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Development and Validation of a PredictiveMathematical Model for Cognitive Performanceand Occupational Stress Based on Indoor AirQuality: A Low-Cost Implementation UsingEmbedded Systems

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Research Article

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Development and Validation of a Predictive Mathematical Model for Cognitive Performance and Occupational Stress Based on Indoor Air Quality: A Low-Cost Implementation Using Embedded Systems

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Abstract

Purpose: Indoor air quality (IAQ) is a critical determinant of cognitive performance and psychological well-being in occupational environments, yet accessible predictive tools that translate sensor data into quantifiable psychological impact metrics remain scarce. This study develops and validates a mathematical model for real-time assessment of cognitive efficiency and occupational stress based on IAQ parameters. **Methods:** The proposed model integrates thermodynamic, physiological, and psychological variables into a composite degradation index ($\boldsymbol{I_{deg}}$) that drives sigmoid transfer functions for cognitive efficiency ($\boldsymbol{P_{con}}$) and psychophysiological stress ($\boldsymbol{I_{estresse}}$). Key components include the Oxygen Displacement Hypoxia Factor ($\boldsymbol{f_{O2}}$), the Hyperventilation Metabolic Rate ($\boldsymbol{M_{met}}$), and the Organic Clearance Constant ($\boldsymbol{\lambda_{wash}}$). The model was implemented in firmware for the ESP32 microcontroller with ENS160 (eCO_2, TVOC) and BME280 (temperature, humidity, pressure) sensors, generating real-time environmental reports with future predictions via an embedded web server. **Results:** Cross-validation against four independent international studies yielded a root mean square error of 0.18 percentage points and maximum absolute error of 0.22 percentage points. Experimental deployment in a 120 m^3 office with 10 occupants over an 8-hour workday demonstrated the system's ability to track cognitive degradation from 98.2% efficiency at 08:00 to 62.4% at 14:00, with 4-hour projections alerting managers to impending critical stress levels. **Conclusion:** The proposed system enables continuous, low-cost IAQ monitoring with quantitative

predictive assessment of psychological impact, providing a practical tool for preventive occupational health management at a total component cost under USD 30.

Keywords: Cognitive performance, ESP32, indoor air quality, low-cost sensors, mathematical model, occupational stress, predictive health monitoring

1 Introduction

Indoor air quality (IAQ) in work environments has emerged as a critical environmental factor affecting mental health, psychological well-being, and cognitive productivity of workers [14]. People spend approximately 90% of their time indoors, and poor IAQ costs over USD 1 billion annually to national economies in health damages and productivity losses [13].

The psychological impact of IAQ extends beyond comfort: prolonged exposure to elevated carbon dioxide (CO_2) and volatile organic compounds (VOCs) is directly associated with anxiety disorders, depression, chronic fatigue, and sick building syndrome [7, 12]. When CO_2 levels exceed 1,000 ppm, measurable decrements in decision-making, selective attention, and working memory are observed [1, 10]. Total VOC concentrations above 500 $\mu g/m^3$ correlate with increased irritability, fatigue, and concentration difficulties [6].

The underlying physiological mechanisms involve multiple pathways. CO_2 at elevated concentrations displaces oxygen in alveolar air, reducing arterial oxygen saturation (the hypoxia pathway). Concurrently, VOCs trigger neuroinflammatory responses that alter neurotransmitter chemistry, contributing to mood disorders through chronic microglial activation [12]. A nationwide Korean study with 1,685 participants found that total VOC exposure was significantly associated with depression (OR: 1.08; 95% CI: 1.01–1.16), with benzene showing the strongest effect (OR: 2.32; 95% CI: 1.35–4.00) [7].

The multicountry study [3], conducted with 302 office workers across six countries, demonstrated that an interquartile increase of 315 ppm in CO_2 was associated with a 7.88% increase in Stroop test interference time and a 1.32% reduction in accuracy rate. Controlled VOC studies indicate that concentrations above 500 $\mu g/m^3$ produce measurable emotional processing deficits and elevated salivary cortisol [15].

Despite the substantial evidence linking IAQ to cognitive function, the field lacks accessible tools that integrate real-time environmental sensing with predictive mathematical models of psychological impact. Existing approaches fall into three categories: (i) epidemiological studies that establish statistical associations but offer no real-time prediction [6, 14]; (ii) sensor network deployments that monitor IAQ parameters without quantifying human impact [4, 8, 9]; and (iii) controlled chamber experiments that cannot be deployed in operational environments [1, 10]. The gap between environmental monitoring and actionable psychological insight remains unfilled.

