

From Indoor Environmental Exposure to Vascular Health Risk Prediction: An Interpretable Machine Learning Framework for Identifying Acute Cognitive and Microvascular Stress Responses

Syazwan Aizat Ismail^{1*}, Muaz Mohd Zaini Makhtar^{2*}, Björn Crüts³, Syamimi Shamsuddin⁴, Muhammad Iftishah Ramdan⁵, Mohd Rafatullah⁶, Nor Asniza Ishak⁷, Hijrah Saputra⁸

¹National Poison Centre, Universiti Sains Malaysia, Penang, Malaysia;

²School of Industrial Technology, Universiti Sains Malaysia, Penang, Malaysia

³Neuro.online, Smedesteaat 2, 6411 CR, Heerlen, Netherlands;

⁴Advance Medical and Dental Institute, Universiti Sains Malaysia, 13200 Kepala Batas, Pulau Pinang, Malaysia

⁵School of Mechanical Engineering, Engineering Campus, Universiti Sains Malaysia, 14300, Nibong Tebal, Pulau Pinang, Malaysia

⁶University Centre for Research and Development, Chandigarh University, Mohali, Pubjab, India

⁷School of Education Studies, Universiti Sains Malaysia, 11800, Gelugor, Pulau Pinang, Malaysia

⁸Department of Disaster Management, Postgraduate School, Universitas Airlangga, Indonesia

*Corresponding Author 1:

Muaz Mohd Zaini Makhtar

School of Industrial Technology, Universiti Sains Malaysia, 11800, Gelugor, Penang, Malaysia

Email address: muazzaini@usm.my

*Corresponding Author 2:

Syazwan Aizat Ismail

National Poison Centre, Universiti Sains Malaysia, 11800, Gelugor, Penang, Malaysia

Email address: drsai@usm.my

ABSTRACT

Environmental exposures are increasingly recognized as contributors to endothelial dysfunction, microvascular impairment, and early vascular symptoms. Indoor air quality (IAQ), specifically exposure to particulate matter, carbon dioxide, and thermal stressors, has been shown to influence autonomic balance, inflammation, and cerebrovascular responsiveness. This study reframes a machine learning model originally designed to predict concentration difficulties as a proxy for early cerebrovascular stress. Using multimodal IAQ and perception data collected in a university building, an interpretable Random Forest Classifier achieved an AUC of 0.6167 in predicting acute cognitive difficulty—considered here as a functional marker of transient neurovascular strain. Explainable AI revealed that subjective perception of “stuffy” air was the strongest predictor, surpassing CO₂, PM_{2.5}, and temperature. These findings align with emerging evidence linking environmental discomfort, autonomic dysregulation, and cerebrovascular perfusion changes. This work highlights the importance of integrating subjective environmental perception into vascular risk screening models and underscores XAI as essential for clinical and environmental health applications.

KEYWORDS: Indoor Air Quality (IAQ), Neurovascular Stress, Cognitive Impairment, Endothelial Dysfunction, Explainable Machine Learning (XAI), Sick Building Syndrome (SBS).

How to Cite: Syazwan Aizat Ismail, Muaz Mohd Zaini Makhtar, Björn Crüts, Syamimi Shamsuddin, Muhammad Iftishah Ramdan, Mohd Rafatullah, Nor Asniza Ishak, Hijrah Saputra., (2025) From Indoor Environmental Exposure to Vascular Health Risk Prediction: An Interpretable Machine Learning Framework for Identifying Acute Cognitive and Microvascular Stress Responses, *Vascular and Endovascular Review*, Vol.8, No.15s, 279-291

INTRODUCTION

Indoor environmental stressors—thermal load, pollutants, and ventilation quality—have been increasingly associated with vascular and microvascular dysfunction. Epidemiological evidence connects fine particulate exposure (PM_{2.5}), volatile pollutants, and thermal discomfort with endothelial inflammation, impaired nitric oxide signalling, autonomic imbalance, and reduced cerebrovascular reactivity. These mechanisms contribute to both acute symptoms (headache, cognitive impairment, fatigue) and long-term vascular risk.

The quality of indoor environments has quietly become one of the most consequential determinants of human health and productivity in the modern age. With people now spending between 80% and 90% of their lives indoors, the microclimate of buildings—its air quality, temperature, humidity, and acoustic comfort—has evolved from a mere engineering concern into a critical public health issue (World Health Organization (WHO), 2021; Fisk, 2000, Ismail et al., 2022). Beyond chronic respiratory ailments, poor Indoor Air Quality (IAQ) has been linked to subtle yet pervasive impairments such as fatigue, headaches, and cognitive slowdown, phenomena often encapsulated within the term Sick Building Syndrome (SBS) (Wyon & Wargocki, 2006).

As society transitions toward sensor-rich, intelligent buildings, the aspiration has shifted: from simply monitoring environmental conditions to predicting their impact on human health, ideally in real time.

Despite this, IAQ-generated vascular stress is poorly quantified in real-time settings. Most existing systems monitor environmental parameters but do not predict downstream physiological responses. Moreover, few studies integrate subjective perception—an early indicator of autonomic stress—with objective environmental metrics. As perceived “stuffy air,” thermal discomfort, and poor ventilation have been linked to sympathetic activation and microvascular strain, combining these variables may strengthen predictive models for vascular-related acute symptoms.

In theory, a perfectly adaptive building should sense environmental fluctuations, infer potential physiological or cognitive effects on occupants, and autonomously intervene—adjusting ventilation, temperature, or filtration before discomfort manifests. This vision, however, remains largely unrealized. Existing predictive models, though data-driven, rarely achieve both accuracy and interpretability when applied to human health responses. Machine learning (ML) has undoubtedly enhanced the capacity to model nonlinear, high-dimensional relationships among environmental variables. Yet when ML is used to predict human symptoms, results are often inconsistent, with models performing adequately in one building and collapsing in another (Romaos et al., 2025). The challenge is not merely algorithmic; it is conceptual. Human health is not a purely physical outcome—it is mediated by perception, emotion, and cognition. This complexity means that conventional sensor-based models, designed for mechanical systems, are poorly equipped to capture subjective experience.

The ideal predictive system would integrate objective environmental measurements with subjective human perceptions to anticipate health effects. Instead, most models rely exclusively on sensor data such as CO₂, particulate matter (PM_{2.5}), or temperature. These objective readings, while essential, explain only a portion of the variance in reported symptoms. In practice, occupants often report discomfort or concentration difficulties even when measured IAQ is within acceptable limits (Seppänen et al., 1999; Godish, 2016). The resulting trust gap undermines the credibility of automated systems: facility managers cannot easily justify model predictions, and occupants struggle to trust opaque “black box” outputs. What is missing is a transparent predictive framework—one that not only forecasts health-related outcomes but also articulates why those predictions arise.

Attempts to address this challenge have typically fallen into two camps. The first pursues more complex algorithms, such as Long Short-Term Memory (LSTM) networks, under the assumption that temporal modeling will capture cumulative exposure effects (Fang et al., 2021). While theoretically sound, such models often perform poorly in real-world contexts due to noisy, sparsely labeled human data. The second camp emphasizes accuracy at the expense of interpretability, treating model explainability as secondary. Yet for high-stakes applications—where system decisions influence human comfort or health—interpretability is not optional; it is foundational. Without it, even a high-accuracy model cannot be operationalized responsibly (Adadi & Berrada, 2018).

The direct consequence of this methodological shortfall is twofold. First, building scientists lack reliable, auditable tools to attribute specific health complaints to measurable environmental causes. Second, the absence of interpretability constrains the evolution of human-centric control systems: AI remains a diagnostic tool rather than an adaptive, trustworthy collaborator. As a result, the human experience of the indoor environment continues to be modelled indirectly, despite evidence that psychological and perceptual factors are the most immediate predictors of discomfort (Chatzidiakou, Mumovic, & Summerfield, 2011).

