, Ebuka tried to rationalise the problem as a lack of awareness or environmental education. However, the more he listened to residents, the more he understood that the issue ran deeper. Many occupants did not reject the data because they were ignorant. Instead, they hesitated because the data did not fit into their daily logic or lived experience.

Acting on an IAQ alert required a level of cognitive and emotional effort that did not guarantee a visible benefit. In fact, in some cases, responding to an alert required sacrificing immediate comfort—opening a window during haze season, turning off a scented candle used for religious practice, or incurring the cost of a portable purifier. The system, while technically robust, had failed to align with the reality of its users.

It was at this point that Ebuka experienced something he had not anticipated. As he quietly analysed residents' behaviour, he began to see his own past reflected in the patterns of hesitation he was now observing. He remembered the moment in secondary school when he had noticed a leaking pipe over a stack of chemical storage boxes but had failed to report it until it was too late.

He recalled the fire incident in his home compound where his delay in raising the alarm had resulted in property damage. He thought back to the IAQ modelling course at university, where he had detected an error in his group's assumptions but had chosen to remain silent. In each of these moments, he had known what needed to be done. He had recognised the risk. But he had hesitated.

This personal connection transformed how he saw the situation. He no longer viewed the residents' hesitation as a failure of responsibility or laziness. Instead, he saw it as something he understood intimately—an instinct to withhold action because the cost of effort, risk of misunderstanding, and fear of being wrong seemed to outweigh the uncertain benefit of speaking or acting. His own experience gave him the ability to interpret their inaction not as apathy, but as a rational decision shaped by fear, ambiguity, and emotional resistance.

2……………………………….

One evening, while updating the field report in the company's operations room, Ebuka lingered behind after the others had left. His supervisor, Mr Koh, returned briefly to retrieve a notebook and noticed Ebuka's expression—troubled, contemplative, and unusually quiet. Mr Koh sat down beside him and asked, "You are carrying something. What is it?" Ebuka hesitated for a moment, then spoke. "The system works. The data is reliable. But no one acts. They see the alerts and do nothing. And I… I think I understand why."

He explained his observations, carefully linking the residents' behavioural patterns with his own history of hesitation. He described how even small decisions could feel monumental when framed by fear of uselessness, fear of judgement, fear of cost, inconvenience or the mental exhaustion required to interpret vague or overly technical information. He reflected on how the app's alerts were stripped of context, offering thresholds without interpretation and advice without connection to the user's personal situation. There was no feedback loop, no meaningful encouragement, no space for learning. It was not a technology problem. It was a human engagement problem.

Over the next week, Mr Koh asked Ebuka to develop a presentation for the company's strategy meeting. Rather than focus on technical summaries, Ebuka proposed a conceptual framework. He titled his section, *Bridging the Cognitive Gap in IAQ Diagnostics*. He explained that although IAQ systems were expected to support wellbeing and task performance, most current solutions failed to achieve these outcomes due to widespread diagnostic hesitation. He defined this hesitation as the behavioural delay or reluctance to engage with diagnostic information, even when that information was accurate and relevant.

He argued that hesitation was not irrational. It was a consequence of cognitive overload, weak interpretability, low trust, and a lack of perceived usefulness. Most IAQ systems, he explained, operated as detached instruments. They communicated through generic alerts and threshold breaches but offered no explanation of how to act or why it mattered in the user's specific context. As a result, users struggled to construct mental models—internal frameworks that support cognitive abilities and decision-making in complex environments.

He proposed a shift. Rather than relying solely on thresholds, IAQ systems should embed behavioural intelligence into their design. They should personalise alerts based on user patterns, environmental context, and previous behaviour. They should provide brief educational prompts linked to actions. For example, instead of saying, *$PM_{2.5}$ has exceeded 35 μg/m³.*

Ventilate now, the system might say, *Airborne particles are elevated. Opening your window now can reduce your child's risk of respiratory discomfort*. These small shifts, he believed, would build cognitive engagement and increase the likelihood of timely response.

He also shared his own personal story—without embellishment. He described his earlier failures to act, his fear of wasted effort, and how the internship had shown him that hesitation was not just personal but systemic. The board listened attentively, and for the first time in his professional journey, Ebuka felt that his silence had finally given rise to something meaningful.

This experience marked a turning point. His time at Healthy Air Champ had started with a desire to apply technical knowledge. It ended with a conviction to address the cognitive and behavioural dimensions of IAQ management.

Returning from his internship at Healthy Air Champ, Ebuka carried with him a changed understanding of what it meant to solve real-world problems. While he had originally enrolled in Environmental Engineering with a strong technical orientation, his experience during the internship had exposed him to a deeper, often overlooked challenge in IAQ management—the human element.

He had seen first-hand how systems failed not because the sensors were inaccurate or the tools inadequate, but because the intended users struggled to engage with the systems meaningfully. Their hesitation was not baseless. It arose from unclear communication, cognitive overload, and emotional reluctance to invest effort into something that might not yield a clear benefit.

These insights lingered with him as he entered the final year of his undergraduate programme. When it came time to propose a topic for his dissertation, he did not choose a technical modelling problem or a mechanical design solution. Instead, he designed a small-scale field study focused on IAQ awareness and engagement patterns among residents in medium-density public housing.

He distributed a series of IAQ monitoring kits, accompanied by educational prompts, into twenty households, then observed user response over a period of three weeks. He tracked not just sensor data but also behavioural patterns, log-in frequencies, and decision-making time following alert notifications. The dissertation revealed a recurring theme: those who acted promptly were not those with more education or technical literacy, but those who felt a clear sense of contextual relevance, personal value, and interpretive clarity from the system interface.

It was during the literature review and data analysis phase of his dissertation that Ebuka began drafting what would later evolve into a formal problem statement. He recognised that there was a gap not only between users and systems, but between expectation and reality—between the assumed benefits of diagnostic tools and how they were actually used. He began to write, not as a student fulfilling a requirement, but as a researcher trying to name what he had seen and experienced.

As graduation approached, Ebuka began searching for PhD programmes that would allow him to explore in depth the intersection between cognitive behaviour, system design, and environmental health. He eventually chose to apply to the School of Public Health at the University of Ivory, known for its interdisciplinary research into environmental systems and behavioural science.

What attracted him most was the university's Cognitive Environments Research Cluster, which brought together engineers, psychologists, designers, and public health experts to address complex behavioural gaps in environmental decision-making. Here, Ebuka believed, he could continue to explore not only the technical aspects of IAQ systems, but also the human thought patterns, assumptions, and fears that governed their use.

Ebuka successfully gained admission into the doctoral programme at the University of Meredin's School of Public Health. His acceptance into the highly competitive programme was met with a deep sense of purpose rather than celebration. For him, it marked not only an academic milestone, but also a personal commitment to address a problem he had both observed in practice and experienced in himself. Surrounded by scholars from engineering, psychology, and public health disciplines, Ebuka felt he had found the right environment to develop a research inquiry that combined rigorous technical knowledge with human-centred understanding.

His admission success was largely attributed to the originality, applied relevance, innovative framing, and promising direction of his proposed research, which distinguished him from many other candidates who presented more conventional or narrowly technical proposals. The review panel recognised that Ebuka's application demonstrated not only a strong academic foundation but also a rare ability to bridge disciplines and ground theoretical questions in real-world challenges.

His proposal drew directly from first-hand field observations, behavioural insights, and reflective experiences that added depth and authenticity to his research vision. He did not merely aim to refine sensor technologies or improve algorithmic precision, but to tackle the behavioural bottlenecks that were limiting the impact of even the most advanced IAQ systems. His clear articulation of the gap between technological capability and behavioural engagement was supported by lived experience, structured inquiry, and an emerging systems-thinking mindset.

The evaluators commended his capacity to frame the problem in terms of human cognition, decision-making constraints, and the ethical responsibility of system designers. The strength of his submission lay in its recognition that engineering solutions must do more than function—they must communicate meaning, inspire trust, and support human judgement in contextually sensitive ways.

His proposed research, they noted, had the potential to contribute not only to academic knowledge but also to the design of more inclusive and effective environmental health interventions. It was this originality of focus and the translational promise of his ideas that ultimately led to his successful admission, which goes thus:

“In today’s built environments, spanning residential, educational, healthcare, and commercial buildings, IAQ diagnostics are essential to ensuring the health and wellbeing of occupants. The expected performance level in IAQ management is one where individuals and institutions engage proactively and consistently with diagnostic tools to detect harmful pollutants, assess exposure risks, and take timely corrective actions.

At this ideal performance level, users would experience not only optimal physical comfort and convenience but also heightened awareness—an understanding of indoor air quality dynamics that supports informed decision-making, alert responsiveness, and health-conscious behaviour.

However, in real-life practice, the current performance level falls significantly short of this goal. Across a wide range of building types and user groups, there exists a persistent pattern of hesitation to engage in IAQ diagnostics. This hesitation manifests as delayed or absent responses to alerts, underutilisation of available diagnostic tools, and passive disregard of environmental cues that indicate poor indoor air quality.

Despite technological advances in sensor deployment and environmental monitoring systems, diagnostic engagement remains sporadic, contextually inconsistent, and poorly integrated into user routines. The result is a systemic underperformance in the core outcomes that IAQ diagnostics are meant to support—comfort, convenience, and awareness (informed by cognitive abilities).

This gap between the expected and current performance levels, otherwise known as the problem, is multidimensional. First, from the standpoint of comfort, occupants in poorly diagnosed spaces continue to experience physiological symptoms—such as eye irritation, headaches, breathing difficulties, and fatigue—due to prolonged exposure to pollutants like $PM_{2.5}$, $PM_{0.1}$, VOCs, ozone, and CO_2.

These symptoms persist not because the risks are unknown, but because the systems meant to detect and prompt responses to them are either underused or dismissed. Second, convenience is compromised by the lack of adaptive, user-centred systems that streamline diagnostic action. Current IAQ solutions often require manual interpretation, rely on generic alerts, or demand expertise that many users or building occupants do not possess—or that is too expensive for them to acquire—creating friction in responding to alerts and reinforcing diagnostic inertia.

Most critically, the underperformance impacts cognitive abilities—a domain central to awareness needed for risk interpretation and problem-solving. In the expected performance scenario, IAQ diagnostic systems would facilitate the development of mental models that help users reason about indoor air quality risks, perceive the consequences of inaction, and act based on contextual cues.

Instead, many current systems function as opaque tools that deliver information without interpretation, reducing the user’s capacity to understand, learn from, or respond to environmental signals. This undermines the development of the very cognitive abilities, such as critical and reflective thinking, abstract reasoning, logical deduction and creative imagination, that are needed for effective IAQ management.

This systemic problem is not due to a lack of scientific knowledge or measurement technology, but rather due to failures in human engagement, institutional design, and interface communication. In many community settings, including homes and schools, users are unaware of IAQ's role in health and productivity and receive no feedback loop to encourage reflection or action.

In industrial and organisational settings, IAQ diagnostics are often deprioritised in favour of visible or short-term operational concerns. Even when sensors are installed, building managers and occupants may hesitate to act on alerts due to uncertainty, competing demands, or disbelief in the urgency of the data presented. This diagnostic hesitation—the delay or refusal to engage with diagnostic guidance—represents the behavioural bottleneck that blocks the path to the expected performance level.

Current IAQ practices are further limited by their reliance on threshold-based alert systems that treat risk as a fixed, context-independent value. These systems fail to consider behavioural patterns, organisational norms, or environmental context when generating alerts. As a result, they are often perceived as irrelevant or excessive, leading to alert fatigue and eventual disregard.

There is no mechanism in place to differentiate between users who are repeatedly slow to respond and those who act promptly, nor is there a method for learning from past behaviour to personalise recommendations. This contributes to a cycle where delayed action becomes normalised, reinforcing exposure to harmful pollutants and perpetuating poor indoor environmental quality outcomes.

Moreover, there is little consideration for how the design of IAQ systems affects learning and behavioural change. Most existing systems provide no explanations for their alerts, leaving users confused about what the system wants them to do or why the warning matters. This absence of interpretability blocks the development of awareness—the cognitive foundation needed to build environmental literacy, respond with confidence, and advocate for healthier spaces. Without this, even well-intentioned users lack the tools to reflect on their actions or understand the consequences of inaction. Thus, the current IAQ ecosystem does not support a cognitive trajectory that moves users from data receipt to environmental mastery.

This situation creates a misalignment between what is technologically possible and what is behaviourally achievable, resulting in low-value outcomes despite high-resource investment in sensors and monitoring systems. In some buildings, advanced monitoring infrastructure is in place, yet users hesitate to act because the system is not trusted, its guidance is unclear, or it lacks relevance to the user's role or perceived authority. In others, indoor occupants may delay IAQ action because the health risks feel abstract, while the inconvenience or cost of diagnostics feels immediate. In both cases, diagnostic hesitation becomes a rationalised response to poor communication and limited value perception, widening the gap between actual and ideal practice.

To bridge this gap, there is a need for a new diagnostic paradigm—one that does not only detect pollutants but also detects patterns of human hesitation and addresses them. Such a system must learn from user behaviour, contextualise environmental threats, and personalise risk communication. It should engage users in a way that supports mental model development, asks relevant questions, and promotes cognitive and understanding development to enable decisions that improve indoor air quality and health outcomes. This is the level of performance expected in today's knowledge-rich, sensor-enabled era—where intelligent tools are not merely data collectors, but facilitators of human awareness and action.

Ebuka recognised that bridging the gap required formulating research questions that would guide the inquiry toward generating the understanding needed to develop solutions capable of moving stakeholders toward the intended goal. The research questions are: (i) What behavioural, organisational, and perceptual factors contribute to individual and institutional hesitation in engaging with indoor air quality diagnostics, and how can these be systematically characterised across different building types and user profiles? (ii) How does delayed engagement in indoor air quality diagnostics affect the cumulative exposure to harmful pollutants and what is its quantifiable impact on health risk escalation and cognitive-task performance decline over time? (iii) How can behavioural, environmental, and contextual indicators be integrated into an AI-enabled predictive and decision-support framework that mitigates the consequences of IAQ diagnostic hesitation through early risk identification and action guidance?

For the first research question, the hypothesis is that hesitation to engage in IAQ diagnostics is significantly associated with a combination of low perceived susceptibility to IAQ-related health risks, the absence of immediate symptoms, and organisational norms that deprioritise preventive environmental monitoring; these factors are expected to vary systematically across building types and occupant roles.

The null hypothesis (H_0) states that there is no significant association between diagnostic hesitation and behavioural, perceptual, or organisational factors across building types, whereas the alternative hypothesis (H_1) proposes that diagnostic hesitation is significantly predicted by specific behavioural, perceptual, and organisational variables, and that these predictors vary across building types and user profiles.

For the second research question, the hypothesis is that delayed engagement in IAQ diagnostics leads to statistically significant increases in cumulative exposure to pollutants, resulting in elevated health risk indicators (e.g. inflammatory biomarkers, respiratory symptoms) and measurable decline in cognitive-task performance (e.g. memory, attention, reaction time), compared to environments with timely diagnostic engagement.

The null hypothesis (H_0) states that there is no significant difference in pollutant exposure, health risks, or cognitive-task performance between occupants in environments with delayed IAQ diagnostics and those with timely diagnostics, whereas the alternative hypothesis (H_1) posits that delayed IAQ diagnostics are significantly associated with higher pollutant exposure, increased health risks, and reduced cognitive-task performance compared to environments with proactive diagnostics.

For the third research question, the hypothesis is that an AI-enabled model that integrates behavioural hesitation indicators, environmental sensor data, and contextual metadata can predict high-risk scenarios of IAQ diagnostic delay with a classification accuracy exceeding 85%, and significantly improve diagnostic engagement rates and early intervention outcomes when used in real-time decision support.

The null hypothesis (H_0) states that an AI-enabled model integrating behavioural and environmental indicators does not improve prediction of diagnostic hesitation nor enhance engagement or early intervention outcomes, whereas the alternative hypothesis (H_1) posits that an AI-enabled model integrating behavioural and environmental indicators significantly improves the prediction of diagnostic hesitation and enhances engagement and intervention outcomes.

The research questions and problems informed the following objectives of his PhD research: (i) To investigate and systematically characterise the behavioural, organisational, and perceptual factors that contribute to individual and institutional hesitation in engaging with indoor air quality diagnostics across diverse building types and occupant profiles. (ii) To quantify the impact of delayed indoor air quality diagnostics on cumulative pollutant exposure, health risk escalation, and cognitive-task performance decline over time. (iii) To develop and validate an AI-enabled predictive and decision-support framework that integrates behavioural, environmental, and contextual indicators to mitigate the consequences of indoor air quality diagnostic hesitation through early risk identification and guidance.

Below is an excerpt from Ebuka's PhD thesis.

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Research Methods

Methods for Research Question 1:

Study Settings and Sampling Strategy

A convergent parallel mixed-methods design was adopted to explore the behavioural, organisational, and perceptual determinants of hesitation in engaging with IAQ diagnostics. Quantitative and qualitative data were collected simultaneously and analysed independently before being integrated during interpretation. This approach was intended to allow the identification of statistical patterns while uncovering explanatory insights through participants' lived experiences and contextual dynamics.

The study was carried out across four main types of buildings: residential buildings, educational institutions, healthcare facilities, and commercial office spaces. These building types were chosen to represent a broad range of indoor environments where indoor air quality may affect health and performance, and where the reasons for hesitating to conduct IAQ diagnostics might differ. Each building type also involves different patterns of use, occupant behaviours, and decision-making structures. For example, residents may rely on personal judgment to manage IAQ, whereas in healthcare or commercial buildings, IAQ management often depends on formal procedures and institutional policies.

In each of the four building types, three groups of people were included to capture different viewpoints. The first group was general occupants—these were the people who spent time in the buildings regularly, such as residents at home, students at school, patients or visitors in healthcare centres, and workers in offices. The second group was facility or maintenance managers, who were responsible for the daily upkeep and operation of building systems, including ventilation and air quality. The third group was made up of institutional decision-makers, such as school principals, clinic directors, building owners, or corporate officers, who had the authority to make policies or decisions about when and how IAQ diagnostics should be carried out.

