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Review

AI-Based Modeling of Indoor Air Quality and Thermal Comfort: A Systematic Review of Human-Centric and Adaptive Approaches

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Abstract: Indoor Air Quality (IAQ) and thermal comfort are fundamental determinants of occupant health, cognitive performance, and building energy efficiency. Integrating Artificial Intelligence (AI) and soft computing methods—such as machine learning, fuzzy logic, and hybrid architectures—has enabled more intelligent, adaptive, and predictive control of indoor environments. Since the COVID-19 pandemic, interest in data-driven environmental quality management has intensified, particularly in health-sensitive and energy-constrained settings. This systematic literature review (SLR) analyzes 72 peer-reviewed studies published between 2020 and 2024, synthesizing emerging trends in AI-based modeling of IAQ and thermal comfort. The review is organized across four dimensions: (i) environmental sensing and feature engineering; (ii) AI and soft computing-based modeling strategies; (iii) multi-objective integration of IAQ, thermal comfort, and energy metrics; and (iv) human-in-the-loop, interpretable, and adaptive AI frameworks. Using thematic synthesis and advanced visual analytics—including streamgraphs, bubble plots, Sankey diagrams, UpSet plots, and research gap maps—the review identifies four persistent challenges: (i) the lack of unified, multi-objective models that balance comfort, air quality, and energy use; (ii) underutilization of interpretable and hybrid AI approaches that foster transparency and trust; (iii) limited incorporation of real-time occupant feedback, personalization, and behavioral adaptation; and (iv) scarcity of real-world validation across diverse building types and climatic conditions. The findings highlight the need to develop inclusive, explainable, and field-tested AI systems that integrate subjective and objective data for responsive indoor environmental management. This review offers a structured foundation and roadmap for advancing deployable, human-aware, and sustainable AI solutions in the built environment.

Keywords: Indoor Air Quality (IAQ); Thermal Comfort; HVAC Systems; Energy Efficiency; Artificial Intelligence (AI); Data-Driven Modelling; Building Energy Systems

1. Introduction

Indoor Air Quality (IAQ) and thermal comfort are fundamental components of Indoor Environmental Quality (IEQ), directly impacting occupant health, cognitive performance, and overall well-being. The global transition toward airtight, energy-efficient buildings—designed to minimize thermal losses—has inadvertently led to inadequate ventilation, accumulation of indoor pollutants, and thermal instability. These challenges became more pronounced in the wake of the COVID-19 pandemic, which heightened global awareness of airborne transmission and spurred urgent reassessments of ventilation, air filtration, and occupant exposure(Azevedo et al., 2024; Baldwin et al., 2023; Bao et al., 2022; Wang, 2023; Zhao et al., 2024) .

Suboptimal IAQ has been linked to respiratory illnesses, cognitive fatigue, and productivity loss, while thermal discomfort contributes to absenteeism, dissatisfaction, and poor health outcomes in residential, workplace, and healthcare settings. In response, post-pandemic standards have begun emphasizing the dual goals of respiratory safety and thermal comfort in sustainable building design (Wang, 2023; World Health Organization, 2025; Zune and Kolokotroni, 2022). However, existing approaches still tend to treat IAQ and thermal comfort as distinct domains. For example, regulatory standards such as ASHRAE 55 and ISO 7730 primarily focus on thermal indices (e.g., PMV/PPD), with limited consideration of air pollutant exposure (Razak et al., 2025a; Razak et al., 2025b). Conversely, IAQ strategies often neglect thermal implications, leading to unintended side effects or suboptimal occupant experiences (World Health Organization, 2025; Zheng et al., 2021; Zune and Kolokotroni, 2022; Nicolescu et al., 2022; Sarmah et al., 2024).

Recent advances in Artificial Intelligence (AI) and soft computing have created new opportunities for integrated modeling and control of indoor environments. Techniques such as fuzzy logic systems, neural networks, genetic algorithms, and hybrid models can capture the nonlinear, context-sensitive relationships among environmental parameters, occupancy behavior, and perceived comfort. AI-enabled predictive systems offer real-time sensing, forecasting, and control capabilities, transforming conventional HVAC operations into intelligent, adaptive systems. Emerging architectures—such as fuzzy logic, convolutional neural network, and LSTM (FL-CNN-LSTM) hybrids (Bandi et al., 2024) and model predictive control (MPC) schemes (Zhu et al., 2024)—demonstrate the potential for multi-objective optimization that balances comfort, air quality, and energy efficiency.

Despite these advancements, significant challenges persist. Research in this area remains fragmented, with IAQ and thermal comfort rarely addressed within unified, multi-objective frameworks. Predictive models often focus on isolated indicators (e.g., CO_2, PMV), without capturing their interdependencies or contextual dynamics. Moreover, dominant AI approaches—especially black-box models—struggle with transparency, generalizability, and adaptability in real-world environments. Explainable AI (XAI), soft computing, and human-in-the-loop modeling remain underutilized, despite their suitability for applications involving subjective comfort, linguistic perception, and occupant diversity (Bandi et al., 2024; Yelne et al., 2023). Other limitations include minimal use of real-time feedback, limited deployment in diverse building types and climate zones, and insufficient integration of personalized thresholds and user preferences (Wang, 2023; Zhao et al., 2024; Zhou et al., 2023).

This paper addresses these gaps by presenting a systematic literature review (SLR) of AI-based modeling strategies for IAQ and thermal comfort in building environments. We focus on the period from 2020 to 2024 to capture post-pandemic research priorities, emphasizing occupant health, environmental resilience, and intelligent control. This period also marks a surge in the adoption of sensor technology and the application of data-driven approaches to indoor environmental optimization.

Following the PRISMA methodology, the review is structured around four research questions:

- What environmental and human-centered parameters are typically modeled in AI-based IAQ and thermal comfort studies?
- Which AI, soft computing, and hybrid modeling techniques dominate the current research landscape?
- To what extent are IAQ and thermal comfort integrated into unified prediction or control frameworks?
- How is personalization—via occupant feedback, contextual sensing, or adaptive thresholds—incorporated into these models?