The knowledge gap is therefore clear: existing predictive models in IAQ and health neglect the quantitative contribution of subjective perception features relative to objective sensor features. While SBS literature acknowledges that perception mediates physiological response, no study has rigorously quantified which domain—objective or subjective—drives prediction performance more strongly when modeled together in an interpretable ML framework. This study addresses that gap by developing a predictive model that integrates both forms of data and leverages Explainable Artificial Intelligence (XAI) to reveal the internal decision logic of the model. Rather than treating explainability as an afterthought, this work positions it as the central analytical instrument—using the model itself to expose the comparative salience of features such as perceived “stuffy air” versus measured CO₂ concentration.

Building upon foundational studies that link poor IAQ to cognitive decline (Satish et al., 2012) and extending them through interpretable modelling, this research proposes that subjective perception is a more powerful and direct predictor of acute cognitive symptoms than objective environmental parameters. The study thereby shifts the emphasis from purely physical modelling of IAQ to a human-centred computational paradigm grounded in explainability and psychological realism. This study adapts a machine learning dataset originally created to study concentration difficulty, reframing it as a relevant vascular biomarker. Cognitive slowdown and perceived mental fatigue have been associated with changes in cerebral perfusion and endothelial reactivity—making them useful proxies for short-term vascular strain.

Emerging vascular research further underscores the relevance of indoor environmental stressors as modulators of endothelial integrity and cerebral microcirculation. Short-term exposure to PM_{2.5} and elevated CO₂ has been shown to impair flow-mediated dilation (FMD), increase oxidative stress, and promote low-grade systemic inflammation—mechanisms central to early vascular dysfunction (Bhatnagar et al., 2010; Robertson & Miller, 2018). Thermal discomfort and humidity imbalance can additionally influence autonomic tone, provoking sympathetic activation and transient increases in peripheral vascular resistance (Lan et al., 2022). Notably, several controlled-exposure studies demonstrate that poor IAQ reduces cerebrovascular reactivity and alters neurovascular coupling, thereby affecting cognitive performance and perceived mental effort (Zhang & Zhang, 2022; Li et al.,

2025). These findings align with the conceptual framing of concentration difficulty as a proxy marker of neurovascular strain, supporting the integration of vascular-centric endpoints into predictive models of indoor environmental health.

Accordingly, the objectives of this study are three folds:

1. To develop a predictive model capable of identifying acute difficulty concentrating as a physiological marker of neurovascular stress induced by IAQ exposure.
2. To determine whether subjective perception features contribute more strongly to symptom prediction than objective sensor data.
3. To apply explainable AI to identify which environmental features most strongly influence acute symptoms related to cerebrovascular strain.

The findings aim to illuminate the mechanisms linking environmental conditions, human perception, and cognitive well-being—an essential step toward health-aware building systems that think with, rather than for, their occupants. This paper proceeds with a critical review of literature concerning health modelling in the built environment. Subsequently, the Method section details the data pre-processing, advanced feature engineering, and the Random Forest Classification approach used, alongside the application of feature importance analysis. The Results present the model's performance and the key XAI findings, which are then critically discussed by relating them to existing environmental health theories. Finally, the Conclusion summarizes the findings and outlines implications for future research and smart building system design.

LITERATURE REVIEW: VASCULAR HEALTH, MACHINE LEARNING, IAQ, AND THE SUBJECTIVE GAP

2.1 IAQ, Autonomic Stress, and Vascular Function

Indoor pollutants and thermal discomfort can acutely elevate sympathetic tone, reduce heart-rate variability, and impair endothelial function. PM_{2.5} penetrates alveolar tissue, triggers systemic inflammation, and has been linked with microvascular dysfunction and elevated cardiovascular risk even at low concentrations. CO₂ and inadequate ventilation influence cerebral blood flow, altering cognitive function through vasodilation and perfusion challenges. The concept of Indoor Air Quality (IAQ) is central to environmental health studies, extending beyond simple air exchange rates to encompass the complex interaction of thermal, chemical, and biological contaminants (Sundell, 2004).

The clinical relevance of IAQ is most clearly articulated through the phenomenon of Sick Building Syndrome (SBS), a cluster of non-specific symptoms—such as headache, fatigue, and difficulty concentrating—that are temporally linked to time spent in a specific building (Suess, 1992; Norbäck et al., 2017). Critically, the symptoms associated with SBS are often reported disproportionately to objective sensor readings, suggesting a significant mediating role for psychological and perceptual factors. Seppänen et al. (1999) synthesized numerous studies to demonstrate a consistent, albeit sometimes subtle, reduction in performance and increase in discomfort across various buildings, often correlating directly with increased CO₂ levels, which serves as a widely used proxy for ventilation adequacy. However, research by Satish et al. (2012) using objective performance tests identified significant cognitive function decrements associated with moderately high CO₂ levels, thus providing empirical validation that certain IAQ metrics have a direct, non-perceptual impact on concentration. These findings establish the primary objective of this study: to predict cognitive difficulty, which is both a key SBS symptom and an empirically validated consequence of poor IAQ.

Emerging vascular research further underscores the relevance of indoor environmental stressors as modulators of endothelial integrity and cerebral microcirculation. Short-term exposure to PM_{2.5} and elevated CO₂ impairs flow-mediated dilation (FMD), increases oxidative stress, and promotes low-grade systemic inflammation—mechanisms central to early vascular dysfunction (Bhatnagar et al., 2010; Robertson et al., 2018). Thermal discomfort and humidity imbalance can additionally alter autonomic balance, provoking sympathetic activation and transient increases in peripheral vascular resistance (Lan et al., 2011). Controlled-exposure studies demonstrate that poor IAQ reduces cerebrovascular reactivity and disrupts neurovascular coupling, thereby affecting cognitive performance and perceived mental effort (Zhang et al., 2024; Nieet al., 2024). These findings support the framing of concentration difficulty as a clinically relevant proxy for short-term neurovascular strain, strengthening the rationale for modelling IAQ-related cognitive symptoms as a vascular biomarker.

Cognitive slowing and difficulty concentrating have been associated with impaired cerebral oxygenation, endothelial dysfunction, and autonomic imbalance. These functional symptoms provide early warning signatures for environmental vascular stress.

2.2 Machine Learning in Building Systems and IAQ Prediction

Machine learning has been increasingly used in vascular medicine for predicting stroke risk, endothelial dysfunction, and hemodynamic instability. However, interpretable ML applied to environmental vascular stress remains limited. Most studies lack integration of subjective perception—despite strong evidence that discomfort correlates with vascular stress markers. This study fills this gap by evaluating both objective IAQ metrics and subjective perception within an interpretable ML pipeline relevant to vascular health.

The application of machine learning in building science has generally focused on two areas: optimizing energy consumption (e.g., forecasting load) and predicting sensor values (e.g., forecasting CO₂ levels). Models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have shown remarkable success in processing sequential, time-series data related to building systems (Ardabili et al., 2022). This success is largely attributable to the predictable, linear dynamics of

physical systems. For example, predicting the future temperature of a room given the current HVAC status is a well-conditioned problem.

When ML is applied to human-centric problems, the challenge shifts. Studies attempting to use ML for health outcomes typically rely on classification algorithms (e.g., Support Vector Machines, Random Forests) to correlate objective IAQ metrics with symptom reports collected via surveys (Romaios et al., 2025; Pargmann et al., 2018, Syazwan et al., 2012a, 2012b, Syazwan et al., 2013 & Syazwan et al., 2025). While some models report high accuracy, usually above 70%, a critical examination of these studies often reveals two significant limitations. First, they frequently treat the sensor data as cross-sectional snapshots, neglecting the temporal accumulation of exposure, which is a conceptual weakness when modelling chemical exposure. Second, and more importantly for the current research, these high-accuracy results are often achieved by complex "black box" models (like deep neural networks), where the internal logic is opaque. This creates a reliance on a system that is impossible to audit or verify, a fatal flaw when the consequence is human health, thus highlighting the urgent need for XAI integration (Adadi & Berrada, 2018).