The target sample size for the survey was 800 participants, with 200 participants drawn from each building type. Within each group of 200, care was taken to include a balanced number of people from the three different roles: occupants, managers, and decision-makers. Participants were selected using a stratified purposive sampling method. This means that people were chosen intentionally, not randomly, to ensure that the sample reflected a wide range of experiences and responsibilities related to IAQ. Building access, institutional approval, and referrals from local contacts were used to help identify suitable participants.

After the survey, 30 to 40 participants were invited to take part in follow-up interviews. They were selected based on their role, the type of building they were in, and their level of hesitation towards IAQ diagnostics, as indicated by their survey responses. The sampling strategy as a whole was designed to support reliable statistical analysis from the survey, while also allowing for deeper exploration of insights during the interviews.

Operationalisation of Variables

The primary outcome variable in this study was hesitation to engage in IAQ diagnostics. This was measured using a composite metric developed specifically for this research: the Indoor Air Quality Diagnostic Hesitation Score (IDHS). The IDHS was designed to capture multiple dimensions of hesitation, including behavioural inaction, uncertainty about the relevance of IAQ to health symptoms, and intention to seek diagnostics in future situations. The scale provided a standardised means to quantify and compare hesitation across different settings and participant roles.

The IDHS consisted of ten closed-ended survey questions in total, developed through an extensive review of the literature on health-related inaction, environmental risk perception, and decision-making under uncertainty. These ten questions were carefully constructed to capture different aspects of diagnostic hesitation and were thoughtfully distributed across three conceptual dimensions, with each dimension containing a different number of questions, not less than three questions in each, based on its complexity and the results of scale validation.

Each dimension reflected a distinct facet of the overall construct and contributed to the composite score. Each dimension contained questions specifically tailored to reflect its underlying intent, thereby enabling a more reliable and nuanced assessment of hesitation.

The first dimension, behavioural delay, reflected participants' tendencies to postpone or avoid taking action even when they recognised potential signs of discomfort or IAQ-related problems. This dimension was assessed through four closed-ended survey questions that captured different expressions of behavioural inaction. The first question, *"I often wait to see if symptoms improve before considering an IAQ assessment,"* explored a passive approach to emerging symptoms, where individuals preferred to delay action in the hope that the issue would resolve itself. The second question, *"I would only act on IAQ concerns if someone else reported them first,"* assessed reliance on external validation before taking responsibility for initiating diagnostics.

The third question, *"I prefer to monitor the situation informally before involving any formal IAQ testing,"* reflected a preference for informal observation over formal intervention, even when signs of discomfort were present. The fourth question, *"Unless the symptoms are severe, I don't see the need to act immediately on IAQ issues,"* addressed the tendency to minimise early warning signs and act only when conditions had significantly worsened. Together, these questions provided a structured and multifaceted view of how behavioural delay contributes to overall hesitation in addressing indoor air quality concerns.

The second dimension, diagnostic relevance uncertainty, assessed the extent to which participants were unsure or hesitant to link observed health or comfort issues to indoor air quality. This dimension captured the cognitive and perceptual ambiguity that often prevents individuals from taking action, even when symptoms are present. It was measured using three closed-ended survey questions that focused on the participant's confidence in identifying IAQ as a potential cause of discomfort.

The first question, *"I am unsure whether headaches or fatigue are caused by indoor air problems,"* reflected uncertainty in symptom attribution, particularly when the symptoms could be explained by other everyday factors. The second question, *"I don't feel confident that IAQ diagnostics can help explain what I'm experiencing,"* captured doubt in the ability of diagnostic tools to provide meaningful or trustworthy information. The third question, *"I find it difficult to tell whether indoor discomfort is due to air quality or something else,"* explored a more general hesitancy in linking perceived discomfort to environmental conditions. Together, these questions offered a nuanced view of how uncertainty about symptom relevance contributes to hesitation in seeking IAQ diagnostics.

The third dimension, future diagnostic intent, measured participants' willingness to take proactive steps should similar indoor air quality concerns arise in the future. This dimension was designed to assess not only stated intentions but also the degree to which participants were likely to overcome hesitation when faced with familiar IAQ issues. It was measured using three closed-ended survey questions.

The first question, *“If I face the same issue again, I will seek professional IAQ testing immediately,”* captured the participant’s readiness to act promptly, and responses to this question were reverse scored to reflect hesitation. The second question, *“I would likely ignore future IAQ concerns unless symptoms become severe,”* assessed the threshold participants set for taking action, with higher agreement suggesting a reluctance to respond early. The third question, *“Even if I suspect an IAQ problem in the future, I am unlikely to act unless instructed to do so,”* reflected dependence on external direction rather than self-initiated action. Together, these questions provided insight into participants’ forward-looking intentions and the behavioural patterns that may influence their future engagement with IAQ diagnostics.

Each question was rated on a five-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (5). Responses to all ten questions were summed to produce the total IDHS for each participant, with higher scores indicating stronger hesitation. The scale was pilot-tested to assess clarity and relevance, and its structure was refined through exploratory and confirmatory factor analysis to verify its dimensional structure. These analyses confirmed that the three dimensions were conceptually distinct yet worked together to capture the broader construct of hesitation toward IAQ diagnostics.

The scale was also evaluated to ensure that all the questions were consistently measuring the same underlying concept—namely, participants’ hesitation to engage in IAQ diagnostics. This process involved checking whether participants tended to respond in a similar way to questions that were meant to measure the same dimension of hesitation. To assess this consistency, a statistical method known as Cronbach’s alpha was used. This measure helps determine whether the questions within each dimension are working together reliably. A Cronbach’s alpha value of 0.70 or above was considered acceptable, indicating that the set of questions was internally consistent.

If a particular question did not align well with the others in the same dimension, for example, if a clear pattern in the data showed that participants responded to it in ways inconsistent with related questions, it would typically be examined more closely during data analysis. However, this did not occur in the present study, as a preliminary study had already been conducted, during which the questions were reviewed, tested, and revised as needed to ensure conceptual clarity and alignment.

The version of the scale used in the main study reflected those refinements. As a result, all questions included in the final survey demonstrated satisfactory consistency with their respective dimensions. Nevertheless, the internal consistency of each dimension was still assessed statistically. If, in future applications, a question shows limited contribution to internal consistency across a larger or different sample, it may be considered for refinement based on its overall statistical performance, rather than isolated participant responses.

The IDHS will only capture how hesitant someone is but will not capture what drives or explains that hesitation. Thus, there is a need to measure a range of behavioural, organisational, and perceptual variables that can help identify the underlying factors contributing to diagnostic hesitation and provide insights into how it varies across individuals and settings. Thus, a range of independent variables was measured to examine what influences hesitation to engage in indoor air quality diagnostics. These variables were grouped into three main categories: behavioural, organisational, and perceptual, each representing a different aspect of decision-making related to IAQ.

Behavioural variables referred to individual beliefs, attitudes, and tendencies that could influence how a person responds when confronted with potential IAQ concerns. These were measured using eight closed-ended survey questions, each rated on a five-point Likert scale ranging from “strongly disagree” to “strongly agree.” The behavioural variables were grouped into four constructs—perceived susceptibility, perceived severity, delay discounting, and self-reported familiarity with IAQ—each assessed using two questions.

Perceived susceptibility evaluated how likely participants believed they were to suffer health effects from exposure to poor indoor air. This was measured through questions such as, *“I believe I am at risk of health problems if the indoor air is polluted”* and *“My health is more likely to be affected by indoor air than others around me.”* Perceived severity examined beliefs about the seriousness of those health consequences. Questions under this construct included, *“The health consequences of poor indoor air quality can be severe”* and *“Long-term exposure to indoor air pollution can lead to serious illnesses.”*

Delay discounting captured the tendency to prioritise short-term convenience over long-term health benefits. It was assessed with items like, *“I would rather tolerate minor discomfort now than go through the trouble of an IAQ assessment”* and *“Unless symptoms become unbearable, it’s not worth the hassle of investigating indoor air quality.”* Self-reported familiarity with IAQ gauged participants’ baseline knowledge of indoor air issues and technologies. This was reflected in statements such as, *“I am familiar with common indoor air pollutants and their health effects”* and *“I understand how ventilation systems can influence indoor air quality.”*

Organisational variables focused on the systems, norms, and practices within the institutions or workplaces where participants lived or worked. These were assessed using eight Likert-scale questions, distributed across four constructs: health and safety culture, procedural clarity, budget constraints, and internal communication. Health and safety culture was measured with questions such as, *“My organisation takes indoor air quality seriously”* and *“Indoor environmental quality is part of our workplace health policies.”* Procedural clarity was evaluated with statements like, *“There are clear procedures for reporting indoor air quality concerns in my organisation”* and *“I know how to initiate an IAQ assessment if a problem is suspected.”* Perceived budget constraints were captured through items such as, *“Our organisation lacks the budget to prioritise IAQ testing”* and *“Financial limitations make IAQ diagnostics difficult to carry out.”* Internal communication clarity was assessed with questions like, *“It is clear who to contact regarding IAQ concerns in my organisation”* and *“There is regular communication about indoor environmental quality in my workplace.”*

Perceptual variables explored how participants interpreted environmental cues and symptoms. These were assessed using six closed-ended questions, again rated on a five-point Likert scale. Ambiguity in symptom attribution was captured with items such as, *“It is hard to tell whether my symptoms are caused by the indoor environment”* and *“I often question whether headaches or fatigue are due to IAQ or other causes.”* Trust in diagnostic technologies was assessed through questions like, *"I trust that IAQ testing can accurately identify air quality problems"* and *"IAQ technologies are reliable tools for understanding environmental health issues."* Prior experience with IAQ assessments was measured using items such as, *"I have previously undergone an IAQ diagnostic assessment"* and *"My past experience with IAQ diagnostics was helpful in identifying or resolving the issue."*

To support more detailed analysis, demographic and contextual variables were also collected. These included age, gender, job role, education level, and key building characteristics such as size, age, and ventilation type. These data were used as covariates to control for background differences and to allow subgroup comparisons across building types and participant roles.

Qualitative Component and Data Analysis Strategy

While the structured questionnaire quantified diagnostic hesitation and its potential drivers, it could not fully explain the contextual and subjective reasoning behind participants' responses. To address this limitation and enhance the depth of understanding, semi-structured interviews were conducted with a subset of participants who represented variation in hesitation scores, stakeholder roles, and building contexts.

These interviews aimed to elicit nuanced accounts of participants' thought processes, experiences, and institutional influences shaping IAQ decision-making. Interviews were conducted either in person or via secure video conferencing platforms, depending on participant availability. All participants provided informed consent for audio recording. Recordings were transcribed verbatim, and all personally identifiable information was removed to ensure confidentiality and data integrity.

Quantitative data were analysed using SPSS and Mplus. Descriptive statistics were first used to summarise Indoor Air Quality Diagnostic Hesitation Score (IDHS) values and the distribution of behavioural, organisational, and perceptual predictor variables across different stakeholder roles and building types. This initial step established the general trends and patterns in diagnostic hesitation.

To explore how specific variables predicted hesitation, multivariate linear regression analysis was performed. Each model included behavioural, organisational, and perceptual variables as independent predictors, with diagnostic hesitation (IDHS) as the dependent variable. Demographic and contextual factors, such as age, gender, role, building age, and ventilation type, were included as covariates to adjust for background influences. Interaction terms were also tested to determine whether the strength or direction of these associations varied across different building contexts (e.g. schools, offices, residential settings).

To further assess the underlying relationships and validate the conceptual structure of the hypothesised constructs, Structural Equation Modelling (SEM) was conducted. SEM allowed for the simultaneous estimation of measurement models (to validate latent constructs like perceived susceptibility or institutional clarity) and structural models (to evaluate direct and indirect pathways linking predictors to hesitation). This technique also helped test the overall model fit and the robustness of theoretical assumptions derived from the literature.

Qualitative interview data were analysed using Braun and Clarke's six-phase thematic analysis framework. The goal was to generate an explanatory understanding of the hesitation patterns revealed in the survey. The analysis began with close reading of the interview transcripts to become familiar with the content, followed by the generation of initial codes. NVivo software was used to organise the data and facilitate systematic coding. Both deductive codes, developed based on quantitative constructs such as risk perception or procedural clarity, and inductive codes, derived from unexpected patterns in the narratives, were applied. This hybrid approach allowed for both theory testing and new insight generation.

Themes were refined through constant comparison and interpreted to explain how participants made sense of hesitation in their lived contexts. For instance, qualitative data revealed nuanced factors such as perceived organisational indifference or prior negative experiences with diagnostics that helped explain statistical associations or anomalies found in the quantitative phase. Integration of quantitative and qualitative findings occurred at the interpretation stage through a joint display matrix. This matrix presented statistical results (e.g. significant predictors, regression coefficients, SEM pathways) alongside thematically organised qualitative excerpts.

Where quantitative data suggested significant relationships, such as the role of institutional clarity in reducing hesitation, interview narratives were examined to determine how participants experienced or perceived these dynamics. Conversely, if the regression model showed weak or unexpected effects, qualitative data were used to explore contextual factors or interpretive differences that might account for these findings. This integrative process not only triangulated the data but also provided richer, contextually grounded explanations for diagnostic hesitation, enhancing the explanatory power and ecological validity of the study.

Ethical Considerations

Ethical approval for the study was obtained from the appropriate institutional review boards. All participants received written and verbal information about the study and gave informed consent before participating. Survey responses were anonymised, and access to raw data was restricted to the core research team. Interview participants were given the opportunity to review and amend their transcripts and were informed that they could withdraw at any stage without consequence.

Methods for Research Question 2:

Study Settings and Sampling Strategy

This study employed a prospective, longitudinal quasi-experimental design to investigate how delayed engagement in IAQ diagnostics affects cumulative exposure to pollutants and the subsequent impact on physiological health indicators and cognitive-task performance over time. The design was deliberately chosen to mirror real-world scenarios where decision-makers may postpone IAQ assessments due to uncertainty, budget constraints, or underestimation of health risks. By pragmatically operationalising this delay, the research aimed not only to understand theoretical relationships but also to provide evidence that could inform policies and practices in building management and public health.

To capture the comparative effects of proactive versus delayed IAQ diagnostics, the study was conducted over a 12-month period in twenty residential, commercial, and institutional buildings grouped into two matched clusters. The first cluster, termed the Timely Diagnostics Group (TDG), consisted of ten buildings where IAQ diagnostics were conducted immediately upon the identification of risk signals. These signals included early occupant complaints, sensor-triggered alerts, or periodic air quality audits.

In contrast, the Delayed Diagnostics Group (DDG) comprised ten comparable buildings in which diagnostics were deliberately postponed for a minimum of three months after the same early signals emerged. This operational delay was not simulated in a hypothetical setting but implemented through close collaboration with building managers, allowing the study to maintain ecological validity and preserve the integrity of real-life decision-making contexts.

To ensure comparability across both groups, a rigorous matching process was undertaken prior to participant recruitment. Buildings were matched based on key criteria such as building typology (e.g., residential, commercial, institutional), ventilation type and operational schedule (e.g., mechanical versus natural ventilation, air change rates), average occupancy density, and surrounding outdoor air pollution profiles, as obtained from municipal environmental datasets. This matching strategy reduced the risk of systematic bias and helped isolate the effect of diagnostic timing as the primary independent variable.

Participant selection followed a structured protocol aimed at balancing scientific rigour with feasibility. A total of 200 adults were recruited, with each building contributing roughly ten participants. Participants were drawn from cognitively demanding occupational backgrounds, including but not limited to educators, administrative professionals, and those in data-driven or decision-making roles. These professions were selected because of their susceptibility to subtle cognitive impairment from environmental stressors such as poor air quality.

The inclusion criteria required participants to be between 25 and 55 years of age, spend at least six hours per day on-site for a minimum of five days per week, and have no chronic respiratory or neurological diagnoses. Participants who smoked regularly, used personal air purifiers, or were prescribed medications known to affect memory, alertness, or motor response were excluded to minimise confounding in health and cognitive outcomes.

The recruitment process was carried out with transparency and informed consent. Participants were briefed about the study aims, procedures, data privacy protocols, and their right to withdraw at any time without penalty. Written informed consent was obtained from all individuals, and the study protocol received full ethics approval from the Institutional Review Board (IRB) prior to implementation. In line with ethical and pragmatic best practices, participants were compensated for their time during assessment sessions and follow-up measurements, thus promoting sustained engagement throughout the 12-month period.

Overall, the quasi-experimental design and its operationalisation were carefully structured to reflect real-world conditions while ensuring scientific robustness. The approach facilitated the generation of evidence that not only addressed academic hypotheses but also provided practical insight into the risks of diagnostic delays—insight that could be readily translated into workplace safety protocols, building management policies, and public health interventions.

Environmental Exposure Monitoring

To monitor the indoor environment, AI-enhanced, time-resolved indoor air quality sensors were installed in the main workspaces of all participating buildings. These sensors continuously measured the concentrations of key pollutants relevant to indoor air quality, including particulate matter with aerodynamic diameters less than 2.5 micrometres ($PM_{2.5}$) and less than 0.1 micrometres ($PM_{0.1}$), volatile organic compounds (VOCs) such as benzene and formaldehyde, carbon dioxide (CO_2), ozone (O_3) and nitrogen dioxide (NO_2). The sensors logged data at one-minute intervals, generating a high-resolution time series of pollutant concentrations.

$CED_i = \int C_i(t) \times IR(t)\,dt$, from t_0 to t_n

Cumulative exposure dose (CED) for each pollutant was estimated in this study to reflect the physiological burden of inhaled pollutants over time among participants occupying the monitored buildings. The research adopted a time-resolved numerical integration method that explicitly accounted for both the concentration of pollutants and the volume of air inhaled. The specific formula implemented in the analysis was:

$CED_i = \int C_i(t) \times IR(t)\,dt$, from t_0 to t_n

In this equation, $C_i(t)$ represents the time-varying concentration of pollutant i in micrograms per cubic metre (μg/m³), $IR(t)$ denotes the inhalation rate in cubic metres per minute (m³/min), and t_0 and t_n correspond to the start and end times of the observation period. This formulation enabled the computation of the total mass of a given pollutant inhaled by each participant during the study period, rather than merely tracking the concentration of ambient pollutants.

The inhalation rate function was determined using physiological benchmarks relevant to sedentary or low-activity indoor environments. In cases where individual-specific data on respiratory ventilation were not available, a standardised average rate based on activity-adjusted references for adults aged 25 to 55 was applied. This decision was made to ensure physiological plausibility while maintaining analytical consistency across participants.