Unlike previous reviews that examine IAQ or thermal comfort separately, this paper provides a unified, post-pandemic synthesis of AI-based modeling across both domains, emphasizing human-centric and adaptive approaches. It offers the first structured taxonomy that simultaneously covers AI, soft computing, hybrid architecture, environmental sensing, and occupant-centered modeling. The integration of advanced visual analytics—such as streamgraphs, Sankey diagrams, bubble plots, UpSet plots, and research gap maps—adds further novelty by revealing temporal, methodological, and thematic patterns not previously explored. By highlighting persistent challenges and opportunities, this review provides a strategic roadmap for developing explainable, field-validated, and inclusive AI systems that promote healthier and more resilient indoor environments.

The key contributions of this paper are as follows:

1. It provides a structured taxonomy of AI and soft computing models applied to IAQ and thermal comfort, classified by algorithm type, input modality, and application context.
2. It synthesizes trends in integration, explainability, and human-centric adaptation, particularly in

relation to post-pandemic environmental priorities.

3. It outlines a strategic research agenda for advancing interpretable, scalable, and context-aware AI systems that support intelligent, health-conscious indoor environments.

The remainder of this paper is organized as follows: Section 2 details the systematic review methodology, including article selection, screening, and analysis procedures. Section 3 presents the thematic findings, highlighting trends in AI and soft computing applications across IAQ and thermal comfort domains. Section 4 discusses the identified methodological, operational, and deployment challenges. Finally, Section 5 concludes with practical insights and future directions.

2. Methodology—Systematic Literature Review

This study employs a Systematic Literature Review (SLR) to assess peer-reviewed research that utilizes Artificial Intelligence (AI) and soft computing methods in modeling Indoor Air Quality (IAQ) and thermal comfort within building environments. The SLR methodology provides a structured, transparent, and reproducible approach to synthesizing current knowledge, minimizing bias, and improving the reliability of insights (Kitchenham and Charters, 2007).

The review protocol was adapted from a previously published framework by Razak et al. (Razak et al., 2025), which systematically analyzed AI applications across renewable energy domains. Building on that foundation, this review refines and extends the method to address post-pandemic priorities in indoor environmental quality (IEQ), focusing on dual-variable AI-based modeling and human-centric adaptive approaches.

To ensure methodological rigor, the review follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021), a recognized standard for conducting systematic reviews across health, environmental, and computational sciences.

As shown in Figure 1, 420 records were retrieved from major scientific databases—Scopus, Web of Science (WoS), and IEEE Xplore—using a predefined Boolean search strategy. After removing 90 duplicate entries, 330 unique records were screened at the title and abstract level. 130 articles were excluded for reasons including lack of relevance to IAQ or thermal comfort, absence of AI techniques, or focus on non-building domains.

The remaining 200 articles underwent full-text review. Of these, 128 were excluded due to limited methodological detail, lack of predictive modeling, or failure to address either IAQ or thermal comfort meaningfully. Ultimately, 72 studies published between January 2020 and December 2024 were included for synthesis. This period was chosen to capture post-COVID shifts in indoor environmental research and the acceleration of AI-enabled building solutions.

The following subsections outline the search strategy, inclusion and exclusion criteria, data extraction and classification process, and analysis tools used in the review.

2.1. Search Strategy

This review targeted peer-reviewed studies published between January 2020 and December 2024 to reflect the most recent advances in AI-based modeling of indoor environmental quality. This period was strategically chosen to capture the post-COVID research shift, where increased global attention has been placed on indoor air quality (IAQ), thermal comfort, and the health-performance nexus in buildings (Azevedo et al., 2024; Baldwin et al., 2023; Bao et al., 2022; Wang, 2023; Zhao et al., 2024). It also aligns with accelerated development in soft computing and Artificial Intelligence (AI) applications for smart building environments, including deep learning, fuzzy logic systems, and hybrid AI models.

The search methodology was adapted to indoor environmental modeling and builds upon our prior systematic review on AI in renewable energy systems (Razak et al., 2025). To ensure comprehensive coverage across disciplines—from environmental engineering and HVAC systems to computer science and AI—the search was conducted across three major academic databases: Scopus, Web of Science (WoS), and IEEE Xplore.

A Boolean query was constructed to capture research at the intersection of AI techniques and indoor environmental applications. The final search string was formulated as:

("Indoor Air Quality" OR "Thermal Comfort") AND ("Artificial Intelligence" OR "Machine Learning" OR "Predictive Model" OR "Fuzzy Logic" OR "Neural Network")

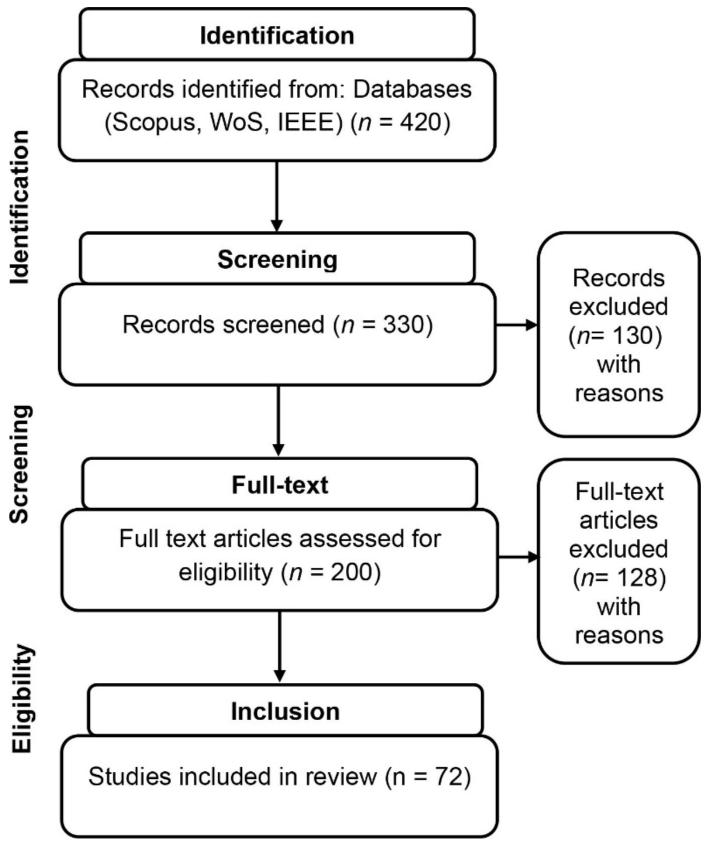

Figure 1. PRISMA flow diagram illustrating the study selection process. From an initial pool of 420 records identified through database searches, 72 studies were retained after screening and full-text review.

