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(Research Article)

IoT Sensing for Green Buildings: An Assessment of Indoor Environmental Risk in Vulnerable Occupants

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Highlights

- A simulation framework is proposed for assessing indoor environmental risk in IoT-enabled green buildings.
- The model combines IEQ indicators, health-condition, monitoring capability, and time-dependent risk evolution.
- Results show that the Green Monitored House remains in the low-risk region, while the Bad Climate House reaches high-risk region.

Abstract

Green buildings not only operate as energy-efficient structures but are also enriched with various sensors and network-supported environments. These are capable of sustaining high indoor environmental quality. This paper presents a simplified deterministic simulation framework for quickly assessing how IoT-monitored green buildings may reduce indoor environmental risk for occupants with chronic health vulnerabilities. The model is motivated by previous work on green residences, housing conditions, and their relationship to physical and psychological health, where indoor air quality, ventilation, thermal comfort, humidity, noise, lighting, dust, chemical exposure, and smoke are treated as relevant housing-related factors.

A simulation (virtual time of 100 days) was conducted using 100 code-generated participants distributed across two building categories: a Bad Climate House and a Green Monitored House. Three chronic-condition profiles were taken into consideration, such as asthma, chronic obstructive pulmonary disease, and anxiety/stress. This prototype version of the developed Octave-compatible code allows the baseline behavior of the proposed risk model to be examined directly. The simulation protocol included nine indoor environmental indicators and a normalized risk score ranging from 0 to 100, with values classified as low, moderate, or high risk.

The results showed a clear difference in quality between the two building categories. In the Bad Climate House, final risk scores extended to high levels. In contrast, the Green Monitored House achieved low final risk scores. At the building level, the final mean risk was approximately 100,00 for the Bad Climate House and 9,37 for the Green Monitored House. These findings suggest that properly structured green buildings, supported by IoT sensing, continuous environmental monitoring, and reliable network services, may provide a useful digital framework for reducing indoor environmental burden in vulnerable populations. The proposed code strategy is not

intended as a clinical diagnostic tool, but as an oriented modelling approach for future IoT-based green building assessment, digital twin integration, and risk-aware environment management.

Keywords: Green buildings, smart buildings, building intelligence, IoT sensors, indoor environmental quality, network service quality, environmental monitoring, chronic disease risk, asthma, COPD, anxiety and stress, health-risk simulation.

1. Introduction

Buildings, as structures, no longer have a passive physical character while providing only shelter, thermal protection, and professional spaces. In the context of sustainable urban development, they have evolved operating as intelligent, energy-aware, and health-supportive environments. This transition is important for residential and semi-residential buildings. Their occupants spend a substantial part of their daily time there, while indoor environmental conditions exert an important impact on physical comfort, respiratory burden, mental well-being, and overall quality of life. Recent studies on indoor environmental quality (IEQ) show that air quality, thermal comfort, humidity, lighting, acoustics, and occupant perception are not isolated variables of building performance. Instead, they are interconnected factors that affect health, comfort, productivity, and sustainability [1].

The relationship between housing conditions and health has become increasingly relevant after the COVID-19 period, during which the importance of sustaining healthy indoor environments, ventilation, and real-time environmental awareness became a needed fact. Poor housing conditions and the corresponding indoor air quality have been correlated to respiratory vulnerability, while recent literature also highlights a probable correlation between indoor air pollution, dampness, mould, and mental health outcomes [2]. Based on the aforementioned facts, vulnerable occupants, such as individuals with asthma, chronic obstructive pulmonary disease (COPD), allergies, anxiety, stress, or other chronic conditions, may be more sensitive to indoor environmental stressors than the general population. This observation is consistent with the conceptual basis of the green-residence protocol explained in [3], which identifies indoor air quality, building and furnishing materials, noise, humidity, temperature, lighting, dust, tobacco, and chemical cleaners as housing-related factors that influence residents' physical and psychological health.

Green buildings are commonly examined in terms of energy efficiency, reduced emissions, and sustainable construction. Nevertheless, a health-oriented strategy in green buildings needs a broader interpretation. A green building should not only consume less energy, but also provide controllable, measurable, and adaptive indoor conditions. So, environmental quality must be continuously monitored through sensing systems (e.g., Internet of Things – IoT) capable of monitoring air quality, CO_2 concentration, particulate matter, temperature, relative humidity, luminance, noise, and other comfort-related parameters. Recent IoT-based IEQ monitoring studies exhibit that wireless sensing networks can detect spatial and temporal environmental variations that are not easily found through periodic surveys, while also supporting facility management and mitigation strategies [1].