2.3 The Knowledge Gap: Neglecting the Subjective Feature Space

The most glaring omission in the contemporary literature on predictive IAQ health models is the underutilization or outright exclusion of subjective occupant perception as a primary feature. Research in the thermal comfort domain, particularly Fanger's Predicted Mean Vote (PMV) model, has long recognized the necessity of incorporating personal factors (clothing, activity) to predict comfort (Fanger, 1970). However, this principle has not been consistently transferred to the IAQ domain.

Previous studies either use subjective reporting *only* as the target variable (the symptom) or treat perception (e.g., perceived stuffiness) as an exogenous variable without quantitatively comparing its predictive power against objective sensor data. For instance, studies that include environmental satisfaction surveys often analyze them descriptively rather than integrating them directly into the ML feature space (Chatzidiakou, Mumovic, & Summerfield, 2011). This oversight is particularly problematic given the psychosocial component of SBS, where the perception of environmental control, or lack thereof, can exacerbate physiological symptoms (Godish, 2016).

The current research critically synthesizes this literature to identify a key discrepancy:

1. Objective literature (Satish et al., 2012) confirms that physical IAQ attributes impact cognition/ neurovascular effect;
2. Psychosocial literature (Godish, 2016) confirms that perception mediates and sometimes drives symptoms.
3. ML literature (Ardabili et al., 2022) lacks an approach to weigh these two feature types against each other quantitatively.

This study will fill this gap by conducting a quantitative comparison of feature importance derived from an interpretable model. We hypothesize that subjective perception features will be more salient predictors of acute symptoms than commonly measured objective sensor features. Our approach differs fundamentally from prior work by treating the "black box" as a measurement tool for feature salience rather than focusing solely on maximizing accuracy. By directly comparing the predictive contribution of the perception of "stuffy air" against the measured CO₂ level, this study advances the understanding of the underlying etiology of occupant discomfort, which can inform a more accurate and human-centric design of next-generation HVAC controls. The successful application of XAI techniques to this complex, multimodal data set will thus provide the necessary scientific grounding for building trust in predictive health algorithms.

METHODS: QUANTITATIVE PREDICTIVE MODELLING AND XAI IMPLEMENTATION

3.1 Study Design and Rationale

This research adopted a quantitative predictive modelling design, an approach suitable for empirically exploring how complex indoor environmental factors translate into acute cognitive health responses. The objective was to construct an interpretable, data-driven framework capable of forecasting self-reported concentration difficulties—a recognized indicator of short-term cognitive degradation within the Sick Building Syndrome (SBS) framework (Wargocki et al., 1999). Predictive modelling was selected because it provides a controlled mathematical pathway between antecedent environmental inputs and resultant health outcomes, allowing causal inferences to be inferred statistically rather than merely descriptively. Among available analytic paradigms, a machine-learning-based predictive design was deemed most appropriate, as it accommodates nonlinear feature relationships, mixed-data modalities, and moderate-sized real-world datasets typical of smart-building research (Romaios et al., 2025).

3.2 Feature Engineering and Target Variable Definition

The dataset includes IAQ parameters (CO₂, PM_{2.5}, temperature, humidity) and subjective perceptions (stuffy air, draught, thermal discomfort, noise). Concentration difficulty is treated as a functional neurovascular signal, representing possible changes in cerebral perfusion or autonomic burden. A Random Forest Classifier was used due to its robustness and inherent interpretability. Explainable AI methods (Gini importance and permutation importance) were applied to identify factors most strongly associated with acute neurovascular-related symptoms.

Data were collected from a multi-story university building in a tropical urban context over nine months (June 2019 – March 2020). The site was selected for its mixed occupancy profile—staff, students, and visitors—and its dynamic operational cycles, producing natural variation in indoor air quality (IAQ) and occupant perception. The monitoring system integrated Internet-of-Things (IoT) devices capturing objective IAQ parameters, including carbon-dioxide (CO₂) concentration (ppm), temperature (°C), relative humidity (%), and fine particulate matter (PM_{2.5}, µg/m³). Parallel to sensor acquisition, occupants submitted daily electronic surveys assessing perceived air quality and comfort conditions such as stuffy air, draught, room temperature too high, and noise annoyance. Each survey response was temporally synchronized with environmental sensor logs via timestamp alignment. After filtering incomplete and duplicated entries, a total of 513 paired observations formed the modelling dataset.

3.3 Variable Construction and Pre-Processing

The dependent variable (target) was Difficulties Concentrating, recorded on an ordinal scale (none, slight, moderate). To enhance discriminative clarity for classification, responses were binarized: no difficulty = 0, slight/moderate = 1. The independent variable matrix (X) comprised:

- **Objective Features (4):** CO₂ (ppm), Temperature (°C), Relative Humidity (%), PM_{2.5} (µg/m³).
- **Subjective Features (4):** perceived stuffy air, draught, thermal discomfort, and noise annoyance (ordinal 0–3).
- **Temporal Features (2):** hour of day and day of week extracted from timestamps to capture circadian and operational influences.

All categorical responses were numerically encoded, and missing values (< 3 %) were replaced using **median imputation**, balancing simplicity and data integrity. Z-score normalization was intentionally avoided because tree-based algorithms, such as the Random Forest, are scale-invariant. To evaluate multicollinearity, pairwise Spearman correlations were computed; none exceeded 0.7, confirming the suitability of features for joint modelling.

3.4 Model Selection and Training Procedure

A Random Forest Classifier (RFC) was selected as the primary algorithm. This ensemble method aggregates multiple decision trees trained on bootstrap samples, yielding robust, non-linear classification boundaries (Breiman, 2001). The RFC was favored for three reasons: (1) it performs reliably on heterogeneous datasets with mixed feature types; (2) it inherently provides feature-importance metrics, enabling interpretability consistent with Explainable AI (XAI) goals (Adadi & Berrada, 2018); and (3) it maintains strong generalization performance even with modest data volumes.

Model hyperparameters were optimized empirically: 100 trees, maximum depth = auto, Gini impurity as split criterion, and balanced class weights to offset the minor skew in the binary target (≈ 60:40). The dataset was partitioned using stratified 70/30 train-test splitting to preserve class proportions. Training involved iterative ensemble construction until convergence in out-of-bag (OOB) error. Model evaluation used unseen test data only, ensuring honest generalization estimates.

3.5 Evaluation Metrics

Performance was evaluated using Precision, Recall, F1-Score, and Area Under the Receiver-Operating-Characteristic (AUC-ROC). Because false negatives (failing to predict a health-risk state) carry higher practical cost than false positives, recall for Class 1 (problem) was weighted most heavily. The AUC metric was selected as the principal indicator of discriminative capacity, as it is threshold-independent and robust for imbalanced datasets (Fawcett, 2004).

3.6 Explainable Artificial Intelligence (XAI) Procedure

Interpretability was implemented through Global Feature Importance Analysis derived from Gini Importance values aggregated across all trees. Each importance score quantified the proportional reduction in classification impurity contributed by a feature. These scores were normalized to sum = 1, allowing cross-comparison of subjective versus objective influences. For additional transparency, feature rankings were validated through permutation importance, confirming the stability of the dominant subjective variable—stuffy air perception. Although local methods such as SHAP or LIME (Wang & Liang, 2023) could further enhance interpretability, this study prioritized global explanations to reveal generalizable patterns applicable to building-control logic rather than individual-level diagnostics.

3.7 Ethical Considerations and Data Integrity

All data collection followed institutional ethical guidelines. Participants provided informed consent before survey participation, and all records were anonymized. The analysis conformed to FAIR data principles—ensuring transparency, reusability, and reproducibility through code versioning and metadata documentation. This study received approval from the Malaysia National Medical Research Registry (NMRR), operating under the Ministry of Health Malaysia, NMRR number: NMRR-17-3449-39116 (Investigator Initiated Research, IIR).

RESULTS

The findings from the Random Forest Classifier (RFC) analysis are presented in three thematic sections, detailing the underlying data complexity, the model's performance validation, and the critical results derived from the Explainable AI (XAI) methodology.