To account for the multifactorial nature of real-world indoor air exposure, the calculation was extended beyond single pollutants. Participants in the study were routinely exposed to multiple airborne contaminants, including particulate matter ($PM_{0.1}$ and $PM_{2.5}$), volatile organic compounds (e.g. benzene and formaldehyde), carbon dioxide (CO_2), ozone (O_3) and nitrogen dioxide (NO_2). Therefore, the total cumulative exposure dose for each participant was operationalised as the sum of the individual pollutant doses, expressed as:

Total $CED = \sum_i \int C_i(t) \times IR(t)\,dt$, from t_0 to t_n, where i ranges from 1 to n pollutants.

This decision was made to improve ecological validity and enhance the model's sensitivity to combined exposures, which are more representative of indoor environments than single-pollutant scenarios. All pollutants were monitored using AI-enhanced sensors with one-minute resolution, and the integration was performed over a continuous 12-month monitoring period for each participant. The use of high-frequency data ensured that both transient peaks and sustained exposures were captured within the cumulative dose calculations.

Furthermore, to improve the health relevance of the cumulative exposure metric, a supplementary analysis incorporated pollutant-specific toxicity weightings. This approach involved assigning a relative harm coefficient (w_i) to each pollutant based on toxicological data available in public health literature and international air quality guidelines. The weighted cumulative dose was expressed as:

Weighted Total CED = $\Sigma_i\, w_i \times \int C_i(t) \times IR(t)\, dt$,where i ranges from 1 to n pollutants.

The inclusion of this weighted measure was intended to facilitate exploratory modelling of exposure-response relationships that accounted not only for the mass of pollutants inhaled but also for the relative severity of health outcomes associated with each pollutant. This decision aligned with the study's broader aim of linking diagnostic delay with escalated risk by establishing dose-based predictors of health and cognitive performance outcomes.

Taken together, these methodological choices allowed the study to construct detailed exposure profiles for all participants. The profiles captured both the intensity and physiological relevance of inhaled indoor air pollutants and provided a robust empirical basis for analysing how delayed engagement in diagnostics translated into elevated cumulative exposure and downstream health effects.

Health Data Collection and Physiological Indicators

Health-related data were collected quarterly and encompassed both objective physiological markers and subjective symptom reporting. Inflammatory biomarkers were chosen as indicators of pollutant-induced stress responses. Exhaled nitric oxide (FeNO) was used to assess airway inflammation and was measured using standardised handheld analysers. Systemic inflammation was evaluated via the collection of dried blood spot samples, from which levels of C-reactive protein (CRP) were analysed in certified laboratories.

Pulmonary function was assessed using spirometry, measuring forced expiratory volume in one second (FEV_1) and forced vital capacity (FVC). These measures provided quantifiable data on lung function changes potentially related to pollutant exposure. In addition to physiological markers, participants completed weekly symptom checklists that tracked a range of discomforts commonly associated with poor indoor air quality, such as respiratory irritation, fatigue, headaches, dry eyes, and difficulty concentrating. These surveys were based on previously validated IAQ symptom scales and provided subjective but valuable data on health deterioration.

Cognitive-Task Performance Assessment

To pragmatically assess the potential impact of delayed IAQ diagnostics on cognitive functioning, the study implemented a standardised and longitudinal cognitive assessment protocol. Participants underwent repeated testing at baseline and at three-month intervals throughout the 12-month monitoring period. This repeated-measures design allowed the study to track temporal changes in cognitive performance, enabling the detection of any deterioration that could be associated with prolonged exposure to suboptimal indoor air conditions due to diagnostic delays.

All cognitive assessments were administered via secure digital platforms using standardised test environments to ensure consistency in delivery and scoring. The digital format allowed for precise measurement of response times and accuracy, minimised variability due to human administration, and ensured feasibility across the twenty participating buildings without requiring a central testing facility. Moreover, it enabled real-time data capture and cloud-based storage, which enhanced data integrity and reduced the likelihood of administrative error.

Cognitive performance was assessed across multiple domains using validated instruments selected for their sensitivity to environmental and physiological stressors. Verbal memory was evaluated using the Rey Auditory Verbal Learning Test (RAVLT), which involved participants listening to and recalling a series of words across multiple trials, followed by a delayed recall phase. This test was chosen for its ability to detect subtle impairments in memory encoding and retrieval that may arise from chronic inflammation or neurocognitive stress related to pollutant exposure.

Sustained attention and vigilance were assessed using the Continuous Performance Test (CPT), which required participants to respond to designated target stimuli interspersed with non-targets over an extended time. The CPT was operationalised to measure lapses in attention, omission errors, and response consistency—parameters known to be sensitive to fatigue, stress, and low-level environmental toxicity. Reaction time was assessed using the Choice Reaction Time (CRT) test, in which participants had to respond quickly and accurately to visual or auditory cues. CRT performance provided a measure of psychomotor speed and executive control, both of which may be affected by pollutant-induced physiological burden.

To complement these psychometric evaluations, a computer-based productivity simulation was also administered. Participants completed routine office tasks such as email sorting, data entry, and document formatting, designed to replicate real-world work demands. Metrics such as time-to-completion and error rates were automatically recorded, offering an applied indicator of task efficiency under environmental stress.

Together, these pragmatic and operationally feasible assessment strategies offered a multi-domain evaluation of cognitive function that reflected both laboratory precision and real-world relevance.

Quantitative Data Analysis Strategy

To examine exposure trajectories and test for group differences in the rate of pollutant accumulation, Generalised Estimating Equations (GEE) were employed. The outcome variable, Y_{it}, represented the actual cumulative exposure dose for participant *i* at time *t*, as previously derived in the *Environmental Exposure Monitoring* section. The GEE model estimated the predicted exposure dose as a function of time, group membership, and relevant covariates, using the following specification:

$$E(Y_{it}) = \beta_0 + \beta_1(Time_t) + \beta_2(Group_i) + \beta_3(Time_t \times Group_i) + Z_{it}\gamma$$

In this equation, $Time_t$ referred to the measurement occasion (e.g. 0 = pre-intervention, 1 = post-intervention), $Group_i$ represented diagnostic timing group or biological vulnerability status, and Z_{it} was a vector of covariates that included contextual and individual-level factors. These covariates comprised building ventilation characteristics, occupancy patterns, outdoor air pollution levels, demographic characteristics (e.g. age, sex, education), and clinically relevant comorbidities such as asthma, hypertension, or mild cognitive impairment.

Comorbidities were included based on baseline clinical screening and self-reported medical histories and were coded as binary or categorical variables depending on type and prevalence. Their inclusion was essential to control for underlying health conditions that could independently influence exposure sensitivity or cognitive-task performance.

Model coefficients (β_0, β_1, β_2, β_3, and γ) were estimated using quasi-likelihood methods with robust standard errors to account for within-subject correlation. The interaction term $Group_i \times Time_t$ allowed for testing whether the rate of change in exposure dose over time differed significantly between groups with timely and delayed diagnostics.

The relationship between the actual and predicted exposure dose was captured by the standard decomposition:

$$Y_{it} = E(Y_{it}) + \varepsilon_{it}$$

where $\boldsymbol{\varepsilon_{it}}$ represented the residual error, accounting for idiosyncratic variability not explained by the model. This formulation supported a robust evaluation of the effect of diagnostic timing on pollutant accumulation, while adjusting for a comprehensive set of environmental, demographic, and health-related covariates.

To assess the mediational pathway between diagnostic timing, pollutant exposure, health outcomes, and cognitive-task decline, Structural Equation Modelling (SEM) was conducted. SEM was selected for its capacity to estimate complex relationships among multiple variables simultaneously, including both direct and indirect effects. This analytical technique enabled the investigation of whether the timing of IAQ diagnostics influenced participant outcomes through a sequenced causal chain.

The hypothesised model tested the sequence:

Diagnostic Delay → Higher Cumulative Exposure → Elevated Inflammation and Pulmonary Impairment → Cognitive-Task Decline

This model structure was implemented to assess whether delays in IAQ diagnostics led to a progressive impact on health and cognitive functioning, mediated by cumulative exposure to indoor air pollutants and physiological responses. The specification of the model allowed for testing of the full pathway as well as intermediate stages, enabling differentiation between direct and mediational effects.

Model fit was rigorously evaluated using standard indices to ensure that the hypothesised relationships were supported by the data. The Comparative Fit Index (CFI) was used to compare the proposed model against a baseline model assuming no relationship among variables. The Root Mean Square Error of Approximation (RMSEA) was employed to estimate how well the model would fit the population covariance matrix, accounting for model complexity.

Additionally, the Standardised Root Mean Square Residual (SRMR) measured the average standardised difference between observed and predicted correlations. Accepted benchmarks for these indices—CFI values above 0.90, RMSEA values below 0.08, and SRMR values below 0.08—were used to determine model adequacy.

To address the potential bias introduced by the non-random assignment of buildings to diagnostic timing groups, propensity score matching was employed prior to SEM analysis. A logistic regression model was used to generate propensity scores based on baseline covariates such as participant age, sex, education level, and initial cognitive performance.

These scores were then used to match participants in the Timely Diagnostics Group (TDG) and the Delayed Diagnostics Group (DDG) on a one-to-one basis or using nearest neighbour matching without replacement, depending on sample balance. This process aimed to reduce systematic differences between the groups that could confound the estimation of mediation effects.

Following matching, the SEM analysis was repeated on the adjusted sample to confirm the robustness of the observed pathways. This two-stage approach—initial SEM modelling followed by confirmatory SEM on the matched sample—enhanced the credibility of the findings. It ensured that the hypothesised causal relationships were not driven by pre-existing group differences but were more likely attributable to the timing of diagnostic intervention and its downstream effects.

In doing so, the study provided a rigorous methodological framework for testing whether a delay in identifying IAQ issues could significantly increase cumulative exposure, exacerbate health deterioration, and ultimately impair cognitive-task performance. The SEM approach offered valuable insights into the interconnected dynamics of indoor environmental exposure and human performance, supporting a deeper understanding of how early diagnostic intervention might serve as a preventive strategy.

Effect Size Estimation, Sensitivity Analysis, and Data Integration

To strengthen the interpretation of the study’s findings and assess their real-world relevance, the analysis included estimation of effect sizes, which are standard statistical measures that help quantify how meaningful the differences are between groups. While p-values indicate whether a result is likely due to chance, effect sizes clarify the magnitude of the difference. For example, Cohen’s *d* was used to assess how much participants’ cognitive performance scores or biomarker readings changed between those in the timely versus delayed diagnostic groups.

Similarly, partial eta-squared (η^2) was used to indicate how much of the variation in those outcomes could be explained by diagnostic timing and other influencing factors. These effect size measures offered insight into whether statistically significant findings were also practically important. In a simple term, P-values ask: “Is this real or just luck?” Effect sizes ask: “If it’s real, how big is it?” Partial eta-squared (η^2), a type of effect size, asks: “How much of the total change can be explained by this one factor?

To test how dependable and generalisable the main findings were, the study included a series of sensitivity checks. First, the full dataset was randomly divided, with 80 percent used for initial analysis and the remaining 20 percent reserved as a hold-out set. All major analyses were repeated on this smaller, independent group to verify whether the patterns found could be reproduced outside the original sample.

In addition, results were further broken down and examined within specific subgroups. For example, outcomes were compared across participants of different ages, genders, building sizes, or ventilation system types. This helped reveal whether delayed diagnostics affected some groups more than others, thereby offering deeper insight into variation that might otherwise go unnoticed.

Some participants had missing data in their health or survey responses. Rather than ignoring these cases or filling in the blanks arbitrarily, the study applied a scientifically accepted method called multiple imputation by chained equations (MICE). This approach used the available data to make statistically informed guesses about the missing values, drawing on relationships found across the dataset.

This allowed the analysis to remain as complete and accurate as possible without excluding participants or weakening the statistical power of the results. All imputation procedures were conducted in SPSS, and the results were combined following established statistical rules to ensure they were valid.

Although this section does not present findings, the study implemented a structured approach to connect different types of data, including environmental, physiological, and cognitive, in a meaningful way. The timing of indoor pollutant measurements was synchronised with participants’ health check-ups and cognitive tests, making it possible to detect whether changes in air quality coincided with shifts in inflammation levels or task performance.

Visual tools such as time-series plots were used to track these changes over time, helping to make sense of complex interactions. In addition, structural diagrams generated from the statistical model helped illustrate the pathways through which diagnostic delay might influence health and mental performance.

Together, these strategies ensured that the study’s conclusions were based not only on sound statistics but also on careful consideration of practical significance, consistency, and interpretability. This multi-layered analysis provided a strong foundation for understanding how the timing of indoor air quality diagnostics could have cascading effects on pollutant exposure, health status, and cognitive outcomes, thus informing both scientific understanding and public health action.

Methods for Research Question 3:

Study Setting and Participants

This phase of the study built directly upon the methodology implemented for RQ2. The same twenty residential, commercial, and institutional buildings, stratified across two urban regions with varying pollution profiles, were used for continuity, logistical feasibility, and temporal synchronisation. Data for RQ3 were collected concurrently with RQ2 to enable real-time integration of behavioural, environmental, and contextual indicators necessary for the AI-enabled predictive framework. A total of 200 participants were retained, including residents of apartment buildings, facility managers, maintenance personnel, and regular building users. Ethical approvals and participant consents were renewed to cover the behavioural analytics component introduced in this phase.

Data Sources and Variable Specification

To build the AI-enabled decision-support framework, the research team used four types of information that were collected at the same time from the same buildings. These included environmental sensor data, behavioural responses, background details about each building, and records of actual decisions to investigate indoor air quality problems. Together, these data sources made it possible to understand when people act, when they hesitate, and how to predict and reduce delays in responding to poor air quality indoors.

First, the environmental data came from high-resolution sensors that had already been installed as part of the earlier phase of the study. These sensors measured indoor air every minute and recorded levels of pollutants such as carbon dioxide (CO_2), ultrafine particles ($PM_{0.1}$), fine particles ($PM_{2.5}$), ozone (O_3), and volatile organic compounds (VOCs), as well as temperature and humidity. This allowed the researchers to build a detailed and time-sensitive profile of air conditions in each monitored space.

Second, the team examined how people responded to changing air conditions by using a validated tool known as the IAQ Diagnostic Hesitation Scale. This scale captured how long it took someone to respond after receiving an air quality alert, how risky they believed the situation was, and whether they felt that taking action was too burdensome. These behavioural indicators helped the AI learn to recognise patterns of hesitation and understand what factors might lead to delayed responses.

Third, additional information about each building was collected to provide context. This included the type of ventilation system, how many people usually occupied the space, how often the building had experienced air quality issues in the past, and how maintenance was managed. This background information helped explain why people in one building might react differently from those in another, even if the environmental data appeared similar.

Finally, the study recorded every time someone formally began to investigate a possible air quality problem. These events were logged with precise time stamps and noted whether the action was triggered by a sensor alert or by the occupant’s own perception. By linking these four sources of data, the research team created a system that could learn from real situations, identify hesitation as it was happening, and provide early warnings and support to help people act before conditions worsened.

Sensor Network and Data Integration Architecture

Each building used in the study continued operating with the same Internet of Things (IoT) sensor system installed during the earlier research phase. This system included distributed edge nodes, which are compact processors installed locally within the building. These edge nodes were responsible for handling sensor readings on-site. They cleaned the data, encrypted it for security, and temporarily stored it before transmitting it to a central database. The processed data were then sent securely to a cloud-based repository using standardised application programming interfaces designed for reliable and protected data exchange.

To ensure consistent and accurate analysis, all incoming environmental data were synchronised with behavioural logs and building-specific contextual information. This integration created a comprehensive and time-aligned dataset housed within a structured temporal database. Each entry in the dataset was linked to observed IAQ-related behaviours, including delays or prompt actions in response to air quality changes. This structured dataset formed the basis for model training and system development.

As is common in real-world studies, some data were incomplete due to temporary device interruptions or missing behavioural records. These gaps were addressed through a two-step process. First, multi-point interpolation techniques were applied to estimate missing sensor values using available readings from surrounding time points. Second, a model-based imputation process was implemented using gradient-boosted decision trees trained to reconstruct plausible sequences. This machine learning approach relied on existing relationships among environmental readings, user behaviour patterns, and historical response profiles.

The chosen model, known as XGBoost, was specifically selected for its strength in detecting patterns within complex, structured datasets. It accurately learned how different parameters varied together across time and across building contexts. The imputation process ensured that missing data did not introduce bias or weaken the dataset’s integrity. Once completed, the fully reconstructed and validated dataset was used to train the AI-enabled framework that powered the real-time decision-support system.

This rigorous and structured approach to data handling supported the development of a reliable and robust predictive model. It enabled accurate identification of IAQ diagnostic hesitation and strengthened the system’s ability to support timely, informed decision-making in diverse building environments. The data pipeline ensured that all inputs used for AI model training were both scientifically valid and operationally dependable.

Model Development: Predictive Analytics and Classification

The predictive engine of the decision-support system was developed using a technique known as supervised machine learning. This method involves training a computer model to recognise patterns in data that have already been labelled with known outcomes.

The specific type of model used was a gradient boosting decision tree, chosen for its proven ability to handle complex and non-linear relationships between different types of data. This model type is also known for working well when the input data includes a mixture of numerical readings, behavioural responses, and contextual building information.

The goal of the model was to classify the level of diagnostic hesitation risk into three clear categories: low, moderate, or high. To make this classification, the model considered several types of input data. These included live readings of air pollutants such as carbon dioxide and fine particulate matter, as well as derived variables such as how quickly pollutant concentrations were rising or how far they deviated from the building's usual patterns. It also used individual behavioural profiles, such as how quickly each person responded to previous alerts, and building-specific characteristics like occupancy levels and ventilation systems.

To ensure that only the most relevant and reliable features were used by the model, a technique called recursive feature elimination was applied. This method involved repeatedly testing and removing less important data points to improve the model's accuracy and avoid the risk of overfitting. Cross-validation was used during this process to confirm that the model's performance would hold up when applied to new, unseen data.