The integration of Internet of Things technologies inside building areas has therefore become an important component of smart and green building research. IoT architectures enable distributed sensing, data acquisition, communication, and processing, while decision support

allows buildings to extend their image from static energy-efficient structures to adaptive and smart living and working areas. Recent reviews underline that IoT applications in smart buildings can support real-time monitoring, energy management, operational efficiency, occupant comfort, and data-informed decision-making. At the same time, the successful implementation of IoT systems depends greatly on the quality of the existing communication infrastructure. Smart buildings need sustainable network services, flawless connectivity, sufficient capacity, and low-latency data transmission, especially when environmental monitoring is used for real-time control, health-related alerts, energy optimization, or digital-twin integration [4].

This network-aware perspective is indeed important because a building with sensors is not necessarily an intelligent structure. Sensor measurements are useful only when they can be acquired, transmitted, stored, interpreted, and converted into useful information. Thus, a properly structured building must combine three complementary stages: a physical green-building, an IoT sensing, and a reliable network/data-service stage. Without the needed network quality, sensing is degraded. For example, delays, data loss, and bottlenecks may degrade the building system's ability to act against unwanted indoor environmental changes. Recent work on IoT-based IEQ systems and smart buildings emphasizes exactly the need for real-time, occupant-centric, and data-driven building operation [1].

This study depends upon this research direction by treating green building as an integrated environmental and digital monitoring system. The conceptual starting point is the protocol introduced in [3]. That protocol proposed the correlation of IEQ with residents' health and quality of life, with particular attention to chronic illnesses such as asthma, COPD, allergies, mental health problems, and Sick Building Syndrome symptoms. The simulated scenario, which is used in this paper, follows the same health-oriented logic but converts it into a deterministic computational model. This involves two building categories, namely a bad climate house (BCH) and a green monitored house (GMH), three chronic-condition profiles, and nine indoor environmental indicators. The simulation protocol used 100 code-generated participants, a 100-day time simulation, and a normalized risk score from 0 to 100, classified as low, moderate, or high risk.

The innovative approach of this work lies in the combination of various factors. These include green-building logic, IoT-based environmental sensing, chronic-condition vulnerability, and network service quality into a simulation, which included risk assessment. Instead of examining green buildings only through energy performance or occupant comfort, the proposed approach models how influential monitored environmental conditions may become toward vulnerable occupants over time. Therefore, the paper interprets IoT sensors not as isolated devices, but as parts of a broader networked building infrastructure. The latter is mainly capable of supporting continuous environmental supervision and risk-aware decision support. Furthermore, the resulting model is not intended as a clinical diagnostic application, but as a research-oriented tool for future studies on IoT green buildings, indoor environmental health, network-supported services, and smart resilience design.

The structure of the paper includes, apart from the Introduction, Section 2, which is relevant to the proposed system architecture and simulation. It is constituted of the general architecture of the proposed simulation framework, a short description of the simulation code workflow, mathematical formulation of the risk score, simulation setup, and results. Then, the final section includes conclusions and future scopes.

2. Proposed system architecture and simulation

2.1. General architecture of the proposed simulation framework

The proposed system is a simplified digital model for assessing how different building conditions may affect vulnerable occupants over time. The proposed strategy combines three main conceptual stages: the building-condition stage, the IoT sensing and monitoring stage, and the health-risk simulation stage. The purpose of this simulated model is to represent a building not only as a physical structure, but also as a monitored smart environment in which the indoor quality indicators can be measured, transmitted, interpreted, and converted into risk scores.

Specifically, the first stage corresponds to the physical building environment. In this simulated environment, two building categories are considered: a BCH and a GMH. The BCH corresponds to an indoor environment with poor environmental quality, limited monitoring capability, and increased deterioration in the main building-related indicators. The Green Monitored House represents a structured green building with low indoor environmental burden, full monitoring, and controlled capability. In the implemented protocol, the BCH is assigned a monitoring/control value of 0,05, while the Green Monitored House is assigned a value of 1,00. The simulation was performed using 100 code-generated participants, a 100-day simulated time, a fixed seed such as 12345, and no stochastic deviations, keeping the logic simple and easier to debug.

The second layer corresponds to the IoT sensing and network infrastructure (Figure 1). In the proposed scenario, each indoor environmental indicator can be associated with one or more sensing modules. These are connected through a reliable building network. The indicators include indoor air quality and particulate matter, CO_2 in correlation to ventilation adequacy, thermal conditions, humidity and mould risk, noise, lighting quality, dust/allergens, volatile organic compounds or chemical cleaners, and tobacco/smoke exposure. These nine indicators are explicitly included in the simulation protocol and correspond to the measurable environmental conditions of each building type.