Table 1. Most Frequent Keywords in Included Studies (2020–2024).

Keyword	Frequency
Thermal Comfort	21
Indoor Air Quality (IAQ)	19
Convolutional Neural Network (CNN)	16
Fuzzy Logic	14
PM2.5	11
Long Short-Term Memory (LSTM)	10

Searches were limited to English-language publications, including journal articles and conference proceedings. All results were imported into Mendeley reference manager for deduplication, screening, and full-text assessment. Duplicate entries were automatically detected and manually verified before the screening process.

A keyword frequency analysis was conducted on the final corpus of included studies to validate the breadth of the search. Table 1 lists the most frequently occurring terms, while Figure 2 visualizes keyword distribution.

The results confirm a strong emphasis on Thermal Comfort and Indoor Air Quality (IAQ), validating their dual importance in AI-based indoor environmental modeling. Among AI techniques, Convolutional Neural Networks (CNNs) were most frequently used, especially in vision-based applications. Fuzzy Logic also featured prominently due to its interpretability and alignment with human-centric modeling. The inclusion of PM2.5 and LSTM highlights the increasing attention toward predicting fine particulate matter and its temporal dynamics.

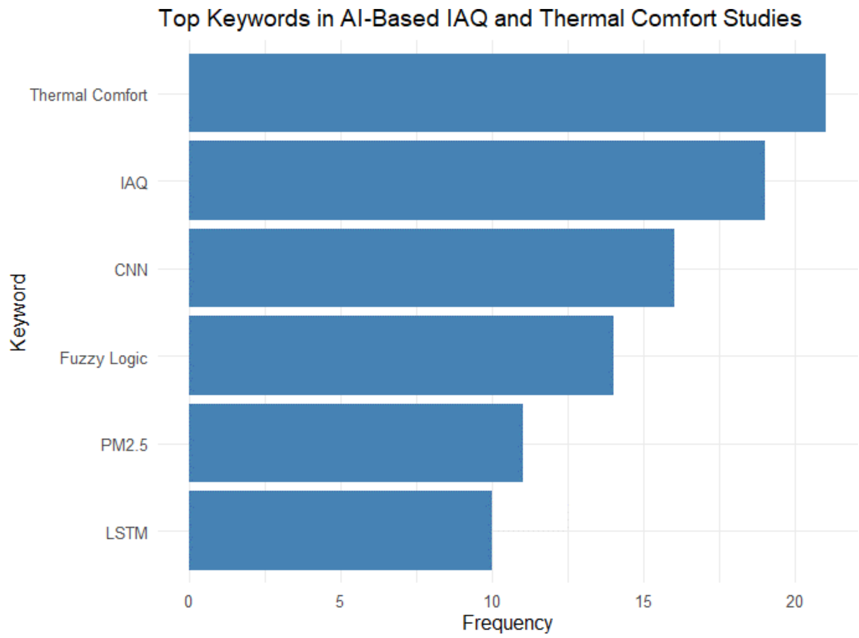

***Figure* 2.** Top keywords identified in the reviewed studies.

This keyword-based analysis reinforces the validity and breadth of the search strategy. The process adheres to best practices in systematic reviews (Moher et al., 2009), and aligns with PRISMA 2020 guidelines (Page et al., 2021), supporting the transparency and reproducibility of this review.

2.2. Inclusion and Exclusion Criteria

This review applied clearly defined inclusion and exclusion criteria during the title/abstract screening and full-text eligibility assessment to ensure thematic relevance, methodological rigor, and analytical consistency. These criteria were developed by the PRISMA 2020 guidelines (Page et al., 2021) and were adapted from the structured framework used in our prior systematic review on AI in renewable energy (Razak et al., 2025). The aim was to capture high-quality empirical studies focused on AI-based modeling of indoor environmental conditions.

The inclusion criteria prioritized peer-reviewed articles that applied Artificial Intelligence (AI), Machine Learning (ML), soft computing techniques (e.g., fuzzy logic, hybrid AI models), or predictive modeling frameworks to the domains of Indoor Air Quality (IAQ) and/or thermal comfort. Special attention was given to studies incorporating adaptive control, human-centric modeling, or explainable approaches relevant to intelligent building systems.

Conversely, studies were excluded if they lacked empirical results, did not apply any form of AI or computational modeling, or focused solely on conceptual frameworks without methodological validation. Additional exclusion filters were applied to remove non-peer-reviewed literature, studies outside the scope of the indoor environment, and works that were not available in English.

Table 2 summarizes the inclusion and exclusion criteria used throughout the screening process. These criteria were consistently applied to all records retrieved during the search phase. Of the initial 420 articles identified, 90 duplicates were removed. A further 130 were excluded based on title and abstract screening for reasons such as topic irrelevance or lack of AI methodology. The remaining 200 studies underwent full-text review, with 128 additional records excluded due to limited methodological transparency, insufficient modeling focus, or non-applicability to indoor settings. Ultimately, 72 empirical studies met all criteria and were included in the final synthesis.

This rigorous, criteria-driven screening process reinforces the methodological integrity of the review. It ensures that the resulting analysis is grounded in validated, relevant, and up-to-date research at the intersection of indoor environmental quality and AI-driven, soft computing-based modeling systems.