The training process involved splitting the full dataset into two parts: 80 percent for model learning and 20 percent for independent testing. Additionally, stratified five-fold cross-validation was applied to evaluate the model's consistency. The model's performance was measured using several standard metrics, including accuracy, precision, recall, F1-score, and the area under the ROC curve. A key benchmark was achieving at least 85 percent classification accuracy. This target was successfully met both in cross-validation and in the separate test data, confirming the model's generalisability.

To help users understand how the model made its decisions, the system incorporated SHAP values. These values clearly indicated how much each input feature contributed to each prediction, allowing users to trust and verify the system's reasoning.

Real-Time Decision-Support Interface and Feedback Loops

The model's predictions were built into an online decision-support interface that was carefully designed with the help of the people who would actually use it. These users, such as building managers, maintenance staff, and residents, participated in a series of planning workshops to ensure the system would be practical, easy to use, and suited to real-world situations.

Their insights directly influenced the layout, wording, and function of the interface, making the final tool more effective and trusted. Importantly, the interface was designed to be fully mobile-compatible, allowing users to receive alerts and interact with the system on their smartphones and tablets. This mobile-first approach ensured timely access to decision support, even when users were on the move.

The system delivered alerts in real time whenever the model detected a risk that someone might hesitate to act on an IAQ problem. These alerts were clearly presented through the web interface, which displayed easy-to-understand graphics showing pollutant levels over time. Alongside these visual trends, the system offered specific, scientifically informed recommendations for what action to take. This helped users make quick and informed decisions. By supporting mobile devices, the system enabled users to respond instantly without being tied to a desktop or control room.

To avoid overwhelming users with unnecessary alerts, the system organised notifications into different levels of urgency. If the predicted risk of hesitation was low, the system delivered gentle reminders. If the risk was moderate or high, the system presented stronger prompts and clearer instructions.

These alerts were also tailored to the specific building conditions and the user's previous behaviour, making the guidance more relevant and personalised. For example, if a user had previously delayed taking action in response to certain pollutants, the system gave firmer prompts in similar situations. The mobile-optimised interface helped ensure that these prompts were delivered directly to users, regardless of location, increasing the likelihood of timely intervention.

Every interaction with the interface was recorded. This included when users opened alerts, how quickly they responded, and whether or not they followed the suggested actions. These data were analysed continuously in the background. They were used to improve the way the system worked over time. If a certain alert design was consistently ignored, the system could flag this for review or automatically adjust how that type of information was presented in the future.

The design included mechanisms for human-in-the-loop learning, which meant that the AI system learned from the decisions and reactions of its users. This approach ensured that the system did not operate in isolation. Instead, it evolved through experience and real-world use. As more data were collected from different users and buildings, the model's predictions became more accurate, and its suggestions more helpful.

Evaluation of System Impact

To evaluate whether the AI-enabled decision-support system improved diagnostic responsiveness and reduced harmful exposure due to delayed action, a mixed-methods research design was employed. This design combined quantitative analysis of behavioural data with qualitative insights from users to provide a comprehensive evaluation of system performance.

The quantitative component focused on comparing diagnostic engagement metrics before and after the system was introduced. These metrics included the average time taken to respond to IAQ alerts and the frequency of diagnostic actions initiated following those alerts. Data were collected from system interaction logs, which automatically recorded user behaviour such as alert acknowledgement and initiation of response measures. These behavioural indicators were time-stamped and linked to specific IAQ events, enabling precise measurement of latency and frequency over the study period.

To ensure the validity of comparisons, generalised linear models were applied. These models accounted for potential confounding variables that might influence diagnostic behaviour independently of the system itself. Examples of such variables included the day of the week, fluctuations in ambient pollution levels outside the building, and building-specific operational characteristics such as cleaning schedules, ventilation patterns, or staff rosters. By statistically adjusting for these factors, the analysis aimed to isolate the effect of the decision-support system on user behaviour.

The qualitative component was designed to explore user experiences, expectations, and perceptions regarding the decision-support system. Data were collected through post-deployment interviews and structured focus group discussions. Participants for this phase were purposively selected to represent the diversity of roles across the study settings. These included building managers, maintenance personnel, and residents of apartment buildings, each of whom interacted with the system in different capacities.

During interviews and discussions, participants were invited to describe how they interacted with the system, how they understood its recommendations, and whether the design of alerts and interfaces supported or hindered their ability to act on IAQ issues. These discussions also included questions about trust in the AI-generated outputs, perceived usability of the mobile and web interfaces, and the practicality of suggested actions in their specific building context.

All qualitative sessions were recorded and transcribed for analysis. A thematic analysis approach was used to interpret the data. This involved a structured process of identifying, coding, and grouping recurrent patterns in participants' responses. The goal of this analysis was to uncover the features of the system that either enabled or constrained its effective use, as perceived by those who engaged with it in real-world environments. Themes were generated inductively to allow user experiences to shape the understanding of system functionality.

The integration of quantitative and qualitative data supported a multi-dimensional understanding of the system's performance. Quantitative measures provided behavioural evidence of changes in engagement patterns, while qualitative insights helped explain how the system was experienced and interpreted by users. This dual approach ensured that the evaluation captured not only what happened but also how and why users responded in the ways they did.

The evaluation process was designed to be iterative and embedded within the overall system development cycle. Insights gained from both strands of the evaluation were used to identify areas for refinement in the system's interface, alert logic, and user training materials. In doing so, the evaluation component of the study contributed directly to the system's ongoing adaptation and alignment with real-world user needs.

This methodologically integrated approach ensured that both the technical accuracy of behavioural monitoring and the human experience of system use were rigorously assessed. By combining structured behavioural metrics with context-rich qualitative feedback, the study ensured a robust evaluation of the decision-support system's potential to support timely and informed IAQ management decisions.

Data analysis

Data analysis for this study was structured to determine whether the AI-enabled decision-support system improved user engagement with IAQ diagnostics. A mixed-methods design was employed, combining statistical modelling with in-depth qualitative interpretation. All data were anonymised and handled in accordance with approved ethical protocols.

Quantitative data came from time-stamped behavioural logs and records generated by the system. These included the time it took users to respond after receiving an alert and the number of diagnostic actions triggered either by system alerts or direct user reports. Analyses were conducted using R and Python software.

Generalised linear models were used to compare behaviour before and after system deployment, controlling for variables such as day of the week, outdoor air quality levels, and the unique characteristics of each building. This ensured that any improvements in engagement could be attributed to the system itself.

Descriptive statistics were used to summarise patterns in key variables, such as average response time and frequency of diagnostics. Continuous variables like response delays were analysed using estimation techniques that account for data that may not follow a normal distribution. For binary outcomes, such as whether a diagnostic action occurred, logistic regression was used. Confidence intervals and effect size measures were reported to make the results easier to interpret and compare across different situations.

Qualitative data were collected through interviews and focus group discussions with selected residents, facility managers, and maintenance staff after the system was deployed. The transcripts of these conversations were analysed using NVivo software. A thematic analysis was conducted, allowing key themes to emerge naturally from what participants said. To improve the accuracy of the analysis, multiple researchers independently coded the transcripts and then discussed any differences to reach a consensus.

A process called triangulation was used to connect what people said in interviews with how they actually behaved. For example, if a participant mentioned that alerts were difficult to understand, the research team looked at whether this person had delayed their response to alerts. This helped to build a fuller picture of how trust in the system, clarity of the interface, and organisational habits influenced the way people responded to indoor air quality issues. Together, the quantitative and qualitative analyses provided a well-rounded understanding of how the decision-support system influenced IAQ diagnostic actions in real-world conditions.

Ethical and Privacy Considerations

Given the behavioural and real-time nature of the system, strong safeguards were implemented to protect participant privacy and ensure responsible AI use. All identifiable data were anonymised at the point of capture, and the system operated under protocols aligned with the General Data Protection Regulation (GDPR). Participants were fully informed of the system's scope, data uses, and their rights, including the option to withdraw from behavioural tracking at any point. Importantly, the decision-support framework was designed to assist, not replace, human judgement, and final IAQ management actions remained under the discretion of qualified professionals.

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Findings for Research Question 1:

This study investigated the behavioural, organisational, and perceptual factors that contribute to hesitation in engaging with IAQ diagnostics across a range of building types. The aim was to uncover the underlying drivers of inaction and to understand how different roles and contexts shape decision-making related to indoor air quality.

Using a mixed-methods approach, the study examined both quantitative patterns and qualitative narratives from residential, educational, healthcare, and commercial environments. The results revealed that hesitation to act on IAQ concerns is not the result of a single cause, but is instead shaped by a combination of beliefs, routines, and institutional systems that vary across user profiles and settings.

Behavioural Contributors to Hesitation

At the behavioural level, two core patterns emerged as consistent and influential predictors of hesitation to engage IAQ diagnostics: low perceived susceptibility to IAQ-related health risks and high delay discounting. These behavioural tendencies significantly shaped how individuals interpreted symptoms, weighed the need for action, and ultimately decided whether to engage with IAQ assessment processes.

The study found that individuals who did not believe they were personally vulnerable to the effects of poor indoor air were significantly less likely to take proactive or timely diagnostic action. This tendency was apparent in both the quantitative data and interview responses, with many participants indicating that they would only act if symptoms became severe, prolonged, or visibly affected others in their environment.

In residential buildings, for example, participants often reported experiencing recurring symptoms such as mild respiratory discomfort, headaches, or general fatigue. However, these symptoms were typically met with informal coping responses rather than formal IAQ investigations. Occupants commonly described opening windows, rearranging furniture to improve airflow, or using scented air fresheners to cover unpleasant odours.

These adaptations were often sufficient when the source of discomfort was minor or easily identifiable. However, they were not perceived as part of a diagnostic process. When such informal strategies were repeatedly used in the face of recurring symptoms or ambiguous conditions, they functioned more as coping mechanisms than as problem-solving approaches, reflecting a behavioural pattern of delay or avoidance in pursuing formal diagnostics.

This tendency to normalise or downplay indoor discomfort, even when persistent, illustrates how behavioural framing can contribute to diagnostic hesitation—particularly in environments where formal IAQ assessment pathways are unclear or inaccessible.

The prevailing belief was that such symptoms were too ambiguous, too common, or too manageable to justify the time, cost, or disruption associated with formal indoor air quality testing. This pattern of informal adjustment delayed recognition of potentially serious IAQ problems and allowed continued exposure to unhealthy conditions without meaningful intervention. Behavioural delay, in this context, was shaped by the belief that minor discomforts were not indicative of environmental risk and did not merit medical or technical investigation.

Another closely related behavioural factor was delay discounting—the cognitive tendency to prioritise short-term convenience or comfort over long-term health benefits. Participants frequently articulated a preference for tolerating unpleasant indoor air conditions rather than dealing with the perceived burden of IAQ diagnostics.

These burdens included not just financial cost or scheduling inconvenience but also the mental and social effort involved in persuading others of the need for testing, especially in shared or institutional environments. For example, one office worker described persistent dry eyes and mental fatigue during long workdays in an enclosed workspace but dismissed the possibility that poor indoor air quality might be contributing. Instead, these symptoms were attributed to extended screen exposure or workload stress.

Despite growing discomfort, no action was taken until other colleagues began reporting similar symptoms, illustrating how collective experience sometimes triggered delayed group-level response. The reliance on non-environmental explanations for symptoms was a recurring theme across interviews and reflected a broader tendency to avoid confronting IAQ problems unless unavoidable.

Crucially, the extent to which these behavioural traits influenced diagnostic engagement varied across building types and user roles. In residential and commercial settings, where there were few or no institutional policies mandating IAQ action, personal thresholds for discomfort heavily determined whether diagnostics were pursued. By contrast, in hospitals and schools, where environmental health standards were more visible and expectations for safety more formalised, individuals were more inclined to override personal hesitation—particularly when they believed that IAQ action was organisationally supported or professionally required.

Nonetheless, even in these structured settings, behavioural dispositions continued to influence the speed and consistency of engagement. For instance, staff who personally undervalued IAQ relevance were slower to initiate action, even when procedural avenues existed, highlighting the persistent influence of behavioural framing on institutional responsiveness.

Organisational Conditions and Norms

Organisational variables had a profound influence on whether individuals and teams responded quickly to IAQ concerns. One of the most consistent findings was that participants who worked or lived in environments with well-established health and safety cultures were more proactive in responding to indoor air quality problems.

In buildings where formal procedures existed for reporting IAQ issues and where communication about environmental health was regular, users were more confident that raising concerns would lead to meaningful responses. For instance, in healthcare facilities, staff members noted that clear protocols for incident reporting gave them confidence to act on suspected IAQ issues, knowing the concern would be taken seriously and followed through.

This sense of organisational support created an enabling environment that reduced hesitation, even among individuals who were personally unsure of the source or seriousness of the issue. When protocols were embedded into routine operations, such as scheduled IAQ audits or periodic environmental checks, participants felt that their role was part of a collective responsibility, rather than a personal initiative.

In such contexts, occupants, facility managers, and institutional leaders aligned more readily in recognising and addressing indoor air concerns. The clarity of process and the culture of responsiveness reinforced proactive behaviours and built trust in the system's ability to protect well-being.

In contrast, in organisations where IAQ diagnostics were treated as non-essential or only carried out when occupants complained repeatedly, hesitation was higher. In these cases, users often felt that raising concerns would be futile. A school teacher described a scenario where she had repeatedly raised concerns about a stuffy, musty classroom, but no formal diagnostic action was taken until a parent complained. She reported feeling discouraged and said she had since stopped reporting minor discomforts, assuming they would be ignored.

This demoralisation was not limited to schools. Similar sentiments were expressed by residents in multi-unit housing and employees in commercial offices, where repeated but unaddressed concerns gradually led to resignation or disengagement. Participants in these contexts often described a "wait-and-see" approach or a preference for self-managed coping strategies over formal escalation. In many cases, their hesitation was not due to disbelief in the importance of indoor air quality, but rather to a learnt expectation that organisational follow-through was unlikely.

Perceived budgetary constraints were another major organisational barrier. Many participants believed their building managers or employers would not allocate resources for diagnostics unless the issue became extreme. This belief was especially prevalent in residential settings managed by strata councils or tenant associations, where IAQ issues often competed with more visible maintenance concerns like water leaks or broken lifts. In these cases, lack of institutional clarity about who was responsible for initiating or paying for diagnostics created confusion and delay.

Even when residents or employees were aware that indoor air quality could be a factor in discomfort, the absence of a clear funding pathway discouraged them from pursuing assessment. Some participants shared that they had made informal calculations, weighing the cost (i.e., expenditure and time spent) and effort (i.e., comfort, convenience and cognitive load or awareness sacrificed) of pushing for diagnostics against the likelihood of action or resolution. In contexts where diagnostics were perceived as expensive and optional, hesitation became embedded in institutional routines and expectations.

Internal communication practices also shaped engagement levels. Participants who knew whom to contact and how to report IAQ concerns were significantly more likely to take action. Conversely, in buildings where roles and responsibilities were unclear or where communication was inconsistent, even those motivated to act found it difficult to navigate the process.

These organisational norms had a particularly strong influence on facility managers. When backed by institutional mandates, they acted quickly; without support or direction, they were more likely to deprioritise diagnostics, especially when no immediate health crisis was evident.

In essence, organisational context framed not only the availability of diagnostic resources but also the behavioural patterns of those tasked with responding to IAQ issues. The presence or absence of supportive procedures, communication channels, and budgetary assurance played a decisive role in either enabling proactive engagement or reinforcing patterns of hesitation and inaction.

It is important to note, however, that not all IAQ issues require formal diagnostics. In many cases, straightforward interventions, such as improving natural ventilation or removing visible pollutant sources, may be sufficient to address minor discomforts. The concern highlighted by this study is not the absence of diagnostic response to all IAQ issues, but rather the pattern of hesitation when formal diagnostics would be scientifically or medically justified.

These include situations where symptoms persist without an identifiable cause, multiple occupants are affected, or vulnerable individuals are exposed to unclear environmental conditions. In such cases, hesitation allows exposure to continue and obscures the opportunity for meaningful intervention. That means, hesitation becomes a problem when the organisation or individual fails to act even when the situation warrants it.

Perceptual Ambiguities and Risk Interpretation

Another key set of findings revolved around perception—how people interpret their environment and symptoms, and how confident they are in the tools used to assess IAQ. Many participants reported difficulty linking symptoms like fatigue, coughing, or eye irritation directly to indoor air quality issues. This ambiguity weakened the perceived value of IAQ diagnostics. For example, residents in older apartment buildings reported living with discomfort for months, attributing it to stress, allergies, or external pollution, without considering that poor indoor air quality related factors might be the root cause.

The challenge in identifying IAQ as the source of symptoms was particularly pronounced in cases where the discomfort was intermittent, mild, or co-occurring with other plausible causes. Participants often described how they rationalised physical symptoms in ways that diminished the perceived need for further investigation. Some assumed that dry eyes were caused by extended screen time, while others blamed headaches on sleep deprivation or dietary habits.

This tendency to explain away symptoms, combined with a general lack of environmental health literacy, reduced the perceived urgency for formal indoor air quality assessments. For many, IAQ remained an invisible and easily overlooked element in the broader set of environmental and personal health factors.

This uncertainty was compounded by a lack of trust in diagnostic technologies. Participants who had previously experienced IAQ assessments that led to no clear resolution or improvement were especially sceptical. One respondent from a commercial setting described an IAQ test that resulted in general recommendations with no specific actions, leaving staff unsure what to change. Such experiences made users feel that diagnostics were unlikely to lead to practical solutions, reducing their willingness to initiate or advocate for assessments in the future.

This scepticism was not always rooted in distrust of science or measurement tools, but rather in disappointment with poorly communicated outcomes or a perceived lack of follow-through. When diagnostics did not produce concrete, actionable changes, they were often seen as superficial exercises. In some instances, vague reports or overly technical feedback alienated the very people who were expected to act on the findings, reinforcing a cycle of hesitation and disengagement.

Experience and exposure also influenced perception. Participants who had never been involved in IAQ assessments or had never seen the tools and processes used were more likely to view diagnostics as complicated, invasive, or unnecessary. In contrast, individuals with prior experience were more likely to appreciate the value of diagnosis, even when symptoms were mild. Educational campaigns and prior training significantly increased comfort with diagnostics and reduced hesitation, though such training was rare outside of healthcare environments.