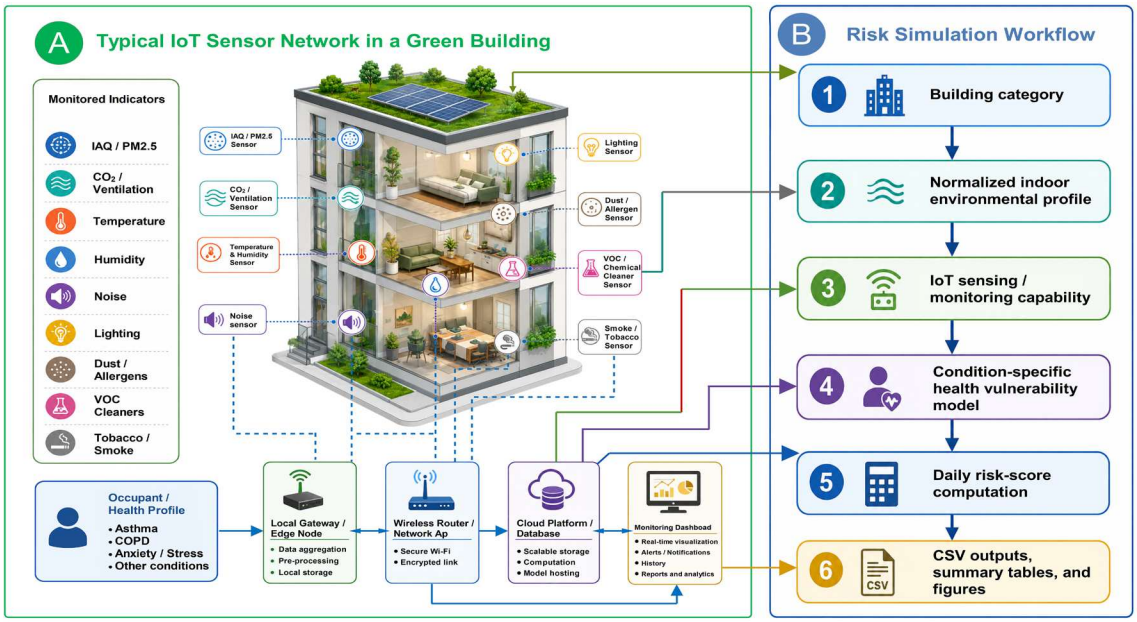


Figure 1. System architecture

The third stage is the computation layer of the proposed risk score. The layer receives the normalized environmental profile of each building, combines it with condition-specific vulnerability weights, applies a monitoring/control correction factor, and updates the simulated risk over the duration of the virtual experiment. The output is a normalized risk score between 0 and 100, classified as Low for values below 33, Moderate for values between 33 and 66, and High for values above 66. This interpretation is also reported in the protocol file generated by the simulator. So, from a system-architecture aspect, the proposed framework can be summarized as shown in Figure 1. This kind of structure makes the simulation compatible with future extensions toward real IoT deployments, where actual sensor measurements could replace predefined environmental profiles. In such a future version, indoor sensors would feed a database or digital twin, while network quality indicators (latency, packet loss, service availability, and throughput) could already be included in the monitoring factor.

2.2 Short description of the simulation code workflow

The proposed simulation system follows a deterministic workflow. In detail, the user defines the pseudo-sample size, sets the random seed, and chooses the duration of the experiment. For the present virtual experiment, the sample size was set to 100 code-generated participants, and the duration was set to 100 days. The model then automatically assigns participants to the available building categories and health-condition groups. Notably, the model intentionally excludes user-defined deviations and Monte Carlo variability. This allows the model's deterministic behavior to be examined without stochastic uncertainty. The basic code workflow is shown below:

1. Protocol initialization: The simulator initializes the selected version, the number of participants, the experiment's duration, the random seed, the building categories, the health-condition categories, and the indoor environmental indicators.
2. Configuration of building profiles: Each category acquires a normalized exposure profile across the nine indicators. The BCH receives high exposure values, whereas the Green Monitored House receives low exposure values.
3. Configuration of health-condition profiles: Three health-related profiles are used, such as Asthma, COPD, and Anxiety/Stress. Each profile has a baseline severity value and a vector of weights expressing its sensitivity to the indoor environmental indicators.
4. Participant assignment: The 100 code-generated participants are distributed across the two building categories and the three health-condition profiles. The final distribution is approximately balanced: 17 participants for asthma, 17 for COPD, and 16 for anxiety/stress in every building category.
5. Daily risk-score calculation: For each participant and simulated day, the model computes a risk score as a function of building exposure, condition-specific vulnerability, monitoring capability, and time-dependent burden or improvement.
6. Output generation: The simulator produces participant-level data, daily group mean risk values, final summary statistics, a protocol file, and graphical outputs.
7. Result visualization: Three main figures are produced: mean risk over time by building category, final risk by housing category, and a final risk matrix by building and health condition profile.