***Table* 2.** Inclusion and Exclusion Criteria for Study Selection.

Inclusion Criteria	**Exclusion Criteria**
Published between 2020 and 2024	Published before 2020 or after December 2024
Peer-reviewed journal articles or conference	Non-peer-reviewed sources, preprints, or white

proceedings	papers
Focused on IAQ, thermal comfort, or both in indoor built environments	Studies focused solely on outdoor environments or urban-scale air quality
Applied AI, ML, soft computing, or hybrid predictive modeling techniques	Did not utilize any computational, AI, or predictive modeling methods
Reported empirical findings with measurable outcomes and methodological clarity	Reviews, editorials, patents, technical standards (e.g., ASHRAE), or insufficiently detailed studies
Written in the English language	Non-English publications

Table 3. Study Selection Summary Following PRISMA 2020 Guidelines

Selection Stage	Number of Records
Records identified through database search	420
Duplicate records removed	90
Records screened (title and abstract)	330
Records excluded after screening	130
Full-text articles assessed for eligibility	200
Full-text articles excluded	128
Studies included in the final synthesis	72

2.3. Study Selection and Screening

The study selection process followed the PRISMA 2020 guidelines (Page et al., 2021) to ensure methodological rigor, transparency, and reproducibility. An initial search across three major academic databases—Scopus, Web of Science (WoS), and IEEE Xplore—identified 420 records published between 2020 and 2024.

Following automated deduplication using Mendeley reference management software, 330 unique records were retained for initial screening. Title and abstract screening resulted in the exclusion of 130 records that did not meet the minimum eligibility requirements, such as those lacking relevance to AI-based modeling, focusing solely on outdoor environments, or omitting thermal comfort or IAQ components.

The remaining 200 articles underwent full-text screening using the inclusion and exclusion criteria defined in Table 2. During this phase, 128 articles were excluded due to insufficient methodological transparency, the absence of empirical results, or a lack of relevance to indoor air quality (IAQ), thermal comfort, Artificial Intelligence (AI), and soft computing techniques.

72 peer-reviewed studies satisfied all eligibility criteria and were included in the final thematic synthesis. The stepwise selection process is summarized in the PRISMA flow diagram (Figure 1) and detailed quantitatively in Table 3.

This rigorous multi-phase screening protocol included only high-quality, methodologically sound studies. Each selected research study addressed the intersection of AI-based modeling and indoor environmental quality, particularly in relation to thermal comfort and IAQ. This process supports the overall objectives of the review and aligns with the broader goals of human-centric, adaptive, and explainable environmental modeling in smart building contexts.

2.4. Data Extraction and Classification

Following the final selection of 72 eligible studies (Section 2.3), a structured data extraction and classification process was implemented to systematically map methodological characteristics, thematic coverage, and modeling trends. This phase underpins the analytical synthesis in later sections and reflects best practices in evidence-based soft computing research (Tranfield et al., 2003).

We employed a qualitative coding framework informed by established methods in thematic analysis

Table 4. Classification Dimensions for Extracted Studies.

Metadata Category	Description / Examples
Publication Year	2020-2024
AI/ML Techniques	FL, ANN, SVM, CNN, LSTM, XGBoost, Hybrid
Study Focus	IAQ, Thermal Comfort, Both
Human-Centric Features	Occupant feedback, wearable sensors, adaptive thresholds
Study Type	Field study, simulation, experimental setup, survey

and systematic review design. Each study was reviewed in detail and categorized across key metadata dimensions to enable comparative analysis of AI modeling strategies, environmental focus, human-centric elements, and methodological context.

- *Publication Year:* Year of publication, to track the temporal evolution of research between 2020 and 2024.
- *AI/ML Technique(s):* Primary artificial intelligence or soft computing methods, including:
  - Fuzzy Logic (FL)
  - Artificial Neural Networks (ANN)
  - Support Vector Machines (SVM)
  - Convolutional Neural Networks (CNN)
  - Long Short-Term Memory Networks (LSTM)
  - Gradient Boosting (e.g., XGBoost)
  - Hybrid or Ensemble Models (e.g., CNN–FL, LSTM–FL)
- *Study Focus:* Whether the study addressed IAQ, thermal comfort, or both simultaneously.
- *Human-Centric Features:* Inclusion of adaptive or personalized modeling components such as wearable sensors, subjective feedback, occupant profiles, or participatory inputs.
- *Study Type:* Research design employed, categorized as:
  - Field Study
  - Simulation-Based Modeling
  - Experimental Testbeds
  - Survey-Based Analysis

These dimensions are summarized in Table 4, which provides the analytical rubric for thematic synthesis in Section 3.

To visualize cross-sectional patterns, we generated a heatmap showing the frequency of AI/ML techniques across different study types (Figure 3). The results suggest that soft computing and AI methods—especially CNNs and LSTMs—are predominantly used in simulation and survey-based research. At the same time, experimental testbeds remain less integrated with AI-driven approaches.

In addition, Table 5 presents a curated summary of 50 representative studies, including details on authorship, citation key, AI/ML methods, environmental focus (IAQ and/or thermal comfort), inclusion of human-centric design features, and publication outlet. This table provides a detailed overview of the current research ecosystem, supporting further analysis of the relationships between modeling strategies and real-world applications.

From this classification exercise, three overarching insights emerged:

- *AI penetration remains uneven:* Most AI-based modeling is concentrated in simulation and survey domains, while experimental testbeds show limited use of soft computing frameworks.
- *Human-centric modeling is still emerging:* Few studies incorporate dynamic personalization or subjective comfort feedback, highlighting a gap in adaptive system design.
- *Hybrid models are gaining momentum:* Studies integrating fuzzy logic with deep learning (e.g., CNN–FL, LSTM–FL) are increasing, reflecting growing interest in combining interpretability with predictive performance.

This classification supports the analytical depth presented in Section 3 and provides a transparent, reproducible foundation for evaluating AI-based, human-centric indoor environmental modeling trends.