Integrative Patterns Across Systems

The integrated analysis of quantitative survey responses, system usage logs, and qualitative interview data revealed a complex web of interrelated drivers that collectively contribute to hesitation in engaging with indoor air quality (IAQ) diagnostics. These behavioural, organisational, and perceptual factors do not operate in isolation; rather, they form mutually reinforcing cycles that deepen inaction. One prominent example was the observed interaction between behavioural delay and organisational fragmentation.

Participants who reported low perceived personal vulnerability to IAQ-related health problems were often situated in environments lacking institutional frameworks for environmental health monitoring. In such settings, particularly residential flats and privately managed commercial buildings, the absence of clear reporting channels or established diagnostic protocols reinforced the notion that IAQ problems were either inconsequential or too burdensome to pursue.

Perceptual ambiguity further compounded this issue. Many participants expressed doubt about whether the symptoms they experienced—such as fatigue, headaches, or difficulty concentrating—could definitively be linked to air quality. This scepticism was especially pronounced in buildings where past diagnostic efforts had failed to produce visible outcomes or were never communicated clearly to occupants.

In these contexts, even those with a moderate inclination to investigate air quality concerns were discouraged by the lack of actionable feedback, leading to a diminished sense of agency. Participants described previous experiences where IAQ evaluations resulted in vague recommendations that were not implemented or yielded no perceivable improvement, eroding trust in future diagnostic processes.

A recurring theme across environments was the perceived trade-off between the cost of diagnostic engagement and the value of potential outcomes. Participants consistently articulated that pursuing diagnostics entailed sacrifices—financial costs, time taken away from other responsibilities, disruption to daily routines, and mental effort required to navigate unfamiliar procedures.

When weighed against uncertain benefits, these perceived sacrifices often tipped the balance in favour of inaction. Even in workplaces with some form of institutional support, if the diagnostic pathway was not seen as streamlined and result-oriented, occupants were reluctant to initiate the process. This decision-making calculus illustrates the broader psychological principle of effort discounting, where individuals devalue actions that require a high investment for an ambiguous return.

The long-term effects of such hesitation were evident in the reported outcomes. Unaddressed IAQ issues were associated with recurring minor illnesses, deteriorating cognitive performance, absenteeism, and a general decline in perceived well-being. In both interviews and focus group discussions, participants acknowledged that over time, persistent discomfort had become an accepted feature of their indoor environments. This normalisation of suboptimal air quality presents a serious public health challenge, particularly in high-occupancy or vulnerable settings such as schools, elder care facilities, and densely populated housing blocks.

Taken together, these insights demonstrate that hesitation is not a simple behavioural oversight but a systemic phenomenon requiring multi-level intervention. Addressing it demands not only improvements in diagnostic technology and accessibility but also reconfiguration of institutional support structures, communication strategies, and behavioural framing to foster confidence in the value and feasibility of timely IAQ assessment.

Conclusion on Findings for Research Question 1

Based on the integrated analysis of quantitative metrics and qualitative insights across diverse building types, the findings clearly demonstrate that behavioural, organisational, and perceptual factors significantly contribute to individual and institutional hesitation in engaging with IAQ diagnostics. These factors were not only identifiable but also systematically varied according to building context and user role.

Low perceived susceptibility to IAQ-related risks, the absence of immediate or recognisable symptoms, and organisational norms that deprioritised preventive diagnostics consistently emerged as dominant predictors of hesitation. Moreover, variation in diagnostic behaviour between residential, commercial, educational, and healthcare environments confirmed that these predictors are not uniformly distributed but shaped by contextual and institutional conditions.

Therefore, the findings directly answer Research Question 1 by identifying and characterising the key drivers of hesitation and mapping how they operate differently across settings. The results provide a scientifically grounded explanation for diagnostic inaction and validate the relevance of behavioural science, organisational psychology, and risk perception frameworks in understanding this phenomenon.

On the basis of these findings, the null hypothesis (H_0) is rejected. The alternative hypothesis (H_1) is supported: diagnostic hesitation is significantly predicted by specific behavioural, organisational, and perceptual variables, and these predictors vary across building types and user profiles.

Findings for Research Question 2:

This study investigated how delayed engagement in IAQ diagnostics affects cumulative exposure to harmful pollutants, health risk escalation, and cognitive-task performance decline. Using a longitudinal quasi-experimental design across 20 buildings and 200 participants, the research employed a mixed-methods approach involving pollutant monitoring, physiological biomarker testing, cognitive performance tasks, and qualitative interviews.

Findings showed that delays led to significantly higher cumulative pollutant exposure, increased inflammation and reduced lung function, and measurable declines in attention, memory, and work performance. The study also identified an approximate eight-week threshold beyond which the risks of delay escalated significantly, especially in vulnerable environments.

Exposure Trajectories and Cumulative Dose Differences

The findings from this longitudinal quasi-experimental study offer compelling empirical evidence that the timing of indoor air quality (IAQ) diagnostics has a statistically significant impact on cumulative pollutant exposure trajectories. Across the 12-month monitoring period, Generalised Estimating Equations (GEE) revealed a pronounced interaction between time and diagnostic timing group (Time × Group, $p < 0.001$), indicating that cumulative exposure dose (CED) increased more rapidly and more persistently in the Delayed Diagnostics Group (DDG) than in the Timely Diagnostics Group (TDG).

This interaction term captures the compounded effects of delayed engagement over time, demonstrating that postponement of diagnostic action allows pollutants to accumulate in a non-linear fashion that escalates with each subsequent monitoring interval.

Detailed analysis of the pollutant-specific CED patterns showed that this divergence was especially notable for fine particulate matter ($PM_{2.5}$), ultrafine particles ($PM_{0.1}$), and formaldehyde. In the DDG, these pollutants followed upward-sloping trajectories with more frequent peak episodes and longer duration of elevated levels, compared to the TDG where such episodes were interrupted or flattened shortly after detection through diagnostics.

For instance, in several buildings within the DDG, daily time-series data revealed clusters of microaccumulation events that, in the absence of corrective action, formed sustained exposure plateaus—particularly in spaces with poor baseline ventilation or frequent emission activities such as cooking or cleaning.

To enhance the interpretability and relevance of these findings, the CED values were further analysed using toxicity weighting. This approach assigns relative weights to each pollutant based on known toxicological burden, transforming raw concentration values into risk-adjusted exposure units. This toxicity-weighted model amplifies the significance of pollutants with lower mass concentrations but high biological reactivity.

When applied, the results demonstrated that the total weighted CED in the DDG was on average 1.7 times higher than that of the TDG (95% CI: 1.45–2.05), underscoring not only a quantitative increase in exposure, but a qualitative amplification in terms of toxic potential.

Ozone and benzene were major contributors to the weighted CED differential. While not the most abundant pollutants by mass, their consistently elevated presence in DDG buildings—especially during high-temperature periods and in poorly ventilated rooms—meant that their influence on cumulative burden was disproportionate.

In particular, temporal mapping of exposure trajectories showed that these pollutants had high persistence indices, meaning their concentration decayed slowly over time unless active interventions were implemented. In contrast, TDG buildings exhibited early disruption of such persistence patterns due to prompt detection and mitigation, resulting in lower exposure slopes and smaller total dose accumulation.

Overall, the exposure findings demonstrate that diagnostic timing is not a neutral variable but a critical determinant of both the trajectory and magnitude of pollutant accumulation. Delayed diagnostics transform episodic or low-grade pollutant presence into chronic, compounding exposure burdens—particularly when the building's inherent ventilation profile or user behaviour permits unchecked accumulation.

These results show that even when no major air quality incident occurs, simply waiting for problems to become obvious—rather than actively monitoring indoor air—allows harmful pollutants to build up faster, stay in the air for longer periods, and include more dangerous substances.

Physiological Indicators of Health Decline

The biological data obtained from quarterly assessments throughout the 12-month study provided robust physiological validation for the observed differences in cumulative exposure between diagnostic groups. The data revealed that delayed engagement in IAQ diagnostics was associated with statistically significant and biologically meaningful alterations in systemic and pulmonary health biomarkers—alterations that are consistent with chronic exposure to airborne pollutants.

Participants in the Delayed Diagnostics Group (DDG) consistently exhibited elevated levels of exhaled nitric oxide (FeNO), a non-invasive and widely recognised biomarker of airway inflammation. By the second quarter, FeNO levels in the DDG had risen significantly above baseline, with mean increases exceeding 15 parts per billion (ppb), compared to modest or stable readings in the Timely Diagnostics Group (TDG).

The GEE models showed a Time × Group interaction effect ($p < 0.001$), indicating that the elevation in FeNO was temporally associated with prolonged pollutant exposure in the absence of early intervention. Elevated FeNO is indicative of eosinophilic inflammation, often preceding clinically diagnosable respiratory conditions such as asthma, particularly when triggered by inhaled environmental irritants like $PM_{2.5}$, formaldehyde, and ozone.

Systemic inflammation was also observed through analysis of C-reactive protein (CRP), a liver-synthesised acute-phase protein that increases in response to inflammatory stimuli. Quarterly blood samples revealed a mean increase of 1.4 mg/L in CRP levels in the DDG, relative to baseline, with levels in the TDG remaining within the physiological reference range.

These values remained below acute pathological thresholds but indicated persistent low-grade systemic inflammation likely driven by chronic inhalation of reactive pollutants. Elevated CRP in the absence of infection or trauma suggests that indoor pollutant exposure can trigger subtle, long-term immune activation, a known risk factor for cardiovascular and neurodegenerative conditions.

Pulmonary function measurements, obtained through spirometry, further substantiated these findings. Both forced expiratory volume in one second (FEV_1) and forced vital capacity (FVC) declined over time in the DDG, with statistically significant group differences by the third quarter.

While the mean reductions did not reach thresholds for clinical diagnosis of obstructive or restrictive lung disease, the downward trends were consistent with environmentally induced subclinical pulmonary impairment. Inhalation of fine and ultrafine particles such as $PM_{0.1}$ and $PM_{2.5}$, particularly in settings lacking filtration or adequate dilution ventilation, likely contributed to these functional deteriorations.

A particularly revealing subgroup trend was observed among participants in naturally ventilated buildings within the DDG. Compared to their counterparts in mechanically ventilated settings, these individuals showed greater declines in both FEV_1 and FVC.

This pattern reinforces the hypothesis that buildings without controlled ventilation or filtration are more vulnerable to indoor pollutant accumulation, and that delayed diagnostic action in such settings amplifies physiological stress responses. These findings demonstrate that the timing of diagnostics is not merely a procedural concern, but a determinant of both exposure magnitude and biological burden.

Cognitive-Task Performance Degradation

Cognitive-task performance was systematically evaluated across the study period using standardised assessments administered quarterly to participants living or working in both residential and workplace settings. Results indicated that delayed IAQ diagnostics were associated with statistically significant declines in several key areas of cognitive function. These effects were observed not only in commercial and institutional buildings but also in residential environments, where participants experienced prolonged exposure due to undiagnosed indoor pollutant accumulation.

In all three building types studied—residential, commercial, and institutional—participants in the Delayed Diagnostics Group (DDG) showed marked impairments in sustained attention, as measured by the Continuous Performance Test (CPT). This neuropsychological test revealed significantly higher omission errors and decreased response consistency in the DDG compared to the Timely Diagnostics Group (TDG) ($p < 0.01$).

These indicators reflect the brain's reduced ability to maintain focus over time—a capability essential for sustaining cognitive performance across diverse indoor settings, such as completing work-related tasks, coordinating household responsibilities, supporting caregiving duties, and engaging in academic or training activities.

The Choice Reaction Time (CRT) test, which measures psychomotor speed and executive functioning, showed that participants in the Delayed Diagnostics Group (DDG) had mean reaction times that were 18 milliseconds slower than those in the Timely Diagnostics Group (TDG) ($p = 0.004$). This response delay was consistently observed among adults across all monitored building types, including high-density residential units, commercial workplaces, and institutional settings.

In these environments, sources of indoor pollutants—such as secondhand smoke, cooking emissions, cleaning agents, and off-gassing from building materials—were often underestimated or overlooked. In buildings where diagnostics were delayed, extended exposure to these pollutants contributed to reduced day-to-day cognitive efficiency, particularly in tasks requiring rapid decision-making, motor coordination, and situational responsiveness.

Verbal memory performance was evaluated using the Rey Auditory Verbal Learning Test (RAVLT), with particular emphasis on delayed recall. DDG participants recalled significantly fewer words after a delay compared to the TDG ($p = 0.009$), indicating diminished short-term memory consolidation.

This decline in verbal memory retention occurred across all environment types studied and was not confined to occupational settings. In homes, for instance, it may affect the ability to retain instructions, manage schedules, or support children's learning. In offices and institutions, such impairments could hinder effective communication, comprehension of complex information, and timely execution of tasks.

To translate these neurocognitive findings into functional impact, the study incorporated simulated productivity tasks that reflected common responsibilities in domestic, professional, and institutional contexts. These included digital communication, basic logistical coordination, and practical problem-solving activities.

DDG participants consistently showed longer task completion times and increased error rates across simulations, demonstrating how delayed IAQ diagnostics translated into measurable performance deficits in everyday environments. Whether managing a household, coordinating team tasks in an office, or performing academic or administrative duties in a school or institutional setting, cognitive inefficiencies stemming from prolonged pollutant exposure were evident.

In sum, the findings affirm that the cognitive effects of delayed indoor air quality diagnostics are not confined to workplace productivity. Residential environments, as well as schools and public institutions, are equally susceptible to cognitive-task performance decline when IAQ concerns are overlooked or addressed reactively.

These results highlight the critical importance of timely diagnostic engagement across all building types—not only to preserve health but to sustain cognitive functioning essential to daily living and social contribution in diverse indoor settings.

Structural Pathway Modelling and Mediation Analysis

Structural Equation Modelling (SEM) is a framework that integrates multiple interrelated models into a single comprehensive system, i.e., one integrated model. In this study, SEM was used to uncover the causal and mediational pathways by which delayed engagement in IAQ diagnostics contributes to adverse health and cognitive outcomes.

Specifically, the model tested whether the relationship between diagnostic delay and cognitive-task performance could be explained by a chain of intermediary factors—namely, increased cumulative exposure to harmful indoor pollutants, followed by physiological stress responses, and ultimately cognitive decline.

The hypothesised structural model was expressed as follows:

Diagnostic Delay → Higher Cumulative Exposure → Inflammation and Pulmonary Impairment → Cognitive Decline.

This sequential pathway was grounded in both biological plausibility and prior empirical literature and was supported by the study's integrated dataset of environmental, physiological, and cognitive measurements. The model's statistical performance was excellent. Goodness-of-fit indices demonstrated strong agreement between the model and observed data: the Comparative Fit Index (CFI) was 0.93, the Root Mean Square Error of Approximation (RMSEA) was 0.042, and the Standardised Root Mean Square Residual (SRMR) was 0.037. These values fall within established thresholds for excellent model fit in complex behavioural health models, confirming that the structure and directional paths of the model were both reasonable and robust.

The SEM analysis revealed that diagnostic delay had a strong direct effect on cumulative exposure to indoor pollutants, as indicated by a standardised path coefficient (β) of 0.63. In Structural Equation Modelling, the standardised path coefficient (β) quantifies the strength and direction of the relationship between two variables along a specific path in the model. In this case, the coefficient of 0.63 implies that delaying IAQ diagnostics substantially increased the level of pollutant exposure experienced over time.

This elevated exposure was subsequently associated with increased levels of biomarkers reflecting physiological stress—specifically exhaled nitric oxide (FeNO) and C-reactive protein (CRP). These two markers served as mediators in the model, capturing airway-specific and systemic inflammatory responses, respectively.

Critically, the indirect effects from diagnostic delay to cognitive-task decline—mediated by FeNO and CRP—were also statistically significant and meaningful. Together, these two physiological markers explained approximately 37% of the variance in cognitive outcomes, such as attention, reaction time, and memory. This mediational pathway confirmed that a sizeable portion of the cognitive deterioration observed in the delayed diagnostics group could be attributed to underlying biological stress triggered by pollutant accumulation.

Of particular note was the pathway linking cumulative exposure to sustained attention deficits via systemic inflammation, represented by a standardised β of -0.21. While this effect size is modest, it is practically important, given the real-world impact of even small cognitive declines on productivity, safety, and quality of life.

To ensure the reliability of these findings, propensity score matching was conducted as a robustness check to minimise the influence of confounding variables due to non-random group assignment. After matching participants on key demographic and contextual variables, the SEM model retained its significant pathways and high model fit.

This confirmed that the relationships observed were not spurious but were likely causal, providing strong empirical support for the conclusion that delays in IAQ diagnostics set off a cascade of adverse outcomes through cumulative exposure and physiological deterioration.

Contextual Insights from Qualitative Data

The qualitative interviews revealed a powerful subtext shaping participants' perceptions and behaviours across different building contexts: the perceived burden and uncertainty associated with the current IAQ diagnostic and problem-solving process. Many participants implicitly referenced this burden when explaining why they hesitated to act or why certain actions were deprioritised even when discomfort or symptoms were present.

The prevailing perception was that IAQ diagnostics require a high investment of cost and effort, often with little assurance of meaningful or timely improvement in air quality or occupant well-being. This perception—deeply rooted in lived experience—shaped the cultural norms, heuristics, and risk tolerances observed in both diagnostic groups.

In the Delayed Diagnostics Group (DDG), participants frequently described a reluctance to initiate IAQ investigations because they associated such efforts with disruption to comfort and routines, as well as cognitive load—especially in contexts where the process was perceived as ambiguous or technically complex. Several participants reported avoiding formal diagnostics due to fears that it would trigger lengthy interventions, relocation, or the need to reduce use of valued spaces (such as bedrooms or meeting rooms).

These hesitations were further reinforced by the uncertainty surrounding value delivery: occupants expressed doubt that diagnostics would produce conclusive results or actionable solutions. This uncertainty often led to temporary or cosmetic fixes, such as masking odours with fragrances, adjusting fans, or increasing air-conditioning usage—interventions that postponed, rather than resolved, the problem.

Participants also frequently normalised suboptimal conditions, such as stale air, minor headaches, or fatigue, especially in high-density residential and institutional environments. These symptoms were often misattributed to non-environmental causes, and the lack of a clear, visible link between IAQ and functional outcomes contributed to inertia.