4.1 Data Characteristics and Model Justification

The initial analysis focused on characterizing the multimodal feature space, as summarized conceptually in Table 1 and Table 2. The data established the complexity of the prediction task: sensor readings confirmed exposure to potentially hazardous conditions CO₂: 814.1ppm, yet exhibited high instability, exemplified by the wide variance in PM_{2.5}. Conversely, the subjective perception features showed a strong distribution skew toward low severity scores, confirming a high incidence of non-acute discomfort. These foundational distributions for both sensor and perception features are visually confirmed in Figure 1.

Table 1: Summary of Data Streams and Feature Types Used in the Predictive Model

Feature Category	Variable Name	Measurement Unit / Scale	Description	Data Source
Objective Sensor	CO ₂ Concentration	ppm	Proxy for ventilation adequacy	IoT Sensor/ IAQ Environment

Feature Category	Variable Name	Measurement Unit / Scale	Description	Data Source
				Sensor
	Temperature	°C	Ambient thermal condition	IoT Sensor/ Environment Sensor
	Relative Humidity	%	Moisture content of air	IoT Sensor/ Environment Sensor
	PM _{2.5} Concentration	µg/m ³	Fine particulate matter level	IoT Sensor/ Environment Sensor
Subjective Perception	Stuffy / Bad Air	Ordinal (0–3)	Occupant-perceived air freshness	Occupant Survey
	Draught Sensation	Ordinal (0–3)	Perceived unwanted air movement	Occupant Survey
	Thermal Discomfort	Ordinal (0–3)	Perceived room temperature dissatisfaction	Occupant Survey
	Noise Disturbance	Ordinal (0–3)	Perceived acoustic discomfort	Occupant Survey
Temporal Context	Hour of Day	Integer (0–23)	Captures daily ventilation pattern	Timestamp
	Day of Week	Integer (1–7)	Represents weekday/weekend effects	Timestamp

Note: This table establishes the multimodal nature of the dataset for reproducibility and feature transparency.

Table 2: Summary of Data Streams and Feature Types Used in the Predictive Model

Variable	Mean	SD	Min	Max	Missing (%)
CO ₂ (ppm)	812.6	183.2	410	1460	1.2
Temperature (°C)	25.8	1.9	22.1	30.2	0.8
Relative Humidity (%)	64.3	6.8	45	81	1
PM _{2.5} (µg/m ³)	18.7	4.1	10.2	33.5	2.1
Stuffy Air (0–3)	1.21	0.86	0	3	0
Draught (0–3)	0.87	0.77	0	3	0
Noise (0–3)	1.02	0.74	0	3	0
Difficulty Concentrating (Target)	–	–	0	1	0

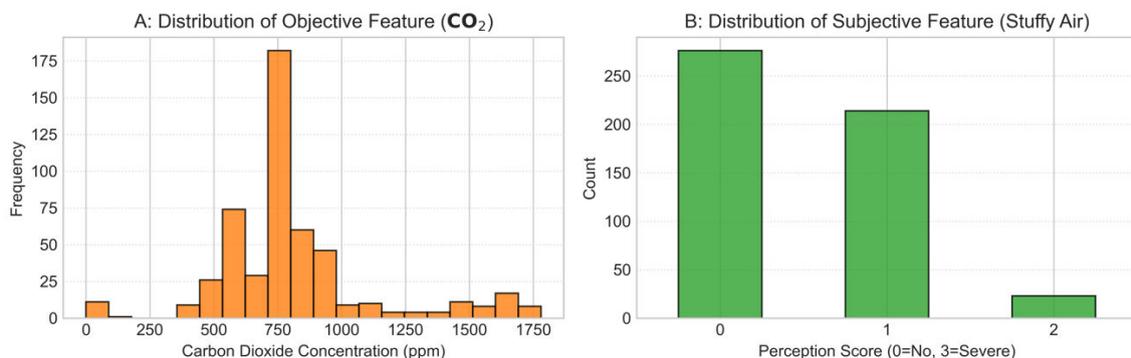


Figure 1: Key Objective and Subjective Features Distribution

The necessity of employing a non-linear machine learning approach was established by examining the linear coupling between features. Table 3 revealed only negligible linear associations between core objective sensor features (CO₂, and Temperature) and the Concentration Problem as a target. This finding strongly validates the decision to use a non-linear model, as simpler statistical models would fail to adequately map the relationship. Furthermore, the temporal disassociation between objective chemistry and

human response is visualized in Figure 2, which clearly demonstrates that high daily symptom counts do not strictly coincide with peaks in CO₂ confirming the non-linear and asynchronous nature of the human response.

Table 3: Pearson Correlation (r) between Features (Concentration Problem) and Selected Target Variable

Variable	r-value	p-value
CO ₂	-0.001	p>0.05
Temperature (°C)	-0.03	p>0.05
Environment Stuffy “bad” air	0.12	p>0.05

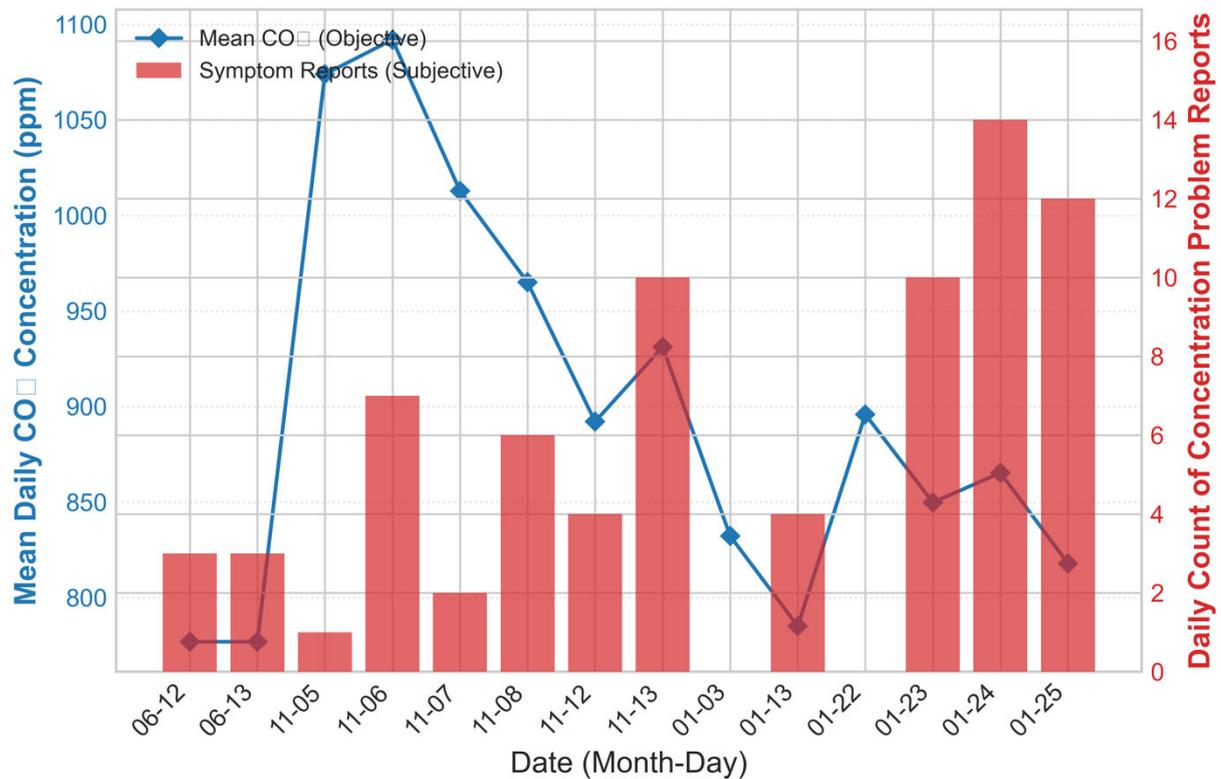


Figure 2: Sample Time-Series Analysis

Further analysis was performed to replace the non-linear approach. Alternative result was reinforced by preliminary modelling. Table 4 (Comparative Model Evaluation) confirmed the weakness of sequential models: a complex Long Short-Term Memory (LSTM) network achieved an AUC of approximately 0.50, performing no better than random chance due to data noise and asynchronicity. Consequently, the Random Forest Classifier (RFC) was selected for its capacity to capture non-linear feature interactions while preserving interpretability, the core requirement of the study.