2.3 Mathematical formulation of the risk score

Let b denote the building category, c the chronic-condition profile, k the indoor environmental indicator, and d the simulation day. Each building is represented by a normalized exposure vector (equation 1). Each chronic-condition profile is represented by a weight vector (equation 2). Also, the environmental exposure score (condition-weighted) for each combination of building type and health-condition profile

$$E_b = [E_{b,1}, E_{b,2}, \ldots, E_{b,k}] \quad (1)$$

where $E_{b,k} \in [0,1]$. A value close to 0 represents an optimal or low-risk indoor condition, while a value close to 1 represents an adverse indoor condition. In the present simulation, K=9, corresponding to the nine indoor indicators used in the protocol. The monitoring parameter is excluded from this equation. The latter is a control/moderator factor that reduces or modifies the final risk.

$$W_c = [w_{c,1}, w_{c,2}, \ldots, w_{c,k}] \quad (2)$$

where $w_{c,k}$ expresses the relative sensitivity of condition c to environmental indicator k.

$$P_{b,c} = \sum_{k=1}^{K} E_{b,k} W_{c,k} \quad (3)$$

The baseline vulnerability of each health condition is represented by a severity coefficient S_c. So the utilized severity coefficients have the values of 1,10 for asthma, 1,20 for COPD, and 1,10 for anxiety/stress. COPD was assigned the highest multiplier supported by recent evidence indicating a strong association between particulate air-pollution exposure and COPD incidence, including reports of approximately 18% increased COPD incidence per 10 μg/m³ increase in PM2.5 [5]. For asthma, the severity coefficient was not directly extracted as an epidemiological effect size, but was derived indirectly. Since the adopted risk scale classifies values of 1–32 as low, 33–66 as moderate, and 67–100 as high, the qualitative certainty levels reported in the literature were mapped to the lower bounds of the corresponding risk intervals. So, two very-low certainty associations were conservatively mapped to the minimum value of the very-low range, one low-certainty association was mapped to the lower bound of the low range, and one moderate-certainty association was mapped to the lower bound of the moderate range. Using very low = 1, low = 16, and moderate = 33, the average evidence score becomes: (1 + 1 + 16 + 33) / 4 = 12,75 on a 0–100 scale. This corresponds to approximately 13%, which was rounded down to a conservative 10% amplification. Therefore, the asthma severity coefficient was set to S_c = 1,10. This value should be interpreted as a normalized simulation assumption reflecting elevated vulnerability to indoor environmental stressors, rather than as a clinically calibrated asthma risk constant [6]. Furthermore, for the anxiety/stress profile, the severity coefficient was found using a reverse interpretation of reported IEQ stress associations. Thach et al. showed that a one-unit increase in perceived air quality, thermal comfort, noise, and light-quality scores was associated with lower odds of stress at work, with odds ratios of 0.88, 0.89, 0.93, and 0.88, respectively. These values correspond to approximate stress-odds reductions of 12%, 11%, 7%, and 12%, with a mean protective association of 10.5%. Since the proposed simulator represents vulnerability under non-

ideal indoor environmental conditions, this protective association was inverted and used as a positive stress-vulnerability multiplier. Accordingly, the anxiety/stress coefficient was set to S_c = 1,10. This value should be interpreted as a literature-extracted parameter rather than as a clinically calibrated risk constant [7].

Also, the monitoring capability of each building is represented by m_b, where values closer to 1 represent higher monitoring and control capability. The monitoring capability is computed based on equation 4. This term reduces the risk score in buildings, where stronger monitoring and control capabilities are applied. Therefore, a green monitored building benefits from a lower effective risk contribution, while a poorly monitored building retains a higher risk score. Specifically, the coefficient a_M was set to 0,35 as a conservative approximation. This value was guided by reported IAQ intervention effects rather than treated as a universal clinical constant. In particular, an international office-building study reported approximately 30.9%–39.4% lower indoor PM2.5 in buildings with higher-efficiency filtration, corresponding to a central value of about 35.15% [8]. In addition, a systematic review reported PM2.5 reductions in the range of 31%–53%, corresponding to a central value of about 42% [9]. Averaging these two central estimates gives approximately 38.6%. Based on the previous calculation, a_M was set to 0,35. This term represents the assumed corrective effect of real-time sensing, environmental supervision, filtration/ventilation support, and adaptive control, and should be recalibrated in future work by using building-specific sensor data.