This behavioural pattern closely mirrors the concept of Sick Building Syndrome and Building-Related Illness going undetected—a consequence of delayed or absent diagnostics. The cost–effort–uncertainty triad appeared to directly underpin this diagnostic hesitation, as occupants weighed the perceived sacrifices against ambiguous benefits and concluded that inaction was more tolerable than confronting a potentially costly and inconclusive process.

By contrast, in the Timely Diagnostics Group (TDG), participants benefitted from contexts where IAQ was institutionally prioritised and sensor-based feedback made air quality visible and easier to interpret. The visibility of real-time IAQ data lowered the cognitive effort required to make informed decisions and reinforced the credibility of taking action.

Consequently, low-cost, low-effort adjustments—such as enhancing natural ventilation, rearranging furniture, or switching cleaning products—were implemented more readily. Participants here described a stronger sense of control and justification for their efforts, even in the absence of severe symptoms. This illustrates how reducing the perceived cost, effort, and uncertainty of diagnostics shifts the cognitive framing of IAQ from a passive background issue to an active domain of value-oriented decision-making.

Taken together, the interview data clearly reflect how the current IAQ diagnostic model—due to its perceived demands and uncertain value—can unintentionally promote avoidance, superficial solutions, and the silent accumulation of harm. The findings underscore that without visible, credible, and cognitively manageable IAQ diagnostic tools, many occupants will continue to underestimate pollutant risks, tolerate preventable symptoms, and experience declines in health and cognitive performance.

Vulnerable populations—such as children, the elderly, and individuals with pre-existing conditions—remain disproportionately impacted. Thus, improving IAQ outcomes requires not only technical solutions but also a reconfiguration of the diagnostic experience to lower barriers and increase perceived value.

Thresholds, Temporal Risk Profiles, and Subgroup Variations in IAQ Diagnostic Impact

The integrated analysis of temporal exposure trajectories and subgroup-specific outcomes provides critical insight into when and for whom delayed indoor air quality (IAQ) diagnostics are most consequential. A key finding was the emergence of a temporal threshold in the Delayed Diagnostics Group (DDG), where cumulative pollutant exposure began diverging significantly from the Timely Diagnostics Group (TDG) approximately eight weeks after the initial risk signals were detected.

This non-linear escalation was particularly evident in the weighted cumulative exposure dose (CED), and it corresponded with worsening physiological and cognitive outcomes. While the eight-week threshold is not an absolute cut-off, it offers a useful benchmark: once this delay point is surpassed, the likelihood of measurable harm increases sharply. Establishing such time-based triggers allows IAQ management systems to transition from reactive to anticipatory, potentially curbing adverse outcomes before they become entrenched.

The risk trajectory was further modulated by environmental context. Buildings situated near high-traffic corridors or characterised by unstable or fluctuating ventilation rates exhibited steeper rises in pollutant accumulation and associated performance declines. These environmental conditions likely amplify the rate at which indoor air becomes compromised in the absence of diagnostic intervention.

In such settings, diagnostic delay acts not only as a passive omission but as an accelerant of cumulative exposure. Therefore, the timeline for IAQ assessment in volatile environments must be significantly shorter and more rigorously enforced. The convergence of temporal and contextual variables strengthens the argument for dynamic, context-sensitive diagnostic thresholds embedded within IAQ protocols.

In parallel, effect size estimates lend further weight to the findings by quantifying their practical significance. Cohen’s d values for weighted CED differences across pollutants ranged from 0.58 to 0.77, suggesting medium to large effects. This means the magnitude of the exposure difference between DDG and TDG participants is not only statistically significant but also materially relevant for real-world health and cognitive functioning.

For cognitive-task outcomes such as sustained attention and reaction time, effect sizes ranged from 0.32 to 0.54—still moderate and meaningful when considering the cumulative impact of such impairments over time. Moreover, partial eta-squared (η^2) statistics indicated that diagnostic timing alone accounted for up to 16% of the variance in pollutant exposure and up to 11% in selected health and cognitive outcomes, underscoring the central role of timing in shaping IAQ-related risk profiles.

Subgroup analyses further revealed that vulnerability to diagnostic delay is not uniform. Adults aged 45 to 55, occupants in naturally ventilated environments, and those with limited understanding of IAQ risks experienced disproportionately severe declines. These findings point to the need for stratified IAQ policies that account for both human and environmental heterogeneity.

In practice, this means prioritising early diagnostics in settings with higher contextual risk and tailoring IAQ education and communication strategies to populations that exhibit lower baseline awareness. Collectively, these insights highlight that timely IAQ diagnostics are not only about identifying environmental threats but also about strategically preventing their disproportionate impact across time, space, and population subgroups.

Conclusion on Findings for Research Question 2

The research findings for Research Question 2 provide robust empirical support for the alternative hypothesis (H_1) and justify the rejection of the null hypothesis (H_0). The hypothesis proposed that delayed engagement in IAQ diagnostics would lead to significantly higher pollutant exposure, increased health risk indicators, and reduced cognitive-task performance, compared to proactive diagnostics.

In contrast, the null hypothesis posited no significant differences between groups. However, across all measured domains—environmental, physiological, and cognitive—the results consistently demonstrated significant and practically meaningful differences between the Delayed Diagnostics Group (DDG) and the Timely Diagnostics Group (TDG).

With respect to pollutant exposure, the results directly support the first part of the alternative hypothesis. Using Generalised Estimating Equations (GEE), the study found a significant Time x Group interaction ($p < 0.001$), indicating that the cumulative exposure dose (CED) rose more steeply and remained elevated longer in the DDG. This group experienced significantly greater accumulation of $PM_{2.5}$, $PM_{0.1}$, formaldehyde, ozone, and benzene.

When toxicity-weighted CED was calculated, the DDG showed an average increase by a factor of 1.7 (95% CI: 1.45–2.05) compared to the TDG. These findings confirm that the assumption made in H_1—that diagnostic delay is significantly associated with increased pollutant exposure—was empirically upheld, warranting the rejection of H_0 in this domain.

In terms of health risk escalation, the second component of the alternative hypothesis, the findings again aligned strongly with H_1. Participants in the DDG exhibited significantly higher levels of airway inflammation and systemic physiological stress, as reflected in elevated FeNO and CRP levels ($p < 0.001$). These biomarkers provided quantifiable indicators of health risks attributable to pollutant exposure.

Spirometry measurements revealed steeper declines in FEV_1 and FVC in the DDG compared to the TDG, although the values remained largely subclinical. These physiological effects were absent or minimal in the TDG. Therefore, the hypothesis that delayed diagnostics result in increased health risks is clearly supported, and the null hypothesis is rejected on this ground as well.

The cognitive-task performance data further reinforce the third part of the alternative hypothesis. DDG participants performed worse on multiple neurocognitive assessments, including the Continuous Performance Test (CPT), which revealed a statistically significant increase in omission errors and reduced sustained attention ($p < 0.01$), and the Choice

Reaction Time (CRT) test, where DDG participants had slower mean reaction times ($p = 0.004$). On the Rey Auditory Verbal Learning Test (RAVLT), DDG participants recalled fewer words in delayed recall ($p = 0.009$).

These statistically significant performance deficits affirm the hypothesis that delayed diagnostics are associated with impaired memory, attention, and executive function. These findings are incompatible with the null hypothesis, which posits no significant performance differences between groups.

Finally, Structural Equation Modelling (SEM) confirmed the causal structure proposed by H_1. The SEM analysis validated that diagnostic delay significantly increased cumulative pollutant exposure, which subsequently elevated physiological biomarkers of stress and led to cognitive-task performance decline. Indirect effects through FeNO and CRP explained 37% of the variance in cognitive outcomes, with the model showing excellent fit indices.

These results substantiate the full pathway articulated in the alternative hypothesis, supporting its central claim that delayed diagnostics produce a cascade of adverse effects not observed under timely intervention. Consequently, the findings of this study comprehensively reject the null hypothesis and provide conclusive support for Hypothesis 2.

Findings for Research Question 3:

The findings from Research Question 3 addressed the integration of behavioural, environmental, and contextual indicators into an AI-enabled decision-support system designed to mitigate IAQ diagnostic hesitation. Diagnostic hesitation was operationalised as the delay between the detection of elevated indoor air pollutants and the initiation of appropriate investigative or corrective actions by occupants or building managers.

The AI-enabled decision-support system developed in this study was conceptually structured as a biologically inspired, cognitively adaptive framework. It comprised three interrelated subsystems: an environmental sensing component, a data-analytic and learning core, and a user-facing communication interface. The sensing component functioned analogously to sensory organs, with environmental sensors continuously monitoring indoor air pollutant concentrations and dynamic variations in temperature and humidity. These inputs formed the observational foundation of the system.

The analytic and learning subsystem, conceptualised as the “brain” of the framework, consisted of a machine learning algorithm, a structured temporal database, and a feedback loop mechanism. Together, these components enabled the system to detect emerging patterns, incorporate behavioural history, and refine its predictive capability through iterative adaptation. The integration of model outputs with user interaction histories supported continuous system learning, allowing the AI to progressively align recommendations with the specific contextual and behavioural profile of each building.

The communication interface, functionally analogous to a physiological output system, translated analytical insights into real-time alerts, visualisations, and guidance. It represented the system’s “mouth” or gesturing capability, allowing the internal cognitive processing of the AI

—its analysis, reasoning, and understanding—to be externalised in a form that humans could interpret and act upon. This component mediated the interaction between the AI system and human users, enabling timely initiation of diagnostic or corrective action in response to emerging indoor air quality risks.

Crucially, the system incorporated a feedback mechanism that captured user responses to alerts, such as acknowledgement delays, intervention timings, and downstream outcomes, and relayed this information to the learning core. Among the most critical behaviours tracked in this study was diagnostic hesitation, defined as delayed or absent action following risk notification. The system used these hesitation patterns to refine its understanding of user responsiveness under varying environmental and contextual conditions.

This feedback loop enabled the AI to refine subsequent predictions and communication strategies based on actual human engagement. Conceptually, this feedback mechanism performs a function akin to the human nervous system, which monitors the consequences of speech or action and informs future behavioural responses. This closed-loop interaction progressively enhanced the system's ability to anticipate and influence user decisions, ensuring improved synchronisation between predicted risk, user behaviour, and environment-specific constraints.

This systems-level conceptualisation reinforced interdisciplinary clarity and supported the operational framing of the AI system as an intelligent, adaptive agent capable of perceiving, interpreting, expressing, and interacting with its built environment. In technical terms, the system's sensors delivered continuous, high-resolution environmental input; the machine learning model and database constituted its analytic and memory capacity; the feedback loop sustained dynamic behavioural adaptation; and the interface enabled decision-support through contextually relevant human–machine communication.

The goal of an AI-enabled decision-support system was to predict such hesitation and prompt timely engagement to prevent prolonged pollutant exposure and its associated health and cognitive consequences. These findings directly responded to the hypothesis that a decision-support model, incorporating real-time data streams from sensors, behaviour logs, and contextual building metadata, would not only predict hesitation with a classification accuracy above 85 percent but also improve diagnostic engagement and reduce exposure-related risk.

Model Performance and Predictive Validity

The integration of behavioural, environmental, and contextual indicators into the AI-enabled decision-support system resulted in a predictive model that demonstrated strong real-time performance in identifying and classifying IAQ diagnostic hesitation. The model correctly identified cases of hesitation about 89.3% of the time (95% Confidence Interval: 87.1–91.4%), which surpassed the predefined benchmark of 85%.

It also showed a strong ability to avoid false alarms while still catching true cases, with an F1-score of 0.87, indicating a reliable balance between sensitivity and specificity. Another key measure, called AUC (Area Under the Curve), was 0.93, confirming that the model was highly accurate in separating low, moderate, and high-risk hesitation situations.

Together, these results showed that the model was dependable for use in important settings, where delays in responding to poor indoor air quality could increase health risks or reduce people's ability to think and work effectively. The AI system, comprising sensing, reasoning, and interface modules, houses the predictive model—a machine learning algorithm responsible for identifying hesitation risk in real time.

The model's predictive accuracy stemmed from its ability to interpret pollutant concentrations alongside time-evolving behavioural and contextual variables. Rather than treating hesitation as a vague or fixed trait, the AI model recognised it as a real-time delay in user action following environmental risk signals. For example, when concentrations of $PM_{2.5}$ and $PM_{0.1}$ rose rapidly —indicating deteriorating indoor air quality—certain users consistently failed to respond promptly.

The AI model learnt that in naturally ventilated buildings, where air exchange could not be tightly controlled, these users often delayed acknowledging alerts or initiating diagnostic action, even when previous alerts had shown similar pollutant excursions. By tracking such repeated delays and combining them with contextual data, the model associated diagnostic hesitation with both environmental triggers and user-specific inaction patterns, enabling it to anticipate who might hesitate and under what conditions.

The AI model also found that when carbon dioxide (CO_2) concentrations rose steadily—often due to overcrowding and poor ventilation—people tended to hesitate before taking action. The system issued an alert when CO_2 levels exceeded the healthy threshold of 1000 parts per million (ppm), but in many cases, users did not act promptly.

When such delays followed the alert, the system classified the situation as a high-risk case of diagnostic hesitation. This behaviour was especially common in rooms with frequently changing occupancy, limited sensor coverage, and a history of users responding slowly to earlier alerts.

Volatile organic compounds (VOCs), especially those released during cleaning, maintenance, or renovation, were useful in identifying moments of hesitation linked to specific contexts. The system issued alerts when VOC concentrations spiked sharply above historical baselines. However, in many facilities where such activities were common but not closely monitored, users often delayed action despite receiving alerts.

The AI model flagged these situations as high-risk, recognising that familiarity with these pollutant sources often led to complacency and reduced vigilance. This finding underscored the importance of designing future interventions that address behavioural habituation and improve responsiveness.

Findings also showed that ozone (O_3) concentrations—though less frequently elevated indoors —were meaningful indicators of hesitation in buildings prone to outdoor air infiltration. When outdoor ozone levels rose and windows were left open, the system detected corresponding increases in indoor ozone concentrations.

Despite receiving alerts, users often delayed taking action. The AI model recognised these delayed responses as hesitation events, especially in cases where users perceived the pollutant source as coming from outside and therefore not something they could control. This highlighted the need for future IAQ interfaces to better link outdoor and indoor air quality cues to support timely decision-making.

Beyond pollutant-specific findings, the AI system captured hesitation patterns arising from the interaction between pollutant concentrations and broader building context. For instance, buildings that relied primarily on natural ventilation and had consistently high occupancy densities exhibited a greater frequency of hesitation classifications—even when pollutant concentrations remained only moderately elevated.

In these cases, the AI system identified a behavioural tendency among occupants to rely on passive airflow for pollutant removal, rather than initiating active diagnostic engagement. This pattern was particularly pronounced when pollutant concentrations rose gradually over time, which appeared to create a false sense of safety or benign conditions.

In some cases, what appeared as hesitation was later validated as pragmatically reasonable—for example, when a short-term pollutant spike resolved naturally without intervention. The AI system learnt from these instances and adjusted future risk classifications accordingly, avoiding over-alerting and maintaining practical value even in complex IAQ scenarios.

While predictive accuracy is essential, the real-world impact of an AI-enabled health decision-support system depends heavily on its interpretability—that is, how well users can understand and trust the system's reasoning. This study addressed that requirement by incorporating SHapley Additive exPlanations (SHAP values) directly into the system's predictive pipeline. SHAP is a technique used in machine learning to explain the contribution of each input variable to the model's decision, helping users see how the AI arrived at its conclusions.

In this system, SHAP analyses quantified how much each feature—such as a rapid increase in carbon dioxide (CO_2), a user's history of delayed responses, or a sudden excursion in $PM_{2.5}$ from the normal baseline—contributed to the model's classification of a situation as high, moderate, or low hesitation risk. These results were not only processed internally but were also transformed into clear, user-facing visual summaries. These summaries were embedded into the administrator and advanced user dashboards, providing visual explanations that could be quickly interpreted in the midst of routine building management.

This layer of transparency enabled human-in-the-loop validation of the AI model's outputs. For instance, when a facility manager received a high-risk hesitation alert, they could review the associated SHAP explanation and confirm whether the alert was triggered by genuine environmental risk (such as elevated fine particulate matter) and whether it aligned with known patterns of user inaction in the past. This interpretability allowed managers to tailor their response strategies—for example, choosing between technical solutions like increasing ventilation or behavioural strategies like staff reminders or educational outreach.

By making the model's reasoning accessible, SHAP also served as a training tool for users. Over time, the consistency and transparency of SHAP-based justifications helped users build confidence in the system's recommendations. This was especially important in environments where IAQ concepts might not be familiar or intuitive. For example, understanding that a high VOC reading combined with a past delay in response contributed to a high-risk classification gave users both the "what" and the "why," supporting better learning and faster decision-making.

Interview data from participants confirmed that users appreciated this transparency. Many remarked that knowing the reason behind a recommendation motivated them to act more quickly than they might have if the alert had simply stated that the air quality was "bad." In this way, the system created a cognitive-behavioural feedback loop: the AI provided not just data but reasoning, and the user, informed by that reasoning, made better and faster choices. Over time, this loop reinforced both knowledge and trust.

In essence, the integration of SHAP values transformed the AI system from a black box into a collaborative partner—one that could explain itself, be validated by users, and improve user behaviour through explanation. This human-centred design approach proved critical in ensuring that the system was not only technically accurate but also socially and behaviourally effective in real-world IAQ management.

Overall, the system's findings reinforced that effective hesitation detection requires more than just pollutant monitoring. It demands a holistic understanding of how human behaviour varies with building characteristics, environmental change patterns, and prior risk-response history. The AI model was not merely reacting to pollutant thresholds; it was learning and reasoning about the contexts in which human hesitation was most likely to occur.

In doing so, the model generated classifications that were not only statistically accurate—such as a classification accuracy of 89.3% (95% CI: 87.1–91.4%)—but also behaviourally and contextually meaningful. This framework offers a scalable foundation for integrating human behavioural insight into environmental health systems across other indoor domains, including schools, hospitals, and mass transit stations.

These results confirmed the critical need for intelligent, adaptive, and context-sensitive IAQ systems. Such systems must go beyond diagnosing environmental conditions alone. They must also account for the cognitive and behavioural dynamics that influence whether, when, and how people respond to IAQ threats. Only by addressing both environmental and human factors can real-time decision-support tools help reduce delays that would otherwise lead to avoidable health and performance risks.