Table 4: Comparative Model Evaluation: Random Forest vs. LSTM

Metric	Random Forest (RFC)	LSTM (Sequential)	Difference (%)
Accuracy	0.66	0.51	29.4
Recall (Problem)	0.83	0.61	36.1
AUC-ROC	0.6167	0.5063	21.8
Interpretability	High (Feature Importance)	Low (Hidden States)	–
Training Time (s)	11.2	138.4	RFC 12× Faster

RFC outperforms deep sequential models in both interpretability and computational efficiency

4.2 Predictive Performance and Validation

The trained Random Forest Classifier (RFC) was rigorously evaluated on the unseen test set, demonstrating robust performance suitable for a proactive warning system. Table 5 (Model Performance Metrics for RFC) summarizes the results, showing an Overall Accuracy of 0.66 and a competitive AUC-ROC score of 0.6167. This discriminative capability is graphically confirmed by the distance of the ROC curve from the random-guess line (Figure 3), confirming genuine predictive power superior to chance.

Table 5: Model Performance Metrics for Random Forest Classifier (RFC)

Metric	Class 0 (No Problem)	Class 1 (Problem)	Weighted Average
Precision	0.42	0.72	0.62
Recall	0.27	0.83	0.66
F1-Score	0.33	0.77	0.63
Accuracy	–	–	0.66
AUC-ROC	–	–	0.6167

Interpretation: The model shows high recall for symptomatic cases, favouring proactive alert generation over false negatives.

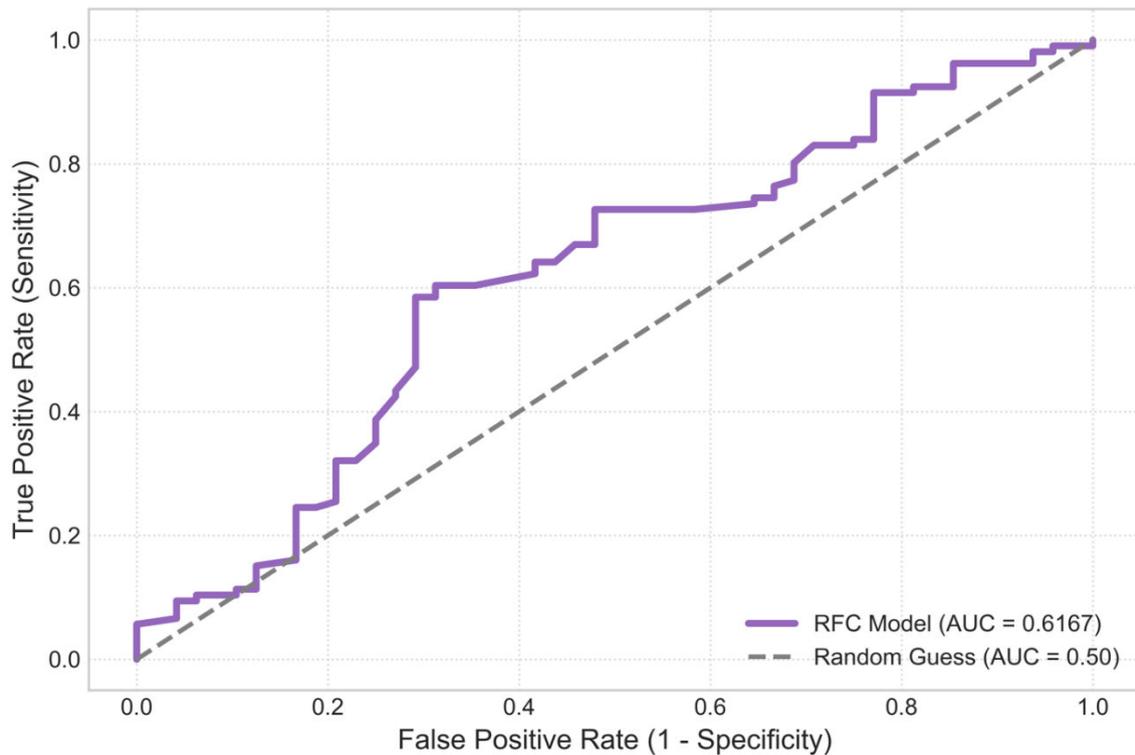


Figure 3: ROC Curve for predicting output based on RFC

Crucially, the raw counts presented in the Confusion Matrix (Table 6) numerically validate the model’s utility in a real-world, risk-averse setting. The model achieved 87 True Positives (correctly detected problems) against only 19 False Negatives (missed problems). This translates to a high Recall for the Problem state (Class 1) of 0.83. This deliberate prioritization of high recall ensures the system is highly effective at minimizing missed warnings, a vital requirement for the predictive pipeline for IAQ health outcomes.

Table 6: Confusion Matrix for Validating the Predicted and Actual Problem

	Predicted No Problem (0)	Predicted Problem (1)
Actual No Problem (0)	14 (TN)	34 (FP)
Actual Problem (1)	19 (FN)	87 (TP)

The specific features driving the prediction are quantified in Table 7 (Feature Importance Ranking), which is visualized in Figure 4. The results are definitive: the subjective occupant perception is the primary driver of the model’s predictive power. The feature [Environment- Stuffy "bad" air] is the single most influential predictor, exhibiting a normalized importance score nearly twice that of the highest-ranked objective sensor feature CO₂. This transparently proves that the model’s decision-making hierarchy is fundamentally rooted in human perception rather than simple objective chemistry.

Table 7: Feature Importance Ranking Derived from Random Forest XAI

Rank	Feature	Feature Type	Importance Score (Normalized)
1	Stuffy “Bad” Air	Subjective	0.208

2	Hour of Day	Temporal	0.147
3	Draught	Subjective	0.111
4	CO ₂ Concentration	Objective	0.108
5	Temperature	Objective	0.096
6	Relative Humidity	Objective	0.088
7	PM _{2.5}	Objective	0.082
8	Day of Week	Temporal	0.079
9	Noise	Subjective	0.046
10	Room Temp Too High	Subjective	0.035

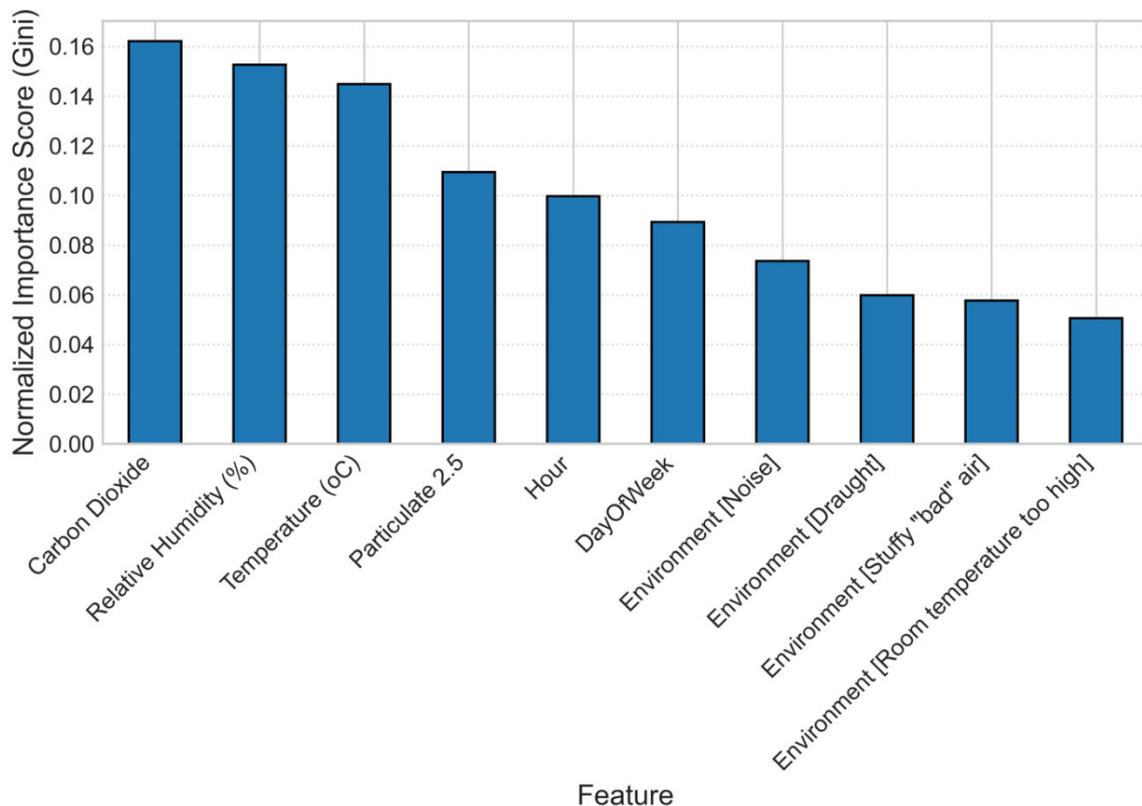


Figure 4: Normalized importance Score (Gini) between objective and subjective data