$$M_b = 1 - a_M m_b \,,\ where\ a_M = 0{,}35\ and\ m_b \in [0,1] \tag{4}$$

The constructed risk score is first defined through an initial risk value, which combines the indoor environmental score, the baseline vulnerability of the selected health-condition profile, and the monitoring/control capability of the building. Thus, the initial risk score for building type b and health-condition profile c is calculated by equation 5.

$$R_{0,b,c} = 100 \cdot P_{b,c} \cdot S_c \cdot M_b \tag{5}$$

where $P_{b,c}$ is the weighted indoor environmental score, S_c is the severity coefficient of health-condition profile c, and M_b corresponds to the monitoring correction factor of building type b. The multiplication by 100 converts the normalized score into a 0–100 risk scale.

To account for the temporal evolution, a time-dependent factor is introduced. Let D denote the total number of simulation days and $a_{c,b}$ the time-slope coefficient associated with health-condition profile c in building type b. The temporal factor is calculated by equation 6. At d = 1, the temporal factor is equal to unity, meaning that the risk score starts from its initial value. At d = D, the full effect of the time-slope coefficient is reached. Therefore, positive values of $a_{c,b}$ represent progressive degradation, whereas negative values represent gradual improvement.

$$T_{(c,b)(d)} = 1 + a_{c,b} \cdot \frac{d-1}{D-1} \tag{6}$$

The final daily risk score is then obtained by applying a bounded saturation operator, as shown in equation 7. The operator $B_{[0,100]}(\cdot)$ constrains the resulting score within the normalized 0–100 range. All participants within the same building-condition group have identical risk trajectories.

$$R_{(b,c)}(d) = B_{[0,100]}\left(R_{0,b,c}T_{(c,b)}(d)\right) \text{ where } B_{[0,100]}(x) = \min\{100, \max\{0, x\}\} \quad (7)$$

2.4 Simulation setup

The simplified simulation experiment was configured as follows in Table 1. Also, the two types of building categories (BCH and GMH) are described through normalized environmental profiles, which are shown in Table 2. As far as the variables of Table 2, these represent normalized risk rather than direct physical units. Therefore, they should be interpreted as dimensionless exposure factors suitable for simulation and comparative assessment. Therefore, the values reported in Table 2 should be interpreted as normalized simulation inputs and, for this virtual experiment, i.e., dimensionless exposure factors suitable for simulation and comparative assessment. So, each indoor environmental indicator was mapped to a dimensionless 0–1 scale, where values close to 0 represent well-controlled conditions and values close to 1 represent adverse indoor environmental conditions. The selected indicators were based on established housing-health and indoor environmental quality literature. WHO housing and indoor air-quality guidance highlights the importance of housing conditions, thermal conditions, dampness and mould, and indoor air pollutants for occupant health, while recent IEQ literature treats air quality, thermal comfort, acoustic comfort, and visual comfort as core dimensions of healthy buildings.

Accordingly, the bad climate house (BCH) was assigned high normalized values, typically between 0,60 and 0,90, presenting obvious adverse indoor environmental conditions such as poor air quality, inadequate ventilation, humidity/mould risk, dust/allergen presence, chemical exposure, and smoke-related burden. In contrast, the green monitored house (GMH) was assigned low normalized values, typically between 0,00 and 0,20, representing a controlled green building environment. The monitoring column is not an environmental exposure indicator, and it will be analyzed later in this paper [10, 11, 12, 13, 14].

Table 1: Simulation configuration

Parameter	Value
Number of code generated participants	100
Duration	100 days
Seed	12345
Building categories	Bad Climate House, Green Monitored House
Health-condition profiles	Asthma, COPD, Anxiety/Stress
Indoor environmental indicators	9
Monitoring/control coefficient	$a_M = 0,35$
Risk-score range	0–100
Risk interpretation	Low: 0–33, Moderate: 33–66, High: 66–100

Table 2: Simulated environmental variables

	Indicators				
TYPE	**IAQ / PM2.5**	**Ventilation / CO_2**	**Thermal burden**	**Humidity / mould**	**Noise**
BCH	0,85	0,80	0,75	0,85	0,70
GMH	0,15	0,15	0,15	0,10	0,20
	Lighting burden	**Dust / allergens**	**VOC / cleaners**	**Tobacco / smoke**	**Monitoring**
BCH	0,75	0,90	0,80	0,60	0,05
GMH	0,15	0,10	0,15	0,00	1,00