Behavioural Impact and Diagnostic Responsiveness

By embedding the predictive engine into a real-time decision-support system, the project demonstrated not only technical feasibility but also measurable improvements in how users responded to IAQ concerns. Analysis of over 18,000 system-user interaction logs showed that the AI-enabled system effectively reduced the delay between when an alert was issued and when the user initiated action to investigate or correct the IAQ issue.

On average, this delay fell from 187 minutes (standard deviation = 51 minutes) to just 64 minutes (standard deviation = 36 minutes) following the system's deployment—a statistically significant 66% reduction ($p < 0.001$). This improvement had a direct effect on indoor air quality outcomes, particularly in cases involving pollutants like $PM_{2.5}$ and volatile organic compounds (VOCs), which are known to cause rapid health impacts if people remain exposed for too long without intervention.

Importantly, the behavioural improvements were not one-size-fits-all. They were adaptive to each user's context and to the severity of the air quality threat, thanks to the model's built-in stratification logic. This logic allowed the system to classify alerts into different risk levels—low, moderate, and high—based on the combination of pollutant concentrations, behavioural history, and contextual data such as building occupancy and ventilation strategy.

Alerts categorised as high-risk led to much quicker action, with users being 4.6 times more likely to respond within 30 minutes compared to alerts that lacked risk classification. This difference in behaviour was confirmed by generalised linear modelling, which accounted for other possible influences like time of day, day of the week, building use schedule, and external air pollution levels. Even after adjusting for these confounders, the system's classified alerts were still strongly associated with higher user engagement (Odds Ratio = 2.73; 95% Confidence Interval: 2.1–3.5).

These findings highlight the system's success in making IAQ alerts more meaningful and harder to ignore. By incorporating data about each user's past responses and tailoring alerts accordingly, the system ensured that the most urgent situations prompted more immediate reactions. For example, a user who had previously delayed acting on rising CO_2 concentrations would receive more assertive and more frequent reminders when similar air quality patterns emerged again.

These prompts were not generic. They were automatically adjusted to reflect real-time building conditions—such as how many people were inside and whether natural ventilation (e.g., open windows) was active or limited. This level of personalisation helped users see the relevance of the alert to their specific environment and role, making it easier for them to prioritise IAQ interventions without guesswork.

Importantly, the AI system retained its usefulness even in complex IAQ scenarios, where multiple pollutants fluctuated simultaneously or where pollutant sources were not clearly identifiable. In such situations, the system's layered reasoning approach allowed it to interpret the cumulative context—such as the co-occurrence of elevated VOCs and $PM_{0.1}$ with a slow rise in CO_2 and inconsistent ventilation patterns—and translate this into a risk classification that captured the underlying complexity.

The model was able to link these multidimensional signals with prior user behaviour and deliver alerts that reflected not only the presence of risk but the intricacies of the situation. Users were more likely to engage when they recognised that the system was accounting for this complexity rather than issuing blanket warnings. Thus, even when IAQ issues were ambiguous or not clearly attributable to a single pollutant, the AI system provided useful guidance by integrating the available evidence and past behavioural data to prompt well-informed decision-making.

What made this approach particularly powerful was the fusion of machine learning, behavioural analytics, and context-sensitive decision-making into a single operational loop. The system not only detected pollution and hesitation but also learnt from past behaviour, reasoned about user tendencies, and delivered the right kind of prompt at the right time.

This closed-loop feedback mechanism mitigated harmful delays that might otherwise result in prolonged exposure to pollutants. As a result, the AI system did more than just monitor indoor air quality, it actively shaped human decision-making in ways that improved environmental health outcomes, even in the face of complex and uncertain IAQ challenges.

User Experience and Qualitative Evaluation

The decision-support system was not only analytically powerful but also intentionally designed with its human users at the centre. While many behavioural insights were gained from quantitative indicators, in-depth interviews and focus groups involving 46 participants uncovered design-related factors that enhanced usability and real-world engagement. Thematic analysis showed that beyond trust and relevance, practical factors like interface accessibility, language clarity, and mobile-first responsiveness shaped user satisfaction.

Several participants emphasised the benefit of the mobile-first design, which allowed real-time interaction with alerts even when users were away from their office or control station. This was especially critical for roles involving mobility, such as facility maintenance personnel and safety officers.

In addition, user feedback drove iterative refinement of alert language and visual cues. While early versions of alerts were dense with technical jargon, subsequent revisions—guided by feedback loops and usage analytics—simplified terminology, added visual severity tiers, and included icons for faster interpretation. These updates made the system more accessible to both technical and non-technical users, improving response rates.

Unlike traditional indoor air quality systems, which typically issue static, one-size-fits-all alerts triggered by fixed pollutant thresholds, the AI-enabled decision-support tool in this study provided dynamic and personalised guidance. Traditional systems often failed to explain the context of alerts or indicate the expected user response, whereas this AI system adapted its recommendations in real time based on user behaviour, environmental context, and participatory feedback. Traditional systems might, for example, display a red light or generic message saying “Indoor air quality poor—take action,” without telling the user why the alert was triggered, what pollutants were involved, or what specific action to take.

In contrast, the system in this study used real-time data and behavioural profiling to tailor its alerts to individual users and specific building conditions. It explained why an alert was issued (e.g., “$PM_{2.5}$ has spiked rapidly due to outdoor infiltration and your previous responses were delayed”), suggested context-specific next steps (e.g., “open the east window and reduce occupancy in this room"), and updated its messaging interface based on user feedback collected during field testing. This design not only made the system more intuitive and actionable but also fostered trust and responsiveness by making users feel seen, guided, and involved in the IAQ management process.

Conclusion on Findings for Research Question 3

The results of this study provide robust evidence to reject the null hypothesis (H_0), which stated that an AI-enabled model integrating behavioural and environmental indicators does not improve the prediction of diagnostic hesitation nor enhance engagement or early intervention outcomes. In contrast, the study findings strongly support the alternative hypothesis (H_1), confirming that such an AI-enabled model significantly improves the ability to predict diagnostic hesitation and facilitates meaningful increases in user engagement and timely response to indoor air quality risks.

This support is not based solely on predictive accuracy, but also on demonstrated behavioural impact, contextual relevance, and system interpretability—all of which align with the functional goals outlined in the alternative hypothesis. The AI model did not act in isolation from users' lived realities; instead, it effectively translated pollutant trajectories, behavioural patterns, and building-specific characteristics into real-time, trust-enhancing prompts. These prompts guided decision-making in ways that traditional systems were not capable of, affirming that integrated behavioural-environmental modelling improves not only prediction but also the practical effectiveness of IAQ interventions.

Taken together, the study validates the premise that AI systems designed with human-centred logic and behavioural insight can address diagnostic hesitation in complex, real-world environments. The alternative hypothesis is thus empirically supported, and the integration of such models into future IAQ management systems is both scientifically justified and operationally recommended.

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By the time Ebuka completed his PhD degree at the University of Ivory's School of Public Health, he had not only answered his research questions but fundamentally reframed the way the industry viewed IAQ management. His PhD research had systematically mapped the complex interplay of behavioural, organisational, and perceptual factors that led individuals and institutions to hesitate in engaging with IAQ diagnostics.

He had quantified, through meticulous longitudinal data, the severe consequences of delayed engagement—showing how even small lapses in early detection led to substantial cumulative air pollutant exposures and measurable declines in cognitive-task performance among building occupants.

Most importantly, he had proven that an AI-enabled predictive and decision-support framework could bridge the gap between detection and action. His AI models could anticipate hesitation before it occurred and provide tailored, context-sensitive prompts that transformed abstract data into clear, actionable guidance. This work earned him significant recognition in academic circles and led to several awards for innovation and public health impact.

Yet for Ebuka, his PhD was not the endpoint but a starting line. He was driven not by the pursuit of academic prestige but by a deeper mission—to ensure that no person, whether a child in a classroom, a patient in a hospital ward, or a family in an apartment, would suffer the consequences of poor indoor air quality simply because of hesitation or lack of understanding. He wanted to give power back to the people, enabling them to engage with IAQ solutions confidently, without being overwhelmed by complexity, fear, or uncertainty.

After completing his PhD, Ebuka joined Healthy Air Champ not as an intern, but as Director of Cognitive-Behavioural Systems Integration—a title that reflected his growing commitment to transforming how indoor air quality solutions were developed and implemented. The company, having followed his doctoral journey closely, recognised that Ebuka's insights were far more than academic exercises. They held practical power to redefine how the IAQ industry served real people in the unpredictable complexity of daily life. For Ebuka, it was clear that practice—not research alone—was the true frontier where lasting change would happen.

From his first day back, Ebuka began steering Healthy Air Champ's operations towards a more human-centred philosophy. He was determined that the transition from research to practice should not simply be about deploying a research prototype at larger scale. It had to mean designing solutions that genuinely fit into the chaotic, varied, and often messy realities of how people lived, worked, and made decisions.

He firmly insisted that before any commercial technology could be built, the team had to deeply understand why people hesitated to act, not just that they did. He launched intensive user research initiatives, sending teams into homes, schools, offices, and hospitals to observe first-hand how people responded—or failed to respond—to IAQ information in their daily routines.

They did not just distribute surveys. They sat beside building occupants, watched how they hesitated over unfamiliar terms, noted the emotional discomfort sparked by technical alerts, and documented the silent moments when users simply chose to ignore warnings because acting seemed too confusing, costly, or futile.

This was the crucial difference from Ebuka's PhD work. During his doctoral research, he had proven that an AI-enabled framework could predict hesitation and recommend tailored actions, and he tested this in real buildings under study conditions. But the PhD had still operated within a controlled research environment—limited in scale, governed by protocols, and focused on demonstrating that the concept worked. Participants knew they were in a study, and interventions were observed and measured with scientific precision.

In contrast, Ebuka's work at Healthy Air Champ moved beyond testing whether the idea could work to ensuring it would reliably work for thousands of diverse users in everyday life, without researcher oversight. The challenges now included commercial viability, system resilience, seamless user experience, multilingual communication, privacy protection, cost reduction, and integration with building management systems. He was no longer designing a research tool; he was building a commercial product that could survive the market, gain user trust, and genuinely transform health outcomes at scale.

Driven by these insights, Ebuka led the creation of ChampSense. The ChampSense is an advanced AI system solution designed to make IAQ management both practical and accessible for everyday people. At its core, ChampSense integrates a network of sensors that continuously monitor the air for hidden pollutants such as fine dust particles, chemical fumes, humidity, and gases that could affect health and comfort.

However, what makes ChampSense truly innovative is that it does not only focus on the environment itself—it also pays attention to how people respond to information about their indoor air quality. It achieves this through intelligent systems that act like sensors for human behaviour, observing patterns such as whether users read alerts, delay actions, or ignore warnings altogether.

The data collected from both environmental sensors and behavioural observations flows back to the AI brain of ChampSense. This brain uses machine learning to recognise patterns, remember past interactions, and adapt its communication strategies. ChampSense delivers its guidance through a thoughtfully designed mobile app—interface—which serves as a bridge between complex indoor air quality data and everyday understanding. Rather than presenting users with raw figures or scientific jargon, the app conveys information in clear, relatable terms that focus on practical actions and personal relevance.

Instead of simply warning that indoor air pollutant concentrations are elevated, it might advise users on specific steps they can take, such as adjusting ventilation or using fans, to safeguard their family's health and maintain comfort indoors. This communication style ensures that even those without technical expertise can grasp what is happening in their environment and feel empowered to act.

What distinguishes ChampSense in real-world use is its ability to interpret not only environmental measurements but also patterns of user behaviour. It observes how individuals interact with alerts and guidance, identifying signs of uncertainty or reluctance, such as frequent dismissals of messages, incomplete follow-through on suggested tasks, or habitual postponement of actions.

Instead of escalating the urgency of notifications, which might create stress or cause users to disengage entirely, ChampSense tailors its approach, offering explanations and suggestions in a manner that feels supportive and relevant. A message might avoid technical detail and instead offer simple, compassionate guidance, like explaining how using a kitchen fan for a short period can significantly lower the concentration of particles that could worsen asthma symptoms.

A standout feature of the system is its Value Delivery Estimation Module, which transforms scientific measurements into tangible, personal benefits. The Value Delivery Estimation Module in ChampSense transforms IAQ management from guesswork into informed decision-making.

It calculates whether the investment of cost and effort—such as money, time, comfort, and mental energy—will genuinely improve indoor air quality to levels that support health and cognitive performance.

Beyond developing technology, Ebuka introduced training workshops and created professional certifications to ensure that technicians, building managers, and even school administrators could confidently apply IAQ solutions in practice, without depending on experts for every decision. His goal was clear: make IAQ management not just a technical task, but a normal, empowered part of people's daily lives.

In essence, Ebuka's post-PhD work was no longer about proving whether his ideas could work —it was about ensuring that they worked reliably, affordably, and meaningfully for real people, at real scale, in real-world conditions. By focusing on practical usability and genuine user experience, he shifted IAQ management from a technically driven field into one deeply rooted in human behaviour, trust, and everyday practice. He ensured that solutions were not only innovative but truly actionable, accessible, and capable of overcoming the very human barriers he had once experienced himself.

While ChampSense made decision-making clearer and confidence stronger, Ebuka knew that affordability remained a crucial barrier. Many IAQ solutions on the market were financially out of reach for lower-income households, exacerbating health inequalities. He partnered with several sensor manufacturers to develop a new line of ultra-low-cost sensors that could integrate seamlessly with ChampSense without sacrificing essential accuracy. By working closely with supply chain engineers, he helped reduce production costs by over 50%, making widespread deployment feasible.

Equally transformative was his work on streamlining diagnostic workflows. Historically, IAQ assessments often required specialist intervention, multiple follow-up visits, and complex reports written in technical jargon. Ebuka's AI models simplified these processes. Instead of waiting for a consultant's report weeks after data collection, building occupants could receive instant, context-specific recommendations directly on their smartphones.

ChampSense would generate easy-to-read visualisations showing indoor air pollutant trends and tailored action plans. In commercial environments, facility managers received dashboard reports prioritising issues based on health risks and potential regulatory implications.

This democratisation of IAQ knowledge meant that solutions were no longer the exclusive domain of experts. Occupants became active participants, empowered to understand and manage their own environments. Ebuka's work did not simply reduce diagnostic hesitation—it reframed IAQ management as a shared, accessible responsibility.

One significant example of this impact was in the Harbourview Flats residential community, where high occupant density and limited ventilation had long caused discomfort and frequent health complaints. Previously, professional IAQ services were far too expensive for many residents.

After deploying affordable ChampSense sensors, families began receiving timely, personalised alerts on how to adopt and improve IAQ mitigation strategies and reduce indoor air pollutant concentrations. Within a few months, self-reported symptoms like headaches and fatigue declined, and community health records indicated fewer clinic visits for respiratory issues.

Similarly, in Cedar Ridge Primary School, staff had often struggled with unexplained student fatigue and high CO_2 levels in classrooms. Before ChampSense, investigations required external consultants and weeks of delay. With the new system, teachers and facility staff accessed real-time indoor air quality visualisations and specific instructions—such as increasing ventilation, reducing or eliminating sources of indoor air pollutants, using air purifiers, or addressing the causes of nonexistence or ineffectiveness of mitigation strategies. As a result, student focus improved, and reported absenteeism due to respiratory and other health symptoms decreased noticeably.

These practical outcomes showed that making IAQ solutions more affordable and removing barriers to understanding did more than reduce costs—it empowered individuals to take charge of their indoor environments confidently. Ebuka's vision turned IAQ management into an everyday tool accessible to all, transforming what was once a complex professional service into a resource for families, schools, and workplaces alike.

Yet, Ebuka himself often emphasised that this transformation did not mean that IAQ experts were no longer needed. Instead, their role evolved. While ChampSense enabled ordinary people to handle many aspects of indoor air quality management themselves, complex scenarios, severe pollution events, and specialised building systems still required expert knowledge and intervention.

Professionals were essential for designing tailored solutions in unique or high-risk environments, conducting in-depth analyses of building materials, and ensuring regulatory compliance for large-scale commercial and industrial facilities.

Crucially, ChampSense also became a powerful tool for IAQ experts themselves. The system continuously collected and organised historical data on IAQ patterns and occupants' health-related responses. This created a rich evidence base that professionals could use to trace long-term trends, identify recurring problems, and correlate specific pollutants with reported symptoms.

When facing complex IAQ issues that demanded physical inspections and expert judgement, ChampSense provided experts with precise, data-driven guidance about where to focus diagnostic efforts. For instance, it might highlight rooms with consistently elevated VOC spikes during certain activities or reveal hidden correlations between high CO_2 levels and reported headaches. Armed with this insight, experts could conduct physical examinations and advanced testing far more efficiently, ensuring no critical clues were overlooked.

For instance, in a hospital's surgical suite where sterile air quality is critical, an AI system like ChampSense can monitor conditions and flag subtle deviations in real time. Yet it is expert engineers and hygienists who must interpret those warnings, inspect ventilation systems, and implement precise solutions. Similarly, in heritage buildings with fragile structures, experts are indispensable to balancing air quality improvements with preservation of historical features.

Ebuka's vision was never about replacing expertise but about creating a strong partnership. ChampSense removed routine burdens from experts' shoulders, empowered everyday users, and delivered professionals the robust data they needed for sophisticated problem-solving. Together, intelligent systems and human expertise could ensure that healthy indoor air became not a privilege, but a universal standard.

As ChampSense began to gain recognition, its reputation spread far beyond national borders. Under Ebuka's leadership, Healthy Air Champ expanded its operations into international markets, securing partnerships with governments, multinational corporations, and global health organisations. Cities from Singapore to Stockholm began integrating ChampSense into public health infrastructure.

The system's adaptability to different climates, languages, and building types made it uniquely positioned for global adoption. As a result, Healthy Air Champ grew from a respected domestic player into a multi-billion-dollar international enterprise, celebrated for making cutting-edge IAQ solutions accessible across socio-economic divides.

Recognising the extraordinary impact Ebuka had brought to the company, the board of directors made a historic decision. They invited Ebuka to become a co-owner of Healthy Air Champ, granting him equity in the firm he had helped transform. This move was more than a business gesture; it was an acknowledgement that his ingenuity, relentless drive, and human-centred vision had fundamentally reshaped the company's purpose and financial destiny. Investors credited Ebuka's innovative approach with unlocking new markets and creating sustainable revenue streams, while also positioning Healthy Air Champ as a leader in ethical and equitable technology solutions.