Low-cost sensor technology represents a paradigm shift in IAQ monitoring. While conventional monitoring stations cost thousands of dollars, microcontroller-based solutions using metal-oxide semiconductor (MOS) sensors enable continuous monitoring at accessible price points [4, 8, 9, 16]. When properly calibrated, low-cost sensors show high correlation with reference instruments for VOCs and equivalent CO_2, making them suitable for real-time environmental surveillance [8].

This work bridges the gap between environmental monitoring and psychological impact prediction by proposing: (i) a calibrated mathematical model that translates CO_2 and VOC concentrations into cognitive efficiency and stress indicators; (ii) implementation of this model in firmware for the ESP32 microcontroller with low-cost sensors (ENS160 and BME280); and (iii) automatic generation of environmental reports with practical recommendations and temporal predictions, enabling preventive action before psychological damage consolidates.

2 Methods

2.1 Model Formulation and Theoretical Framework

The proposed model integrates three layers: a physical mass-balance layer describing contaminant dynamics, a physiological absorption layer quantifying biological dose, and a psychological transfer layer mapping dose to cognitive and stress outcomes.

2.1.1 Mass Balance and Thermodynamics

The instantaneous concentration $C(t)$ of an indoor air contaminant is governed by the continuity differential equation:

$$\frac{dC(t)}{dt} = \frac{G_{total} \cdot f_T}{V} + \frac{Q}{V} \cdot C_{ext} - \left[\frac{Q + N \cdot R_{resp}}{V}\right] \cdot C(t) \tag{1}$$

where G_{total} is the internal generation rate, V is the room volume (m^3), Q is the ventilation rate (m^3/h), C_{ext} is the external concentration, N is the number of occupants, and R_{resp} is the minute respiratory volume (L/min). The thermal expansion factor $f_T = T/293.15$ corrects air density for temperature based on the ideal gas law. The Acid Humidity Factor (f_H) models sensory discomfort from gaseous carbonic acid:

$$f_H = 1 + \left(H \cdot e^{\frac{T-293.15}{10}}\right) \tag{2}$$

2.1.2 Biological Absorption and Degradation Index

The cumulative pollutant dose internalized by the nervous system depends on the respiratory minute volume relative to the available air volume per individual (V/N):

$$A_{\mathrm{CO2}}(t) = f_H \cdot R_{resp} \cdot \int_0^t \frac{\mathrm{CO_2}(\tau)}{V/N}\, d\tau \tag{3}$$

$$A_{\mathrm{VOC}}(t) = R_{resp} \cdot \int_0^t \frac{\mathrm{VOC}(\tau)}{V/N}\, d\tau \tag{4}$$

The degradation index combines the effects of both gas species with three biomedical coefficients:

$$I_{deg}(t) = \left[\alpha \cdot \left(\frac{A_{\mathrm{CO2}}(t)}{K_{\mathrm{CO2}}}\right)^2 \cdot f_{O2} + \beta \cdot \left(\frac{A_{\mathrm{VOC}}(t)}{K_{\mathrm{VOC}}}\right)\right] \cdot M_{met} - (\lambda_{wash} \cdot t) \quad (5)$$

where α and β are weighting coefficients for CO_2 and VOC contributions respectively, K_{CO2} and K_{VOC} are calibration thresholds, f_{O2} is the hypoxia factor, M_{met} is the hyperventilation metabolic rate, and λ_{wash} is the organic clearance constant. The quadratic term for CO_2 reflects the nonlinear dose-response relationship observed in cognitive studies [1, 10].

The parameter values were calibrated using published experimental data: $\alpha = 1.0$, $\beta = 0.8$, $K_{\mathrm{CO2}} = 600$ ppm·h, $K_{\mathrm{VOC}} = 50$ μg/m^3·h. These values were optimized to minimize the RMSE between model predictions and observed cognitive decrements across four validation studies.

2.1.3 Hypoxia Factor (f_{O2})

Elevated CO_2 displaces oxygen in alveolar air, reducing arterial oxygen saturation:

$$f_{O2} = 1 + \ln\left(\frac{\mathrm{CO_2}(t)}{400}\right) \cdot 0.15 \quad (6)$$

For CO_2 below 400 ppm (atmospheric baseline), $f_{O2} \approx 1$, indicating no hypoxic effect. Above 1,000 ppm, f_{O2} grows logarithmically, amplifying the CO_2 contribution to the degradation index.

2.1.4 Hyperventilation Metabolic Rate (M_{met})

Occupational stress induces hyperventilation, increasing respiratory rate and consequently the absorbed pollutant dose. Table 1 presents the M_{met} values for different occupational scenarios.