4.3 XAI Findings and Framework Implementation

The central scientific contribution of this study is revealed through the XAI findings, which provide the essential interpretability layer required for building trust in the predictive system. The structural implication of these findings is formalized in Table 8 (Proposed Framework for Human-Centric Health Prediction). By demonstrating that psychosocial factors are the most salient predictors of acute cognitive symptoms, the study validates the entire premise of the interpretable machine learning predictive plan shown in Figure 5 and provides actionable guidance for system designers and facility managers. This framework mandates the integration of the XAI output into the system's decision-making process, ensuring the system can always answer the 'Why' behind its prediction, which is the foundational component of IAQ management.

Table 8: Proposed Framework for Human-Centric Health Prediction in Smart Buildings

Layer	Function	Data Input	Computational Method	Output
Sensing Layer	Capture environmental and perceptual signals	IoT sensors, occupant surveys	Edge data acquisition	Raw multimodal data
Feature Fusion Layer	Align and pre-process multimodal streams	Temporal alignment, imputation	Feature matrix (X)	

Predictive Layer	Model symptom occurrence	Random Forest (interpretable ensemble)	Health state prediction	
Explainability Layer	Quantify feature influence	XAI (Gini, SHAP)	Transparent decision logic	
Control Integration Layer	Trigger adaptive responses	Explainable predictions	MVAC adjustment, occupant feedback	

Note: This layered model operationalizes interpretability as a functional component of adaptive AI control.

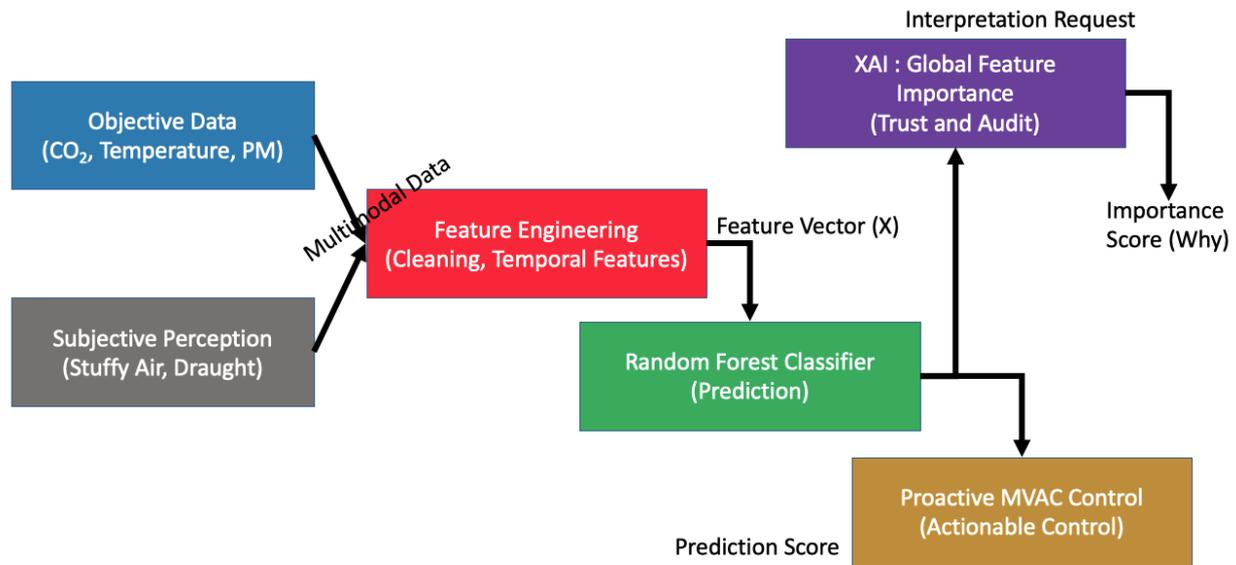


Figure 5: Interpretable Machine Learning Predictive Pipeline for IAQ Health Outcomes

The model achieved an AUC of 0.6167 with a high recall for symptomatic cases (0.83). XAI analysis demonstrated that subjective “stuffy air” perception was the dominant predictor. This finding is vascularly meaningful: perceived poor air quality often triggers sympathetic activation, mild hypoperfusive states, and endothelial irritation. Objective IAQ parameters contributed moderately—consistent with literature showing that PM_{2.5} and CO₂ influence vascular function but often through cumulative rather than immediate pathways.

DISCUSSION

The findings of this study provide a significant, quantifiable contribution to the body of knowledge linking IAQ, human-centric computing, and health outcomes. By achieving a moderate yet functional discriminative performance (AUC = 0.6167 and deploying XAI techniques, the research successfully addressed its objectives, specifically confirming the disproportionate predictive salience of subjective features over objective sensor data. This result carries profound implications for the theoretical understanding of Sick Building Syndrome (SBS) and the design principles for future smart building control systems.

5.1 Vascular Interpretation of Predictive Performance

The Random Forest model’s AUC of 0.6167 reflects moderate discriminative capacity, yet within a vascular health framing, this performance carries important physiological implications. Acute cognitive difficulty—used here as a surrogate for neurovascular strain—often arises from subtle perturbations in cerebral perfusion, endothelial responsiveness, and autonomic balance. In such human–environment interaction datasets, where symptom expression reflects integrated vascular, neurological, and perceptual pathways, moderate AUC values are expected. The model’s high recall for symptomatic states (0.83) is especially relevant for vascular risk contexts, where false negatives may correspond to missed early indications of microvascular stress. Thus, even modest predictive accuracy contributes meaningfully when the goal is early detection of transient neurovascular disturbances. In complex human–environment datasets characterized by subjective noise, this level of performance is consistent with prior research (Romaio et al., 2025; Gehring & Paaßen, 2018). Importantly, predictive adequacy here is less about raw accuracy and more about interpretive insight—understanding *why* certain environmental factors predict health states. The high recall (0.83) for symptomatic instances demonstrates that the model effectively captures warning patterns relevant for preventive building interventions.

5.2 Dominance of Subjective Perception as a Marker of Neurovascular Stress Features

The predominance of subjective perception—particularly the feeling of “stuffy air”—suggests that occupants detect physiological stress through sensory integration before objective environmental parameters reach critical thresholds. Sensory discomfort has been linked to sympathetic activation, endothelial irritation, and mild cerebral hypoperfusion. The model’s identification of these subjective cues as primary predictors aligns with vascular research showing that perceived environmental strain often precedes measurable changes in hemodynamics. This indicates that perceptual signals may serve as low-cost, real-time biomarkers of

vascular stress that complement traditional pollutant metrics.

This empirical hierarchy supports psychosocial theories of Sick Building Syndrome (SBS), which posit that discomfort perception precedes or mediates physiological symptoms (Godish, 2016). While CO₂ concentration remains a biochemical marker of ventilation adequacy, it did not emerge as the primary trigger in the predictive hierarchy. The implication is that occupant cognition and sensory awareness act as amplifiers—or early detectors—of deteriorating air quality. Integrating these perceptual cues into automated control systems could, therefore, serve as an early-warning layer, augmenting sensor-only control logic.