2.5 Simulation results

The simulation produced three main output stages: daily risk evolution, final building-level comparison, and final risk matrix by building and health condition profile. The final summary table (Table 3) shows strong uncorrelated conditions between the BCH and the GMH. At the building level, the weighted final mean risk was approximately 100,00 for the BCH and 9,37 i.e., [(17x8,59)+(17x10,02)+(16x9,50)]/50 for the GMH. Thus, the final risk in the GMH was approximately 90% lower than in the BCH across the three simulated health-condition profiles. For each building type b and health-condition profile c, the participant subset is denoted as $\Omega_{b,c}$, with cardinality $N_{b,c}$. The initial mean risk, final mean risk, and mean risk variation reported in Table 3 are calculated as follows in equations 8, 9, and 10. Also levels low, moderate, and high are found by the classification of $\bar{R}_{final}(b,c)$.

$$\text{Initial mean: } \bar{R}_{initial}(b,c) = \frac{1}{N_{b,c}} \sum_{i \in \Omega_{b,c}} R_i(1) \tag{8}$$

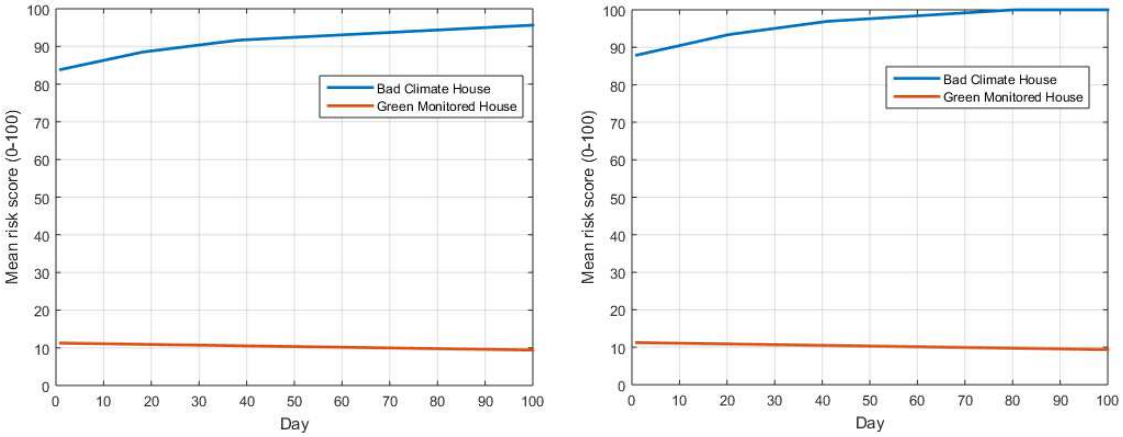
$$\text{Final mean: } \bar{R}_{final}(b,c) = \frac{1}{N_{b,c}} \sum_{i \in \Omega_{b,c}} R_i(D) \tag{9}$$

$$\text{Mean delta: } \Delta\bar{R}_{(b,c)} = \bar{R}_{final}(b,c) - \bar{R}_{initial}(b,c) \tag{10}$$

Table 3. Final risk by building and health condition

Building	Condition	N	Risk			
			Initial mean	Final mean	Mean delta	Level
BCH	Asthma	17	89,16	100,00	+10,84	High
BCH	COPD	17	93,55	100,00	+6,45	High
BCH	Anxiety/ Stress	16	80,62	100,00	+19,38	High
GMH	Asthma	17	10,48	8,59	−1,89	Low
GMH	COPD	17	11,39	10,02	−1,37	Low
GMH	Anxiety/ Stress	16	11,88	9,50	−2,38	Low