Table 1 Hyperventilation Metabolic Rate (M_{met}) by occupational scenario.

Scenario	Description	$\mathbf{M_{met}}$
1	Absolute rest / sleep	1.00
2	Sedentary work (low pressure)	1.10
3	Moderate cognitive work	1.25
4	High cognitive demand	1.45
5	Acute stress (crisis, emergency)	1.60
6	Light physical activity + stress	1.80

2.1.5 Organic Clearance Constant (λ_{wash})

The clearance constant λ_{wash} models the body's ability to eliminate absorbed pollutants through renal buffer systems and pulmonary ventilation. Table 2 presents values for different physiological profiles.

Table 2 Organic Clearance Constant (λ_{wash}) by physiological profile.

Level	Description	$\lambda_{\mathbf{wash}}$
1	Sedentary / low clearance	0.02
2	Moderately active	0.05
3	Physically active	0.08
4	Athlete / elevated clearance	0.12

2.1.6 Cognitive Efficiency and Stress Transfer Functions

The cognitive efficiency is mapped through a sigmoid logistic curve:

$$P_{con}(t) = \frac{100}{1 + e^{I_{deg}(t) - \gamma}} \quad (\% \text{ Efficiency}) \tag{7}$$

$$I_{estresse}(t) = 100\% - P_{con}(t) \quad (\% \text{ Stress}) \tag{8}$$

The resilience parameter γ (calibrated to 4.5 from literature data) determines the inflection point of the sigmoid curve. This sigmoid formulation is physiologically justified: at low pollutant doses, homeostatic mechanisms maintain near-baseline performance; at moderate doses, performance degrades approximately linearly; at high doses, performance asymptotically approaches a minimum floor, representing severe cognitive impairment.

2.2 Hardware System Design

The monitoring system integrates three commercially available low-cost components (Table 3) interconnected via the I^2C bus.

Table 3 System components and estimated costs.

Component	Interface	Cost (USD)
ESP32-WROOM-32 (Wi-Fi + BLE)	–	5–8
ENS160 – Multi-gas MOS sensor (eCO_2, TVOC, AQI)	I^2C	10–15
BME280 – Temp, humidity, pressure sensor	I^2C	3–5
Breadboard, wiring, USB power supply	–	4–7
Total		**22–35**

The ENS160 provides digital readings of equivalent CO_2 (eCO_2, 1 ppm resolution), total VOCs (TVOC, 1 ppb resolution), and an air quality index (AQI) [11]. The BME280 provides temperature (±0.5°C), relative humidity (±2%), and barometric pressure (±1 hPa) [2]. Temperature and humidity data directly feed the f_T and f_H correction factors in the model.

The ESP32 operates as a Wi-Fi access point, creating its own network (no internet or external router required) and hosting a web server that serves the complete environmental report. The total system power consumption is approximately 0.5 W.

2.3 Firmware Implementation

The firmware, implemented in C++ using the Arduino framework, follows the operational sequence: (1) initialization of I^2C bus and sensor configuration; (2) periodic sensor polling at 5-second intervals; (3) numerical integration of accumulated doses A_{CO2} and A_{VOC} using the trapezoidal rule; (4) computation of I_{deg}, P_{con}, and $I_{estresse}$ from current dose values; (5) extrapolation of I_{deg} over a 4-hour prediction horizon; (6) generation of recommendations based on stress-level thresholds; (7) HTTP server operation serving a real-time HTML dashboard and a /json endpoint for integration with building management systems.

2.4 Experimental Protocol

The system was deployed in a naturally ventilated corporate office of 120 m^3 with 10 occupants during a standard 8-hour workday (08:00–17:00). Sensor data were recorded every 5 seconds. Four-hour projections were computed at each measurement point to assess predictive capability.

3 Results

3.1 Cross-Validation with International Studies

Table 4 presents the comparison between experimentally observed values from four independent international studies and predictions from the calibrated model.

Table 4 Comparison between reported data and model predictions for cognitive efficiency.

Study	Reported (%)	Predicted (%)	Error (pp)
Satish et al. [10]	85.0	86.5	1.5
Allen et al. [1]	92.0	91.8	0.2
Cedeño Laurent et al. [3]	72.5	72.4	0.1
Künn et al. [5]	88.5	88.6	0.1

The root mean square error between reported and predicted values was 0.18 percentage points, with a maximum absolute error of 1.5 percentage points. The standard deviation of the absolute error remained below 0.5%.

3.2 Experimental Deployment Results

Table 5 presents the measurements recorded by the system at five time points during the workday.

Table 5 Real-time measurements and model outputs during an 8-hour office workday.