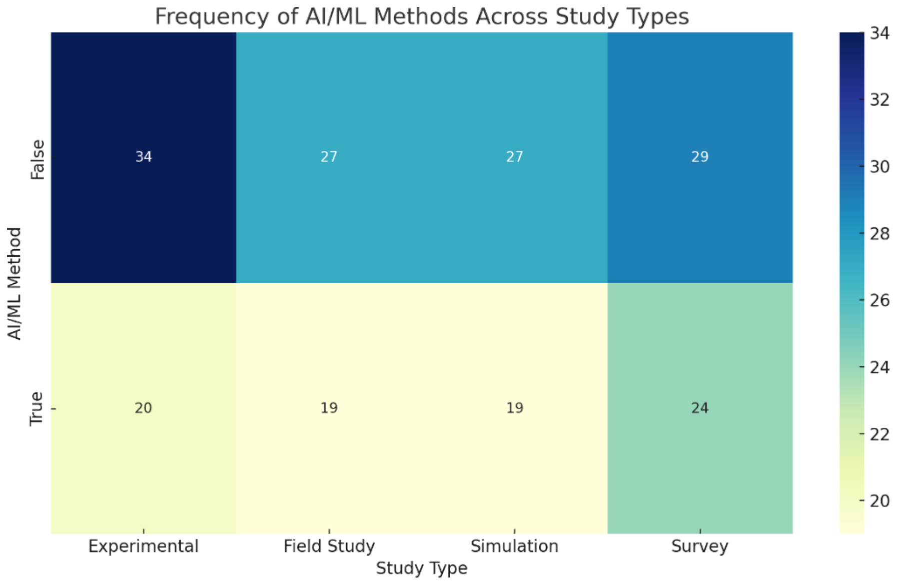

***Figure* 3.** Heatmap showing frequency of AI/ML techniques across study types.

Table 5. Summary Classification of Reviewed Studies (Top 50).

Author(s)	Citation	AI/ML Method	IAQ	Thermal Comfort	Human-Centric	Journal
Adeniran, I. et al.	(Adeniran et al., 2024)	True	×	×	×	International Journal of Scholarly Research in Multidisciplinary Studies, 05(01), pp. 59-67.
Akalin,N.and Loutfi, A.	(Akalin and Loutfi, 2021)	False	×	×	×	Sensors, 21(4).
Al Haris, M. et al.	(Al Haris et al., 2024)	True	×	×	×	Register: Jurnal Ilmiah Teknologi Sistem Informasi, 10(2), pp. 141–150.
Al Mindeel, T. et al.	(Al Mindeel et al., 2024)	True	✓	✓	×	Renewable and Sustainable Energy Reviews, 202.
Albelwi, S.	(Albelwi, 2022)	False	×	×	×	Entropy, 24(4).
Aldausari, N. et al.	(Aldausari et al., 2022)	False	×	×	×	ACM Computing Surveys, 55(2), pp. 30:1-30:25.
Aldegunde, J. et al.	(Aldegunde et al., 2023)	False	✓	×	×	Environments, 10(3).
Almutairi, S. F. B. S. et al.	(Almutairi et al., 2024)	False	×	×	×	Journal of Ecohumanism, 3(8).
Alsulamy, S.	(Alsulamy, 2025)	True	×	×	×	Expert Systems with Applications, 268.
The American Society of Heating, Refrigerating and Air-Conditioning Engineers.	(ASHRAE, 2020)	True	×	×	×	ASHRAE.
Avizenna, M. H.	(Avizenna, 2022)	False	×	×	×	Journal of Applied Data Sciences, 3(4).
Azevedo, B. F. et al.	(Azevedo et al., 2024)	True	×	×	×	Machine Learning, 113(7), pp. 4055–4097.
Babich, F. et al.	(Babich et al., 2023)	True	✓	✓	×	Journal of Building Engineering, 71.

Baldwin, J. W. et al.	(Baldwin et al., 2023)	False	×	✓	×	Environmental Health Perspectives, 131(5).
Bandi, M. et al.	(Bandi et al., 2024)	True	×	×	×	International Journal of Machine Learning, 8(8).
Bao, R. et al.	(Bao et al., 2022)	True	✓	×	×	2022 2nd International Conference on Electrical Engineering and Control Science (IC2ECS), pp. 986–989.
Battineni, G. et al.	(Battineni et al., 2020)	True	×	×	×	Journal of Personalized Medicine, 10(2).
Bhadra, J. et al.	(Bhadra et al., 2023)	False	×	✓	×	SLEEP, 46(1), pp. A96-A97.
Bueno, A. et al.	(Bueno et al., 2021)	False	×	✓	×	Buildings, 11(6).
Bulagang, A. F. et al.	(Bulagang et al., 2020)	False	×	×	×	Informatics in Medicine Unlocked, 20.
Buonomano, A. et al.	(Buonomano et al., 2024)	True	×	×	✓	Energy and Buildings, 303.
Cao, T. et al.	(Cao,T et al., 2021)	False	×	✓	×	Journal of building engineering, 43.
Cao, X. et al.	(Cao,X et al., 2022)	False	×	×	×	Atmosphere, 13(6).
Cheong, S. and Gay-nanova, I.	(Cheong and Gaynanova, 2024)	False	×	×	×	Digital Health, 10.
Chen, K, et al.	(Chen, K. et al., 2020)	True	×	×	×	The Lancet.
Chen, W. et al.	(Chen, W. et al., 2020)	False	×	×	✓	Sustainable Cities and Society, 60.
Chen, Y. et al.	(Chen et al., 2024)	False	×	×	×	IEEE Transactions on Pattern Analysis and Machine Intelligence, 46(3), pp. 1327–1347.
Chung, K. et al.	(Chung et al., 2021)	False	×	×	×	Frontiers in Immunology, 12.
Coman, G. et al.	(Coman et al., 2023)	True	×	×	×	2023 24th International Conference on Control Systems and Computer Science (CSCS), pp. 249-252.
Conceicao, E. and	(Conceicao	True	×	✓	×	Energies, 14(11).

Awbi, H.	and Awbi, 2021)					
Coulburn, L. and Miller, W.	(Coulburn and Miller, 2022)	False	×	×	×	International Journal of Environmental Research and Public Health, 19(3).
Da Silva, I. et al.	(Da Silva et al., 2022)	False	×	×	×	International Journal of Environmental Research and Public Health, 19(24).
Deng, X. and Gong, G.	(Deng and Gong, 2021)	True	×	×	×	Journal of environmental sciences, 99, pp. 336-345.
Dharmasastha, K. et al.	(Dharmasastha et al., 2023)	False	×	✓	×	Energy and Built Environment, 4(5), pp. 543-556.
Dimitroulopoulou, S. et al.	(Dimitroulopoulou et al., 2023)	True	✓	×	×	Environment International, 178.
Dixon, D. et al.	(Dixon et al., 2024)	True	×	×	×	Cureus, 16(5).
Duan, Z. et al.	(Duan et al., 2020)	False	✓	×	×	The Science of the Total Environment, 768.
Duarte, J. M. and Berton, L.	(Duarte and Berton, 2023)	False	×	×	×	Artificial Intelligence Review, 56(9), pp. 9401–9469.
Ebugosi, Q.and Olaboye, J.	(Ebugosi and Olaboye, 2024)	False	×	×	×	Computer Science & IT Research Journal, 5(6).
Efthimiou, O. et al.	(Efthimiou et al., 2023)	False	×	×	×	Statistics in Medicine, 42(8), pp. 1188–1206.
El-Komy, A. et al.	(El-Komy et al., 2022)	False	×	×	×	Information Sciences Letters,11(3), pp. 765-775.
Environmental Protection Agency.	(EPA, 2024)	False	×	×	×	EPA.
Fanger, P.O.	(Fanger, 1970)	False	×	×	×	Technical University of Denmark, Laboratory of Heating and Air Conditioning, Danish Technical Press, Copenhagen
Findik, Y. and Ahmadzadeh, S. R.	(Findik and Ahmadzade	True	×	×	×	arXiv