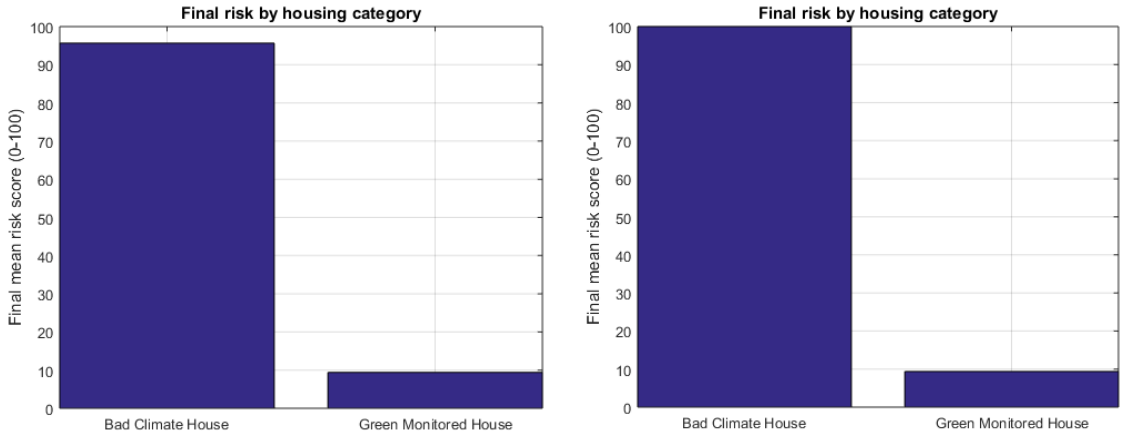
The produced Figures 1(a) and 1(b) depict the mean risk evolution over the 100-day period. The comparison between the two monitoring-correction settings shows that the GMH remains consistently within the low-risk region for both α_M = 0,20 and α_M = 0,35. This indicates that the green monitored environment is risk-stable, since it's advanced IoT-based sensing and control capability, combined with improved indoor environmental conditions, allows the system to sustain low-risk operation even under different monitoring-correction assumptions. In contrast, the BCH does not benefit substantially from the monitoring condition because its corresponding value is very low. As a result, the adverse indoor environmental profile dominates the simulation, and the risk trajectories progressively increase, reaching the maximum risk boundary of 100. Therefore, the comparison highlights that monitoring capability becomes meaningful only when it is embedded in a properly structured green building environment. In poorly monitored and poorly conditioned buildings is obvious that the lack of effective sensing and control allows risk deterioration to reach saturation levels.



(a) for $a_M = 0{,}20$ (b) for $a_M = 0{,}35$

Figure 1. Mean risk score by housing category.

Figures 2(a) and 2(b) depict the final mean risk by building category for the two monitoring-correction settings, $\alpha_M = 0{,}20$ and $\alpha_M = 0{,}35$, respectively. In both cases, the BCH reaches a very high final mean risk, while the GMH remains within the low-risk range. The comparison indicates that the BCH is practically unable to benefit from the monitoring correction, since its monitoring/control value is very low. Furthermore, it is evident that the deterioration of about 10% for $\alpha_M = 0{,}35$,. Therefore, the adverse indoor environmental profile dominates the final outcome. Conversely, the GMH remains consistently low-risk under both settings, showing that the improved indoor environmental profile, together with advanced IoT-supported monitoring and control capability, sustains a stable low-risk operation.

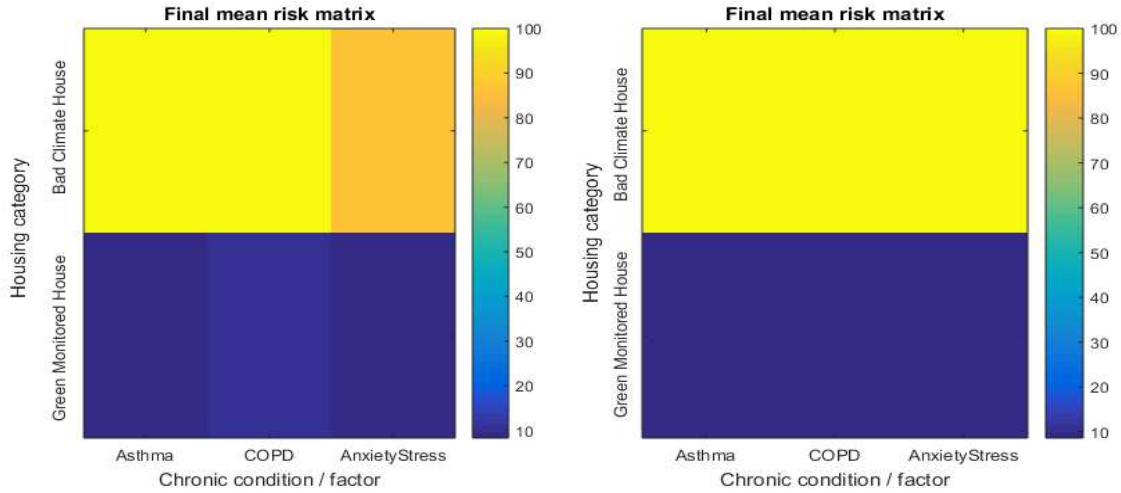


(a) for $a_M = 0{,}20$ (b) for $a_M = 0{,}35$

Figure 2. Final mean risk.