Ebuka's journey from a hesitant young man to a global innovator and co-owner of a thriving enterprise was proof that a single individual, armed with vision and empathy, could change not only an industry but the lives of millions. For Healthy Air Champ, his presence ensured that the pursuit of healthier indoor air would forever remain grounded in both scientific excellence and a profound respect for the human experience.

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Following his elevation to co-owner of Healthy Air Champ, Ebuka's influence on the company only deepened. No longer just an innovator within the organisation, he became a strategic force who helped define its mission, global reach, and long-term scientific vision.

He spearheaded Healthy Air Champ's expansion into international markets, building partnerships with governments, multinational corporations, and public health bodies around the world. Under his guidance, the company evolved from a national leader into a globally recognised multi-billion-dollar enterprise, renowned for merging advanced technology with human-centred design.

Yet for Ebuka, commercial success was not enough. He was determined that Healthy Air Champ should remain grounded in scientific excellence and become a lasting driver of social good. He firmly believed that the true test of any technology was whether it could deliver measurable benefits to people's daily lives and contribute meaningfully to public health.

Recognising the need to sustain innovation and cultivate the next generation of talent, he proposed the creation of a dedicated research centre. Thus, was born the Centre for Indoor Environmental Quality and Solutions, a new research hub established as a collaboration between Healthy Air Champ and the University of Ivory's School of Public Health, where Ebuka had once completed his PhD.

This centre was not merely an internal Research and Development unit but a bridge between rigorous academic research and real-world industry practice. Its mission was twofold: to produce cutting-edge scientific research into IAQ management and to develop practical solutions that could be deployed rapidly in buildings worldwide. The partnership with the university ensured that Healthy Air Champ's technological leadership was continually refreshed with the latest scientific insights, while providing a fertile ground for academic researchers to test and refine their ideas in real-life environments.

As part of this innovative collaboration, Ebuka was appointed, on secondment from his co-ownership role, as Professor of Practice of Healthy Buildings Management at the University of Ivory. This title recognised both his profound industry expertise and his dedication to bridging theory and practice. In his academic capacity, he played a unique role that combined applied research, teaching, and mentorship. His presence was transformational, bringing a dynamic perspective that blended academic rigour with the practical realities of industry challenges.

Ebuka's lectures were highly sought after, renowned not merely for their technical detail but for their compelling narratives that wove scientific principles with human stories. Students were captivated as he recounted real-world challenges—from navigating cultural barriers to communicating health risks, to designing systems that people could trust and use instinctively. His teaching went beyond indoor air pollutant physics, biology, and chemistry, and mechanical systems; it delved into how human behaviour, cognitive biases, and emotional responses shaped the success of any indoor air quality and environmental intervention.

One day, standing in front of his undergraduate class, Ebuka adjusted his glasses and looked around the lecture theatre, gauging the attentive faces before him. As a professor, he believed that real learning went beyond textbooks and lectures—it required connecting abstract knowledge to the messy realities of human experience. He wanted his students to understand that the world of indoor air quality (IAQ) was not just technical, but deeply human, shaped by the costs, fears, and uncertainties people faced when trying to make the right choices.

To illustrate this, he shared an experience from a recent professional engagement where he had spoken to a group of industry professionals and building managers about the challenges surrounding IAQ diagnostics and solutions. He wanted his students to hear exactly what he had told that earlier audience, so they could appreciate both the scientific and human complexities involved. He told his student he said the following to the industry professionals.

“The current IAQ diagnostic and problem-solving process solution often requires high investment of cost (i.e., expenditure and time) and effort (i.e., sacrifices of comfort, conveniences, and cognitive load). There is little or no guarantee that the process solution will lead to an appropriate quantity of indoor air with the quality and safety needed to support and enhance the health of indoor occupants exposed to the air.

This is required in order to achieve or enhance the required comfort, convenience, and awareness (i.e., cognitive function) needed for enhancing excellence in performance in tasks performed in the indoor space. Hesitation to diagnose IAQ problems allows chemical and biological air pollutants to remain undetected, leading to Sick Building Syndrome and Building-Related Illness. These health issues often go unaddressed due to high diagnostic costs, effort required, and uncertainty in value delivery.

As a result, temporary fixes are used, masking root causes and delaying action. Unresolved indoor air pollutants impair health, reduce concentration, and weaken cognitive performance, leading to absenteeism and underachievement. Daily functioning suffers across living, learning, and work environments. Vulnerable groups are most affected. Without proper diagnosis, IAQ remains a hidden barrier to well-being and productivity.”

Ebuka paused for a moment, letting the weight of those words settle in. Then he continued, shifting his focus directly to his students, his tone earnest and encouraging. He wanted them to know there was hope and innovation amidst these challenges, and that solutions were within reach. He further said the following to his students.

“I told them (referring to the industry professionals) that to overcome the hesitation towards IAQ diagnostics that contributes to unresolved health and performance problems, the solution lies in a system enabled by ultra-low-cost, widely available sensors. These sensors must be easily deployable. They can be placed across an entire building, including accessible and hard-to-reach indoor spaces, and also relevant surrounding outdoor areas. These sensors collect data continuously.

AI embedded in a mobile platform analyses the data in real time to predict concentrations, identify sources, and estimate emission rates, eliminating manual sampling and reducing reliance on experts while providing accurate, context-specific insights and actionable guidance. This makes the needed diagnostics effective and accessible.”

Under Ebuka’s leadership, the university’s curriculum in environmental health underwent a profound transformation. He introduced new courses focused on applied learning, where students worked on simulated crisis scenarios such as managing a chemical spill or mould growth in a hospital or addressing sudden spikes in indoor pollutants during a heatwave.

These exercises demanded that students think under pressure, balancing technical decision-making with clear communication and ethical considerations—exactly the skills required in professional IAQ practice. Ebuka believed that knowledge was only powerful if it could be applied instinctively and effectively when stakes were high.

Beyond formal degree programmes, Ebuka devoted considerable energy to Continuous Education and Training (CET) initiatives. He understood that many professionals working in facility management, healthcare, education, and the building industry could not afford the time to pursue full academic degrees.

To serve these practitioners, he designed flexible, modular courses that delivered practical, immediately applicable knowledge. These programmes equipped building managers, cleaners, HVAC technicians, and even teachers with the skills to diagnose IAQ problems, interpret sensor data, and implement mitigation strategies tailored to their specific environments. For example, one module developed for school facility staff included interactive case studies that guided participants through diagnosing poor classroom air quality, identifying pollutant sources, and communicating with parents and school boards about interventions in plain language.

Another CET programme tailored for hospital administrators focused on how IAQ management could integrate seamlessly into infection control protocols—a crucial concern in the wake of global health crises. Participants emerged from these trainings with not just technical knowledge but confidence in making quick, informed decisions that could protect health and wellbeing.

Meanwhile, the Centre for Indoor Environmental Quality and Solutions evolved into a vibrant hub of forward-looking applied research, dedicated to pushing the boundaries of what defines a healthy indoor environment. Under Ebuka's visionary leadership, the centre's mission extended far beyond traditional indoor air quality studies, embracing a holistic concept of Indoor Environmental Quality (IEQ) that recognises the complex interplay among multiple environmental factors.

At the heart of this mission was an ambitious commitment: to become a leading academic-industrial platform for supervising a new generation of researchers—particularly PhD students—focused on investigating how individual environmental mandates or collective environmental mandates could be integrated with IAQ management.

These mandates encompass dimensions such as thermal comfort, acoustic quality, lighting conditions, visual perception, and spatial layout. Each of these factors plays a crucial role in influencing human health, cognitive performance, and overall wellbeing, yet historically, they have been studied in silos rather than as interconnected systems.

Ebuka believed that to achieve truly healthy and high-performing indoor spaces, researchers needed to understand how these mandates could work in synergy rather than in isolation. For instance, he encouraged PhD candidates to explore questions such as how mitigation strategies designed to improve air quality might inadvertently influence thermal comfort, or how acoustic insulation choices could affect air movement and pollutant dispersion. Other students focused on how daylight optimisation for visual health and mood could be balanced against potential heat gains affecting HVAC loads and indoor air quality dynamics.

Through the centre's guidance, PhD projects were designed to tackle multi-dimensional problems, often involving real-world building environments. Students were embedded in collaborative projects with Healthy Air Champ's engineering teams, sensor developers, and user experience designers, ensuring their research addressed both scientific complexity and practical application. Field experiments took place across diverse building types, from schools and hospitals to office towers and residential developments, allowing students to gather rich, context-specific data.

One doctoral project, for example, investigated how advanced sensors could simultaneously capture air pollutant concentrations, thermal gradients, and noise profiles, enabling AI systems to deliver holistic guidance that considered all these factors in concert. Another PhD student developed predictive models that integrated occupant behaviour patterns with both IAQ and lighting conditions, to support personalised recommendations for energy-efficient and health-supportive environments.

Beyond purely technical work, Ebuka ensured that the centre's research embraced human-centred principles, training PhD students to consider psychological and social responses to environmental interventions. Students examined how people perceived trade-offs among comfort, energy use, and health risks, and how communication strategies could be crafted to build trust and engagement rather than confusion or resistance. Value delivery to indoor occupants and its perception formed the basis of all research conducted at the centre.

The centre also maintained close ties with the University of Ivory's curriculum, integrating its research findings into teaching and continuous education programmes. This created a feedback loop where insights from doctoral research informed educational content, while industry needs helped shape the questions future students would tackle.

Under Ebuka's guidance, the Centre for Indoor Environmental Quality and Solutions positioned itself as a global leader in integrated indoor environmental research. Its unique approach—linking advanced technology, human behaviour, and practical building management—promised to transform the way industries, governments, and communities approached healthy indoor environments.

For Ebuka, the centre was not merely a research entity but a crucible where science, practice, and education merged to ensure that the next generation of professionals would be equipped to solve the complex challenges of indoor environmental quality in a rapidly changing world. This body of evidence became a persuasive tool for convincing governments and businesses alike that healthy indoor environment was not merely a health issue but a critical driver of economic resilience and productivity.

Under Ebuka's vision, the research centre blossomed into an international reference point, attracting scholars, policymakers, and industry leaders eager to learn from its integrated approach. Graduates emerging from this collaborative ecosystem carried with them not only technical expertise but the practical wisdom to apply it meaningfully in real-world contexts.

Through his dual roles as co-owner of Healthy Air Champ and Professor of Practice, Professor Ebuka Nwafor became a linchpin connecting scientific discovery with industry application. His legacy lay not only in the technologies he helped develop but in the generations of professionals he inspired and trained. His work ensured that innovation would not remain trapped within laboratory walls but would continually flow into buildings, schools, hospitals, and homes, making healthy indoor environments a universal reality rather than a privileged exception.

For all his professional achievements, Ebuka never lost sight of the personal journey that had brought him here. He often recalled the younger version of himself, standing silently beside a leaking pipe in his secondary school chemistry lab, afraid to speak up because he feared he might be wrong or might be laughed at. Or he would remember watching, helplessly, as a small fire grew in his family's compound, paralysed not by physical danger but by the anxiety of drawing attention to himself and possibly sounding foolish.

These moments haunted him for years, shaping not only how he saw himself but how he understood the broader human struggle with hesitation and fear. It was precisely because he had known hesitation so intimately that he had been able to build solutions to overcome it.

As he rose through the ranks of his profession, Ebuka became determined that others would not suffer the same paralysis that had once held him captive. Standing at conferences or training workshops, he would often begin his presentations by sharing his own story, unembellished and raw. He spoke candidly about anxiety, the mental load of decision-making, and how even the most technically elegant systems could fail if they did not account for human needs and emotions.

For him, systems had to be designed not just for technical function, but for human comfort, convenience, and awareness, all while being affordable. He spoke too of the costs involved—both financial and in terms of time—and how people often hesitated to act because they feared wasting resources or disrupting routines. He told audiences that empowering users was not simply about technology, but about ensuring that no person would ever feel as paralysed and alone as he once had.

Ebuka's career trajectory, from hesitant boy to global leader in IEQ innovation, had come full circle. He had transformed what he once considered a personal flaw into a source of empathy and insight, creating solutions that bridged the stubborn gap between knowledge and action. He understood that knowing the science and engineering of indoor air quality and indoor environmental quality was only part of the challenge.

The real breakthrough came when people felt confident enough to act on that knowledge, to interpret signals and warnings without fear of judgment or confusion. His work focused on developing communication tools, educational materials, and system designs that made complex information understandable and relevant, thus lowering the mental barriers that so often led to dangerous inaction.

His legacy was not merely technological, but profoundly human. Through his research, innovations, and tireless advocacy, millions of people could now breathe easier—both literally and figuratively. They could live with improvement thermal, acoustic, light/visual and spatial conditions. They could trust that their efforts to protect their indoor environments would be meaningful, effective, and worth the sacrifice of effort and cost sacrificed.

For Ebuka, that was the true measure of success: a world in which no one was held back by fear or hesitation, and where knowledge became not a burden, but a pathway to action and well-being. **The End!**

Supplementary information

[***Note****: In the research methods section, the values of the model coefficients, represented as β_0, β_1, β_2, β_3, and γ in the Generalised Estimating Equation (GEE) model, were not assumed in advance but were calculated directly from the study data. These coefficients describe how much each factor in the model, such as time, group membership, or participant characteristics, contributes to changes in cumulative exposure dose over time. To determine these values, the study applied a statistical technique that is widely used in longitudinal research when individuals are measured repeatedly across multiple time points.*

The process of estimating these coefficients is based on a form of regression analysis. This technique involves providing the model with large amounts of real-life data collected from participants. These data include measured exposure levels, time of observation, diagnostic group assignment, age, comorbidities, and building characteristics. The model then uses this information to find the most accurate and consistent relationship between the predictors and the outcome variable, which in this case is the cumulative exposure dose. The model systematically searches for the combination of values that best explains the observed variation in exposure among participants across different times and conditions.

In simpler terms, this process works much like a sophisticated calculator embedded in a statistical software program, such as SPSS, R, or Mplus, that uses participants' real-life data to discover patterns and relationships. The computer is provided with a table containing various pieces of information about each person: their exposure levels, how much time has passed, what group they are in, their age, whether they have other health problems, and the characteristics of the building they work in. Using this table, the software runs a series of calculations to determine how all these factors are related to the outcome of interest. In this case, the cumulative amount of pollution a person has been exposed to over time.

Rather than simply assuming a relationship, the software tests thousands of possibilities through an iterative process. It starts with an initial guess for the value of each coefficient, checks how well this guess predicts the actual data, and then refines the guess repeatedly until the best-fitting values are found. These refined values—the coefficients—then serve as summaries of how strongly each factor is associated with changes in cumulative exposure. For instance, the program might find that people in the delayed diagnostics group accumulate significantly more exposure over time than those in the timely group, or that exposure increases more quickly for people with underlying health conditions.

The model also uses what are called "quasi-likelihood" methods with robust standard errors, which make the results more reliable. This means the calculations are adjusted to reflect the fact that the same person is measured more than once and may have responses that change unpredictably over time. These adjustments help ensure that the final coefficient values aren't overly influenced by any single person's unusual data.

Rather than trying just one solution, the model performs many rounds of mathematical trial and error. It begins with a set of initial estimates, checks how well those estimates match the real data, and then adjusts the estimates repeatedly until it finds a set of values that produces the most reliable predictions. This iterative process ensures that the coefficients reflect actual patterns in the data, not assumptions.

For example, the coefficient β_1 captures the effect of time, specifically, how cumulative exposure changes before and after the intervention period. The coefficient β_2 measures the difference in exposure levels between diagnostic groups, such as between those who were biologically vulnerable and those who were not. The interaction term β_3 estimates whether the effect of time differs between groups, whether, for instance, the biologically vulnerable group experienced a steeper increase in exposure over time. The vector γ includes the effects of other covariates like age, pre-existing health conditions, comorbidities, occupancy density, ventilation type, and outdoor pollution.

To make the model's estimates more reliable and less sensitive to inconsistencies in the data, robust standard errors were used. These provide a safeguard against underestimating the uncertainty of the estimates when individuals have different patterns of variability over time. In practice, this means the model did not assume that all participants responded in exactly the same way, which is more reflective of real-life variation.

By grounding the coefficient estimation in the actual data collected from participants, the model allowed for statistically valid and practically meaningful inferences about how diagnostic timing and individual characteristics influenced pollutant exposure across time. The integration of multiple variables into a single analytical framework enabled the research to test not only whether differences existed between groups but also how those differences changed dynamically across the study duration.

In addition to improving model accuracy, this approach supported transparency and reproducibility. Because the estimation process is data-driven and conducted using established software tools, other researchers can replicate the procedure with different datasets or apply the same model structure in related studies. This consistency strengthens the reliability of the findings and provides a basis for cumulative knowledge development in IAQ research.

Moreover, estimating these coefficients provided the quantitative foundation for modelling expected exposure trajectories in different diagnostic contexts. By comparing observed exposure doses against predicted values derived from the GEE model, researchers could assess whether participants in the delayed diagnostics group experienced disproportionate increases in pollutant burden, even after accounting for individual characteristics and environmental factors. This comparison between actual and predicted values also helped identify potential outliers, anomalies, or subgroups that may require further investigation.

For stakeholders and non-specialists, such as building managers, policy-makers, or public health officials, this kind of statistical modelling translates complex datasets into actionable insights. The resulting coefficient values inform evidence-based recommendations on when and how to intervene with IAQ diagnostics to minimise exposure and protect health. For *example, if the model shows that cumulative exposure rises sharply after three months of delay, with a pronounced effect in older or immunocompromised individuals, this can guide more targeted and timely diagnostics in future applications.*

In summary, the process of coefficient estimation in this study was not an abstract mathematical exercise, but a concrete and essential step in understanding how real-world IAQ decisions affect people's exposure to pollutants. The use of the GEE framework, combined with rigorous statistical fitting procedures and robust error handling, ensured that the final model captured not only the average trends across participants but also the nuanced interactions between diagnostic timing, personal vulnerability, and environmental conditions. The simplified explanation, that statistical software is used to detect patterns in data by testing many combinations of variable relationships, helps make this process accessible to non-technical audiences while preserving scientific accuracy.]