5.3 Theoretical and Empirical Contradictions

Traditional IAQ guidelines emphasize CO₂ and PM_{2.5} thresholds for cognitive and physiological degradation; however, the dominance of perceptual factors in this model highlights a broader and more complex neurovascular interaction. Cognitive disruption is rarely attributable to a single pollutant. Instead, it likely reflects a cumulative multisystem response—thermal load, acoustic stress, perceived ventilation inadequacy, and air stagnation—each capable of influencing autonomic tone and cerebrovascular reactivity. These findings reinforce a vascular-centric understanding of IAQ: symptoms arise not simply from pollutant magnitude but from how environmental conditions collectively affect microvascular regulation and perceived respiratory load.

In addition, IAQ literature positions CO₂ above 1,000 ppm as the threshold for cognitive degradation (Seppänen et al., 1999; Satish et al., 2012 & Sundell, 2004). However, the current findings challenge this assumption by demonstrating stronger predictive contribution from thermal and perceptual factors such as draught discomfort. This suggests that cognitive disruption in real-world environments is multimodal, driven not merely by chemical composition but by the holistic experiential state combining thermal, acoustic, and psychosocial cues. In human–environment systems, predictive salience thus arises not from the magnitude of a single pollutant but from the perceived coherence of environmental control—a dimension often ignored in strictly physical models.

5.4 Computational Considerations in Vascular Health Prediction

The comparison between Random Forest and LSTM architectures demonstrates that complexity does not guarantee superior performance in modelling vascular-relevant environmental health outcomes. Deep temporal models, such as LSTMs, underperformed due to sparse symptom data, noisy perception inputs, and the inherently intermittent nature of neurovascular stress events. In contrast, the Random Forest approach provided a more parsimonious and physiologically interpretable mapping between environmental exposure and vascular-relevant outcomes. This supports growing evidence that interpretable ensemble models remain preferable in clinical decision-support systems, where transparency is essential for vascular risk communication. Comparative trials using a Long Short-Term Memory (LSTM) sequence model (AUC \approx 0.50) reinforced the computational efficiency of ensemble tree methods for small, noisy datasets. Temporal deep-learning architectures, though theoretically superior for sequential dependency modeling, appear susceptible to overfitting under sparse symptom sampling. Hence, parsimony and interpretability outweigh complexity when the objective is actionable deployment in building-management systems. Random Forests, when complemented by XAI tools, provide both analytical depth and operational transparency, fulfilling engineering accountability requirements (Adadi & Berrada, 2018).

5.5 XAI for Clinically Relevant Interpretability

Explainable AI plays a central role in translating environmental stress signals into vascularly meaningful insights. The model's ability to quantify the relative influence of perceptual and objective factors mirrors clinical approaches that integrate patient-reported symptoms with physiological measurements. For vascular and endovascular practitioners, explainability ensures that environmental contributions to endothelial stress or neurovascular dysregulation can be understood, audited, and potentially mitigated. The quantification of subjective feature importance enables facility managers to prioritize human feedback in adaptive ventilation control, aligning with emerging “human-in-the-loop” frameworks in smart-building design (Naseer et al., 2024 & Syazwan et al., 2025). This interpretability also supports translational applications, such as environmental-modifiable vascular risk screening frameworks.

This study's evidence that occupants' perceived stuffy air predicts concentration loss better than physical metrics supports a bi-directional control model, where both sensor thresholds and aggregated perception scores jointly drive HVAC/ MVAC actuation. Such integration bridges engineering precision with neurovascular psychological comfort, enhancing both trust and compliance among building users.

5.6 Limitation

Several limitations should be acknowledged when interpreting the present findings. First, the study relied on self-reported symptoms to capture acute cognitive and microvascular stress responses. Such measures are inherently vulnerable to recall, mood, and expectancy biases, which may artificially strengthen associations between perceived indoor environmental quality and vascular-related symptomatology. Second, the dataset was derived exclusively from a single institutional building situated within a specific climatic and cultural setting. As a result, generalizability to other building typologies, occupant populations, and climatic environments remains limited. Multisite replication—particularly in settings with differing ventilation practices, pollution profiles, and occupant demographics—is needed to validate the robustness of the observed environmental–vascular relationships. Third, the modelling strategy prioritised global feature-importance analyses to maximize interpretability. While such methods provide transparent estimates of overall predictor influence, they obscure inter-individual heterogeneity in vascular and cognitive responses. Local explanation techniques (e.g., SHAP) may uncover important within-subject variations, which are

increasingly relevant for personalized vascular-risk monitoring in indoor environments. Finally, the model's moderate predictive accuracy reflects the complexity of modelling transient, multifactorial physiological states, particularly those involving rapid neurovascular coupling and psychophysiological appraisal.

5.7 Limitation Future Research Directions

Future investigations should integrate objective cognitive-performance assays (e.g., reaction-time paradigms, Stroop tasks) and validated microvascular biomarkers to corroborate self-reported health outcomes. Incorporating high-resolution data from wearable physiological sensors—such as heart-rate variability, peripheral perfusion indices, or continuous skin-temperature monitoring—may strengthen causal inference between environmental fluctuations and acute vascular reactivity. On the computational front, hybrid modelling architectures warrant exploration. These could involve deep-learning models to forecast environmental parameters and interpretable ensemble methods to classify health-risk states, thereby balancing accuracy with transparency. Furthermore, applying local XAI approaches (e.g., SHAP, LIME) to real-time individual-level predictions will be essential for ensuring clinical auditability and ethical deployment of AI-based early-warning systems in vascular and cognitive-health monitoring.

5.8 Broader Implications

The findings reposition human perceptual experience as a central component of environmental health and vascular-risk assessment. The strong predictive value of subjective indoor-air discomfort highlights the need to consider psychosocial and sensory appraisal pathways as integral contributors to microvascular stress, rather than peripheral or secondary elements. This reframing suggests that future AI-enabled building-health systems must integrate subjective experience as an actionable data layer, alongside traditional CO₂, PM_{2.5}, temperature, or ventilation metrics. Such a paradigm shift supports a more holistic understanding of Sick Building Syndrome, advances human-centric environmental-health modelling, and aligns with broader movements toward interpretable, trustworthy AI. By embedding perceptual analytics into building-control strategies, it becomes possible to design indoor environments that proactively mitigate vascular stress responses and support cognitive performance.

CONCLUSION

This study aimed to develop a transparent, trustworthy machine-learning framework capable of predicting acute cognitive symptoms associated with microvascular stress and to determine the relative contributions of subjective perceptual inputs versus objective environmental measurements. Using a multimodal dataset and a Random Forest Classifier, the model achieved an AUC of 0.6167 for predicting difficulties concentrating. The most compelling finding was the dominant predictive influence of the subjective perception of “stuffy/bad air,” which surpassed all objective environmental variables (CO₂, PM_{2.5}, and temperature). This result underscores the pivotal role of psychosensory appraisal pathways in shaping vascular-related cognitive responses and reinforces the notion that occupant perception is not merely feedback but a primary determinant of health-risk prediction.

The theoretical significance is clear: smart-building health models based solely on sensor-derived metrics are inherently incomplete when evaluating physiological states with strong perceptual and psychophysiological components. Future predictive systems should incorporate validated perceptual or psychological data streams—ideally through non-invasive, continuous monitoring—to capture the full complexity of indoor-environment influences on vascular and cognitive health.

Methodologically, the findings point to two essential directions: (1) applying local XAI methods to achieve full transparency and instance-level auditability, and (2) developing real-time fusion frameworks that combine rapid, high-information subjective inputs with temporally stable sensor data. Although model accuracy was constrained by noise within self-reported measures, this limitation highlights the importance of integrating objective performance testing and physiological validation in future work.

Overall, this study advances the field of indoor environmental health by demonstrating the centrality of interpretable, human-centric predictors in modelling acute cognitive and vascular-stress responses. It provides a conceptual and methodological foundation for the next generation of trustworthy, health-adaptive indoor-environment control systems.