Figure 3(a) represents a more robust scenario relevant to BCH, where the monitoring-correction coefficient is set to $\alpha_M = 0{,}20$ and the anxiety/stress severity coefficient is assigned to $S_c = 0{,}90$. This setting intentionally assumes a favorable anxiety/stress condition, corresponding to a 10% reduction relative to the neutral reference level of $S_c = 1{,}00$. In simple words, anxiety/stress is not treated as an aggravating vulnerability factor in case of Figure 3(a). The purpose of this

configuration is to examine whether the separation between the Bad Climate House (BCH) and the Green Monitored House (GMH) remains evident even under a stress-reduced occupant assumption in favor of the BCH. Figure 3(b) represents the revised literature-based calibration (correct one), where α_M = 0,35 and the anxiety/stress coefficient is set to S_c = 1,10, based on logical literature-based assumptions (examined earlier in this paper). In both cases, the BCH remains in the high-risk region, whereas the GMH remains in the low-risk region, indicating that the observed separation is mainly driven by the indoor environmental profile and monitoring capability rather than by a single health-condition coefficient.



(a) for α_M = 0,20 and S_c=0,90 (b) for α_M = 0,35 and S_c=1,10

Figure 3. Final mean risk matrix

Overall, the comparison between α_M = 0,20 and α_M = 0,35 shows that a better value for monitoring (α_M = 0,20 about 40% better than α_M = 0,35) does not even artificially improve a poorly monitored building such as the BCH. Instead, the BCH remains dominated by its adverse indoor environmental conditions and progressively reaches the highest risk range. The GMH, on the other hand, remains robustly within the low-risk region, indicating that monitoring and control capability becomes meaningful when embedded in a properly structured green building environment with improved indoor environmental characteristics.

3. Conclusions and Future Scopes

The results exhibit that the proposed simulation strategy can clearly distinguish between an adverse indoor environment and a green monitored indoor environment. In the BCH, the combination of poor air quality, insufficient ventilation, thermal burden, humidity/mould, and all other previously mentioned variables produces high risk levels for all simulated chronic-condition profiles. Asthma and COPD are particularly sensitive to the air-quality and ventilation-related components of the model, which explains their rapid progression toward the maximum risk boundary. Anxiety/stress also increases substantially, reflecting the contribution of thermal discomfort, noise, lighting burden, and general environmental drawbacks.

In the GMH, the simulated environmental pressure is substantially lower across all indicators. The full monitoring/control capability further reduces the effective risk contribution. As a result, all three health-condition groups remain within the low-risk range throughout the experiment. This is consistent with the green-residence hypothesis that improved indoor environmental quality, superior micro-environmental systems, and reduced exposure sources may produce better physical and psychological outcomes in vulnerable occupants.

A key observation is that this deterministic simulated scenario acts as a baseline model. Since no deviations or Monte Carlo uncertainty are conducted, the results should not be interpreted as population-level clinical predictions. Instead, they demonstrate the expected tendency and magnitude of risk non-correlating conditions under idealized assumptions. This makes the scenario useful for explaining the model's architecture, validating the mathematical logic, and providing a clear comparison between poor and green monitored building conditions.

The innovative aspect of the proposed approach is that it does not treat the green building merely as an energy-efficient structure. Instead, it treats the building as an IoT-enabled, health-aware indoor environment. The simulation connects building quality, sensing capability, network-supported monitoring, and occupant vulnerability into a single risk-score framework. This is important because the quality of a smart green building depends not only on materials and energy performance but also on its ability to sense, communicate, and act relevant to indoor environmental conditions. From a digital infrastructure perspective, the model also highlights the need for high-quality network services inside green buildings. The proposed framework supports the view that green buildings should be designed as integrated systems combining environmental quality, IoT sensing, and robust communication infrastructure.

From an engineering perspective (future scope), the proposed model can be extended toward a real IoT deployment. In such a scenario, the normalized indicators used in the present simulation could be replaced by real sensor measurements. For example, IAQ/PM2.5 sensors, CO_2 sensors, temperature/humidity sensors, acoustic sensors, lighting sensors, and VOC sensors could continuously update the environmental profile of the building. These measurements could be fed through a reliable building network to a local edge processor or cloud-based platform. The risk-score stage could then operate as a decision module, identifying whether specific occupant groups should be exposed or not to increasing indoor environmental burden.

Overall, this study confirms the conceptual hypothesis that green-monitored buildings can substantially reduce simulated indoor environmental risk for vulnerable occupants when these structures are compared with poorly conditioned buildings. Future work should introduce Monte Carlo variability, individual deviations, real sensor data, calibration against measured clinical or questionnaire-based outcomes, and network-quality parameters such as latency, packet loss, availability, and data freshness. These extensions would allow the framework to evolve from a deterministic simulation into a broader digital twin for health-oriented smart green buildings.

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