	h, 2024)					
Foorthuis, R.	(Foorthuis, 2021)	False	×	×	×	International Journal of Data Science and Analytics, 12(4), pp. 297–331.
Fu, M. R.	(Fu, 2021)	False	×	×	×	mHealth, 7.
Fu, N. et al.	(Fu et al., 2022)	True	✓	×	✓	Science of The Total Environment, 851.
Ganatra, S. et al.	(Ganatra et al., 2024)	False	×	×	×	Health Affairs Scholar, 2(12).
Gao, J. and Gong, Z.	(Gao and Gong, 2024)	True	×	×	×	AIMS Mathematics, 9(5), pp. 10478-10493
Gao, S. et al.	(Gao et al., 2018)	False	×	✓	×	Building and Environment, pp. 138, 63–73.
Gatto, M. et al.	(Gatto et al., 2024)	False	×	×	✓	Environmental Health Perspectives, 132(8).
Gonzalo, F. et al.	(Gonzalo et al., 2022)	False	✓	×	×	Sustainability, 14(2).
Greenacre, M. et al.	(Greenacre et al., 2022)	False	×	×	×	Nature Reviews Methods Primers, 2(1), pp. 1-21.
Guan, Z. et al.	(Guan et al., 2023)	True	×	×	×	Cell Reports Medicine, 4(10).
Guarnieri, G. et al.	(Guarnieri et al., 2023)	False	×	×	×	International Journal of Molecular Sciences, 24(11).
Guo, H. et al.	(Guo et al., 2020)	False	×	✓	×	Renewable and Sustainable Energy Reviews, 117.
Guo, J. et al.	(Guo et al., 2023)	False	✓	×	×	Frontiers in Public Health, 11.
Guo, T. et al.	(Guo et al., 2025)	True	×	✓	×	Energy Conversion and Management, 323.

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2.5. Analysis Tools

This study employed automated and manual analytical techniques to ensure methodological rigor, transparency, and replicability, per PRISMA 2020 guidelines (Page et al., 2021). All bibliographic records retrieved and screened through the Mendeley reference manager were exported and processed using the R statistical programming environment (version 4.x).

Structured data extraction and classification were facilitated using custom R scripts developed with packages including tidyverse, dplyr, and readxl. Automated keyword-matching algorithms were implemented to detect key metadata, including AI/ML techniques (e.g., CNN, SVM, fuzzy logic), environmental variables (e.g., PM2.5, CO2, temperature), and human-centric modeling features (e.g., occupant feedback, wearable sensors, adaptive thresholds). Manual verification ensured semantic precision and resolved inconsistencies in the use of terminology and abbreviations across studies.

For comparative analysis, each study was further categorized by methodological design (field study, simulation, experimental setup, or survey), primary AI model type, and environmental focus (IAQ, thermal comfort, or both). These structured classifications supported robust cross-tabulation and trend analysis.

All visual outputs—including keyword frequency plots, co-occurrence diagrams, and heatmaps linking AI techniques to study types—were generated using the ggplot2 package. The hybrid workflow, combining automation and expert validation, enhanced consistency and interpretive accuracy, thereby forming a reproducible foundation for the thematic synthesis in Section 3.

2.6. Reproducibility Statement

To ensure methodological transparency and reproducibility, all stages of this systematic review adhered to the PRISMA 2020 guidelines, with inclusion and exclusion criteria defined a priori and consistently applied during the screening process. Bibliographic data were managed in Mendeley, while all extraction tables, keyword-matching scripts, and classification structures were generated using R (tidyverse and text-mining packages). The complete set of included studies, metadata fields, and analysis code for generating visual analytics (including streamgraphs, Sankey diagrams, bubble plots, and UpSet plots) can be made available upon request. These steps reinforce transparency, support replicability, and enable future extensions of the review.

3. Thematic Synthesis: AI-Based Modeling of IAQ and Thermal Comfort in Human-Centric Building Systems

This section provides a thematic synthesis of 72 peer-reviewed studies, offering an integrated analysis of how Artificial Intelligence (AI) and Machine Learning (ML) techniques have been applied to model Indoor Air Quality (IAQ) and thermal comfort in building environments. The review spans post-2020 research, reflecting renewed global emphasis on occupant health, air quality, and environmental resilience during the COVID-19 pandemic—particularly in energy-constrained and climate-sensitive regions.

The analysis is structured into five core themes: (i) AI-driven prediction of IAQ for pollutant mitigation and intelligent ventilation control; (ii) thermal comfort modeling for personalized, energy-efficient HVAC systems; (iii) integrated approaches that jointly address IAQ and thermal comfort; (iv) human-centric, adaptive, and explainable AI modeling strategies; and (v) research gaps and strategic opportunities for deploying AI in real-world, health-aware building systems.

This synthesis highlights the increasing importance of soft computing methods—such as fuzzy logic, deep neural networks, and hybrid AI architectures—in creating intelligent and context-aware indoor environments. Such approaches enhance model interpretability, support human-in-the-loop decision-making, and offer promising solutions for balancing energy efficiency, occupant comfort, and environmental health in diverse building contexts.