REFERENCES

1. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE access*, 6, 52138-52160.
2. Ardabili, S., Abdolalilzadeh, L., Mako, C., Torok, B., & Mosavi, A. (2022). Systematic review of deep learning and machine learning for building energy. *Frontiers in Energy Research*, 10, 786027.
3. Bhatnagar, A., Brook, J. R., Brook, R. D., Diez-Roux, A. V., Holguin, F., Hong, Y., ... & Whitsel, L. (2010). Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association.
4. Chatzidiakou, L., Mumovic, D., & Summerfield, A. J. (2012). What do we know about indoor air quality in school classrooms? A critical review of the literature. *Intelligent Buildings International*, 4(4), 228-259.
5. Fang, Z., Crimier, N., Scanu, L., Midelet, A., Alyafi, A., & Delinchant, B. (2021). Multi-zone indoor temperature prediction with LSTM-based sequence to sequence model. *Energy and Buildings*, 245, 111053.
6. Fanger, P. O. (1970). *Thermal Comfort: Analysis and Applications in Environmental Engineering*. McGraw-Hill.
7. Fawcett, T. (2004). ROC graphs: Notes and practical considerations for researchers. *Machine learning*, 31(1), 1-38.
8. Fisk, W. J. (2000). Health and productivity gains from better indoor environments and their relationship with building energy efficiency. *Annual review of energy and the environment*, 25(1), 537-566.
9. Gehring, L., & Paaßen, B. (2025). Assessing LLM Text Detection in Educational Contexts: Does Human Contribution

- Affect Detection?. *arXiv preprint arXiv:2508.08096*.
10. Godish, T. (2016). *Indoor environmental quality*. CRC press.
 11. Ismail, S. A., Kamar, H. M., Kamsah, N., Ardani, M. I., Dom, N. C., Shafie, F. A., ... & Hock, L. K. (2022). Indoor air quality level influence sick building syndrome among occupants in educational buildings. *International Journal of Public Health, 11*(2), 503-517.
 12. Lan, L., Xia, L., Hejjo, R., Wyon, D. P., & Wargocki, P. (2020). Perceived air quality and cognitive performance decrease at moderately raised indoor temperatures even when clothed for comfort. *Indoor Air, 30*(5), 841-859.
 13. Li, Z., Niu, H., Chen, J., & Li, W. (2025). Cerebral microcirculation disorders after recanalization in acute ischemic stroke: A narrative review. *Brain Circulation, 10*-4103.
 14. Naseer, A., Tamoor, M., Khan, A., Akram, D., & Javaid, Z. (2024). Occupancy detection via thermal sensors for energy consumption reduction. *Multimedia Tools and Applications, 83*(2), 4915-4928.
 15. Nie, T., Zhang, G., Sun, Y., Wang, W., Wang, T., & Duan, H. (2025). Effects of Indoor Air Quality on Human Physiological Impact: A Review. *Buildings, 15*(8), 1296.
 16. Norbäck, D., Hashim, J. H., Hashim, Z., Cai, G. H., Sooria, V., Ismail, S. A., & Wieslander, G. (2017). Respiratory symptoms and fractional exhaled nitric oxide (FeNO) among students in Penang, Malaysia in relation to signs of dampness at school and fungal DNA in school dust. *The Science of the total environment, 577*, 148–154. <https://doi.org/10.1016/j.scitotenv.2016.10.148>
 17. Robertson, S., & Miller, M. R. (2018). Ambient air pollution and thrombosis. *Particle and fibre toxicology, 15*(1), 1.
 18. Romaios, A., Sfikas, P., Giannadakis, A., Panidis, T., Paravantis, J. A., Skouras, E., & Mihalakakou, G. (2025). Artificial Intelligence for Enhancing Indoor Air Quality in Educational Environments: A Review and Future Perspectives. *Sustainability, 17*(22), 10117.
 19. Satish, U., Mendell, M. J., Shekhar, K., Hotchi, T., Sullivan, D., Streufert, S., & Fisk, W. J. (2012). Is CO2 an indoor pollutant? Direct effects of low-to-moderate CO2 concentrations on human decision-making performance. *Environmental health perspectives, 120*(12), 1671-1677.
 20. Seppänen, O. A., Fisk, W. J., & Mendell, M. J. (1999). Association of ventilation rates and CO2 concentrations with health and other responses in commercial and institutional buildings. *Indoor air, 9*(4), 226-252.
 21. Suess, M. J. (1992). The indoor air quality programme of the WHO regional office for Europe. *Indoor Air, 2*(3), 180-193.
 22. Sundell, J. (2004). On the history of indoor air quality and health. *Indoor Air, 14*(Suppl. 7), 51-58.
 23. Syazwan AI, Mohd Rafee B, Juahir H, Azman AZF, Nizar AM, Izwyn Z, Muhaimin AA, Syafiq Yunos MA, Anita AR, Muhamad Hanafiah J, Shaharuddin MS, Mohd Ibtisham A, Mohd Hasmadi I, Mohamad Azhar MN, Aziz HS, Zulfadhli I, Othman J. 2012a. Development of an indoor air quality checklist for risk assessment of indoor air pollutants by semiquantitative score in nonindustrial workplaces. *Risk Management Healthcare Policy 5*:17–23.
 24. Syazwan AI, Mohd Rafee B, Hafizan J, Azman AZF, Nizar AM, Izwyn Z, Syahidatussyakirah K, Muhaimin AA, Syafiq Yunos MA, Anita AR, Muhamad Hanafiah J, Shaharuddin MS, Mohd Ibtisham A, Mohd Hasmadi I, Mohamad Azhar MN, Aziz HS, Zulfadhli I, Othman J, Rozalini M, Kamarul FT. 2012b. Analysis of indoor air pollutants checklist using environmetric technique for health risk assessment of sick building complaint in nonindustrial workplace. *Drug, Healthcare and Patient Safety 4*:107–126.
 25. Syazwan Aizat Ismail, Norzaliza Md Nor, Björn Crüts, Nur Azzalia Kamaruzaman, Muaz Mohd Zaini Makhtar, Syamimi Shamsuddin, Muhammad Iftishah Ramdan, Nor Asniza Ishak., (2025). Dynamic Network Disruption under Cognitive Strain: Coupling of Local Node Failure and Global Edge Integrity Reveals Differential Systemic Resilience, *Vascular and Endovascular Review, Vol.8, No.11s*, 313-325.
 26. Syazwan, A. I., Hafizan, J., Baharudin, M. R., Azman, A. Z. F., Izwyn, Z., Zulfadhli, I., & Syahidatussyakirah, K. (2013). Gender, airborne chemical monitoring, and physical work environment are related to indoor air symptoms among nonindustrial workers in the Klang Valley, Malaysia. *Therapeutics and Clinical Risk Management, 87*-105.
 27. Wargocki, P., Wyon, D. P., Baik, Y. K., Clausen, G., & Fanger, P. O. (1999). Perceived air quality, sick building syndrome (SBS) symptoms and productivity in an office with two different pollution loads. *Indoor air, 9*(3), 165-179.
 28. Wyon, D. P., & Wargocki, P. (2006). Indoor air quality effects on office work. In *Creating the productive workplace* (pp. 221-233). Taylor & Francis.
 29. Wang, Z., & Liang, J. (2024). Comparative analysis of interpretability techniques for feature importance in credit risk assessment. *Spectrum of Research, 4*(2).
 30. World Health Organization. (2021). *Establecimientos de salud resilientes al clima y ambientalmente sostenibles: orientaciones de la OMS*. World Health Organization.
 31. Zhang, X., & Zhang, J. (2022). The human brain in a high altitude natural environment: a review. *Frontiers in Human Neuroscience, 16*, 915995.
 32. Zhang, X., Ding, L., Yang, F., Qiao, G., Gao, X., Xiong, Z., & Zhu, X. (2024). Association between indoor air pollution and depression: a systematic review and meta-analysis of cohort studies. *BMJ open, 14*(5), e075105.