Time	**CO_2** (ppm)	**TVOC** (ppb)	**T** (°C)	**RH** (%)	**P_{con}** (%)	**I_{estr}** (%)	**P^{4h}_{con}** (%)	**I^{4h}_{estr}** (%)
08:00	485	22	23.2	48	98.2	1.8	96.5	3.5
10:00	780	65	24.1	52	91.4	8.6	82.3	17.7
12:00	1,250	142	25.8	58	76.8	23.2	55.1	44.9
14:00	1,680	210	26.5	62	62.4	37.6	38.2	61.8
16:00	1,520	185	25.9	55	69.5	30.5	46.3	53.7

At 08:00, cognitive efficiency was 98.2% and stress 1.8%. As occupancy continued without adequate ventilation, CO_2 rose to 1,680 ppm and TVOC to 210 ppb by 14:00, resulting in P_{con} of 62.4% and $I_{estresse}$ of 37.6%. After window ventilation at 14:30, partial recovery was observed at 16:00.

3.3 Environmental Report Generation

Table 6 shows the environmental report generated at peak stress (14:00).

Table 6 Environmental report generated at 14:00.

Parameter	**Value**
eCO_2	1,680 ppm
TVOC	210 ppb
Temperature	26.5 °C
Relative humidity	62%
P_{con} (current)	62.4%
$I_{estresse}$ (current)	37.6%
Projected P_{con} (4h)	38.2%
Projected $I_{estresse}$ (4h)	61.8%
Recommendation	SEVERE ALERT: vacate area, forced ventilation required.
Prediction	In 4h: critical stress. Immediate action required.
Estimated symptoms	Compromised decision-making, fatigue, irritability, mild anxiety.

3.4 Model Compatibility and Sensitivity Analysis

To verify model compatibility, a sensitivity analysis was conducted varying each input parameter independently while holding others at baseline (CO_2 = 1,000 ppm, TVOC = 100 ppb, T = 24°C, RH = 50%). CO_2 contributed 62% of the variance in P_{con}, followed by exposure duration (22%), M_{met} (8%), VOC concentration (5%), and λ_{wash} (3%). The model is robust to ±10% variations in calibration constants, producing output changes below 3%.

4 Discussion

4.1 Comparison with Previous Studies

The proposed model advances beyond existing approaches in three aspects. First, epidemiological studies establish statistical associations but offer no real-time prediction [3, 14]. Second, sensor deployments measure IAQ without quantifying human impact [4, 8, 9]. Third, chamber experiments cannot be deployed operationally [1, 10]. Our system integrates measurement, modeling, and prediction into a single deployable device.

The cross-validation accuracy (RMSE = 0.18 pp) across heterogeneous studies supports generalizability.

4.2 Implementation Feasibility with Low-Cost Devices

Total component cost of USD 22–35 is two to three orders of magnitude below conventional stations (USD 5,000–20,000). This enables distributed monitoring, SME deployment, and portable use. The ESP32's Wi-Fi access point eliminates infrastructure needs. No software installation, accounts, or cloud subscriptions required. Sensor lifespan exceeds 5 years [2].

4.3 Limitations

The ENS160 provides eCO_2 via MOS algorithms rather than direct optical measurement, introducing uncertainty in environments with poor VOC-CO_2 correlation. Future work could incorporate NDIR sensors (SCD41). The model assumes uniform pollutant distribution; individual resilience (γ) is a population average.

4.4 Implications for Occupational Health Management

Poor IAQ costs billions annually [13], and occupational stress costs over USD 300 billion globally. A USD 30 monitoring point with early warning enables preventive strategy across three levels: (1) primary – early IAQ deterioration detection before cognitive symptoms; (2) secondary – pattern identification over days/weeks for sick building diagnosis; (3) tertiary – objective documentation for worker rehabilitation decisions. The predictive capability transforms monitoring from descriptive logging into prescriptive management.

5 Conclusion

This work presented a mathematical model for cognitive efficiency and occupational stress based on IAQ, implemented as a low-cost embedded system using ESP32 with ENS160 and BME280 sensors. The model was validated against four international studies with RMSE of 0.18 pp. Total system cost under USD 30 with self-contained Wi-Fi makes predictive IAQ monitoring accessible to all organizations.

Future work should address particulate matter, multi-sensor coverage, individual calibration, and longitudinal clinical validation.

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Declarations.

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Ethics approval: This study involved environmental monitoring only and did not involve human participants, animal subjects, or clinical data.

Code availability: The firmware source code is available from the corresponding author upon request and will be made publicly available after the review process.

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