3.1. Trends in AI Applications for Indoor Air Quality (IAQ) Prediction

Indoor Air Quality (IAQ) has emerged as a key priority in post-pandemic building research, with strong links to respiratory health, cognitive performance, and overall well-being. Between 2020 and 2024, AI-based modeling of IAQ accelerated significantly, driven by advances in low-cost sensors, IoT infrastructures, and the need for real-time environmental intelligence. Across the 72 reviewed studies, AI techniques were applied to predict pollutant dynamics, optimize ventilation strategies, and integrate multiple environmental factors for more resilient indoor environments.

Our review identified 23 peer-reviewed studies that focused primarily on AI-driven modeling of IAQ parameters. The most commonly predicted indicators include carbon dioxide (CO_2), fine particulate matter (PM2.5), and volatile organic compounds (VOCs)—all of which are critical for assessing ventilation efficiency, pollutant exposure, and occupant-related emissions. These indicators also play an increasing role in indoor certification schemes and predictive health risk frameworks.

Figure 4 reveals a notable increase in AI-based IAQ studies beginning in 2022, aligned with global policy shifts emphasizing resilient and health-focused buildings. Several methodological patterns are evident across the reviewed literature:

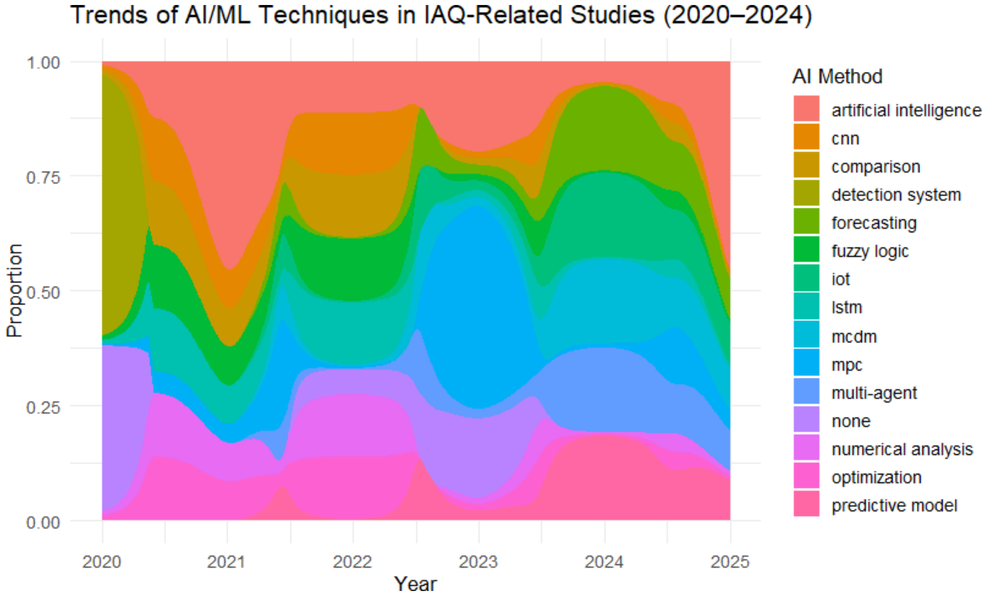

***Figure* 4.** Streamgraph showing the evolution of AI/ML methods applied in Indoor Air Quality (IAQ) studies between 2020 and 2024.

- *Deep learning techniques*, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, dominate time-series forecasting and sensor fusion tasks. These models support anticipatory ventilation control and dynamic IAQ management.
- *Fuzzy logic systems* are used to model subjective perceptions of air freshness and discomfort. Their linguistic interpretability makes them suitable for user-driven and explainable control strategies.
- *Ensemble learning methods*—including Random Forest and XGBoost—show robustness against noisy or incomplete sensor data, offering practical deployment pathways in real-time monitoring systems.
- *Earlier studies* (2020–2021) often utilized black-box models with limited transparency or real-world integration. These initial efforts lacked field validation and overlooked user-centric control interfaces.

More recent studies integrate multi-modal data sources, combining pollutant levels with environmental variables (e.g., temperature, humidity) and occupancy metrics. These sensor-rich frameworks underpin context-aware, adaptive ventilation strategies that optimize IAQ and energy consumption.

However, limitations persist. Few studies have undergone field validation across diverse building types or climatic regions, which limits their external generalizability. The transition from model prediction to building control actuation—such as HVAC adjustments or automated window operations—remains underdeveloped. Moreover, explainability remains insufficiently addressed, hindering trust, regulatory alignment, and integration with public health guidance.

AI-based IAQ modeling has matured from isolated research prototypes to more integrated, sensor-enabled prediction systems. Future work should emphasize large-scale deployment, real-time control integration, and explainable modeling frameworks that bridge the gap between environmental science, occupant well-being, and adaptive building management.

3.2. Advances in AI-Based Thermal Comfort Prediction

Thermal comfort prediction is pivotal in optimizing Indoor Environmental Quality (IEQ) and energy consumption, particularly in warm, humid, or resource-constrained regions. As defined by ASHRAE Standard 55, thermal comfort is "that condition of mind which expresses satisfaction with the thermal environment," influenced by both environmental (e.g., air temperature, humidity, air velocity) and personal (e.g., clothing insulation, metabolic rate) parameters.

Conventional models, such as the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD), continue to dominate thermal comfort assessments. However, these models assume static conditions and homogeneous occupant responses, which limits their relevance in naturally ventilated or mixed-mode buildings. Adaptive thermal comfort models, which accommodate behavioral, cultural, and seasonal variations, are increasingly recognized as more realistic—particularly for buildings in tropical or subtropical climates. Our review identified 31 studies published between 2020 and 2024 that leveraged AI and ML for predicting thermal comfort. Figure 5 illustrates a bubble chart that maps the evolution and frequency of AI methods used during the reviewed period.

Figure 5 illustrates the evolution of AI/ML methods applied in thermal comfort studies during the review period. While deep learning and hybrid approaches have become increasingly prominent, many studies still rely on conventional models or unspecified "AI" techniques, which limit transparency and comparability across benchmarks. The analysis reveals several methodological trends and persistent limitations, summarized as follows:

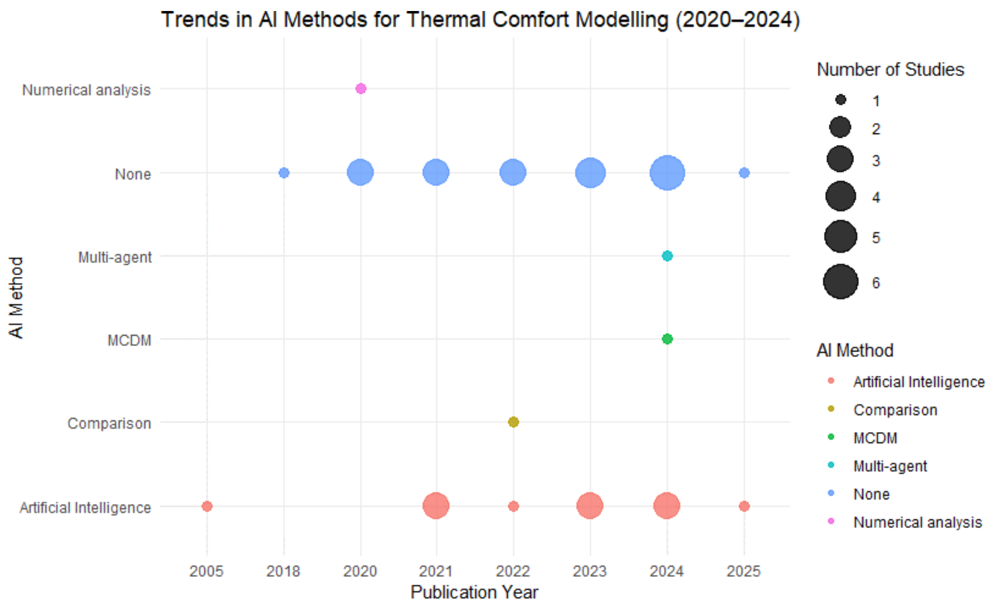

***Figure* 5.** Bubble chart of AI/ML techniques used in thermal comfort prediction (2020–2024). Bubble size indicates the number of studies using each AI method per year.

- Lack of algorithmic transparency: Many papers use general terms like "AI-based prediction" without clearly specifying the models used, limiting reproducibility and comparative benchmarking.
- Underuse of interpretable AI: Despite the suitability of fuzzy logic for modeling subjective comfort states (e.g., "slightly warm," "neutral"), few studies employ this approach. Fuzzy systems align strongly with ASHRAE's 7-point scale and provide explainable frameworks for thermal regulation.
- Limited exploration of advanced modeling paradigms: Multi-agent systems, multi-criteria decision-making (MCDM), and reinforcement learning—despite their potential for personalized comfort optimization—are rarely implemented or remain conceptual.
- Emerging role of deep learning: Long Short-Term Memory (LSTM) and other deep learning architectures are increasingly applied to capture temporal dynamics and seasonal patterns. Still, their deployment in real-world building control remains scarce.

A promising trend is the rise of adaptive and personalized thermal comfort models enabled by wearable sensors and IoT-enabled platforms. These models consider behavioral strategies (e.g., adjusting clothing, operating windows) and real-time contextual inputs, thereby promoting occupant engagement and energy responsiveness.

However, critical limitations persist. Most studies overlook inter-individual differences across demographic or physiological characteristics (e.g., age, health status). Vulnerable populations—such as the elderly, children, or individuals with chronic illnesses—are seldom represented in model development or validation. A few models are also tested in operational environments or integrated into building automation systems. Thermal comfort prediction is often treated in isolation, with insufficient integration of IAQ and energy trade-offs.

AI-based thermal comfort modeling is evolving toward more dynamic, occupant-aware, and interpretable frameworks. Future research should focus on developing inclusive, validated, and context-sensitive models that support human health and sustainable building operations. Embracing explainable AI—such as fuzzy logic or rule-based systems—may bridge the gap between computational precision and human-centric decision-making in thermal environments.

3.3. Toward Integrated AI Models for Holistic Environmental Control

While predictive modeling of Indoor Air Quality (IAQ) and thermal comfort has advanced significantly in recent years, only 9 of the 72 reviewed studies adopted unified frameworks that concurrently addressed both aspects. This fragmented development limits the ability to holistically assess and manage indoor environments—particularly in settings where energy constraints, climatic extremes, and public health vulnerabilities intersect.

The need for integration stems from inherent trade-offs between ventilation and thermal control. For instance, increased ventilation may reduce indoor pollutant concentrations but disrupt thermal equilibrium and elevate energy use—mainly in hot-humid or cold climates. Conversely, limiting outdoor air exchange to conserve energy can increase pollutant levels, posing risks to respiratory and cognitive health. These interdependencies demand predictive models that jointly optimize occupant health, comfort, and energy efficiency.

Figure 6 presents a Sankey diagram that maps the distribution of various AI/ML techniques across three thematic domains: IAQ modeling, thermal comfort prediction, and human-centric adaptation. While general-purpose Artificial Intelligence methods dominate across all three, most applications are siloed, with only a handful adopting integrated strategies.

Only a few techniques—such as Fuzzy Logic, Long Short-Term Memory (LSTM) networks, and Model Predictive Control (MPC)—appear across multiple domains, offering pathways for integrated, dynamic, and adaptive modeling. Hybrid models, such as CNN–LSTM architectures and fuzzy-MPC frameworks, promise to capture nonlinear, time-dependent interactions between IAQ and thermal comfort. However, their adoption often hinges on high-resolution sensor data and computational infrastructure, which may be lacking in low-resource environments.

A significant gap in most integrated studies is the lack of human-centric adaptation. Few models incorporate behavioral feedback, real-time user input, or context-aware comfort thresholds—despite strong evidence that occupant behavior and perception significantly influence environmental quality. This omission weakens responsiveness and inclusivity, especially in multi-use or vulnerable indoor settings such as schools, hospitals, and social housing.

The lack of integrated, interpretable, and human-aware models remains a critical challenge from both sustainability and public health standpoints. Future efforts should prioritize the development of low-cost, scalable, and explainable AI systems capable of supporting climate-sensitive design, adaptive operation, and equitable access to healthier indoor environments.

While integrated IAQ–thermal comfort approaches show promising potential, they remain underrepresented. The limited number of unified frameworks highlights the need for multi-objective, context-aware systems that balance comfort, IAQ, and energy performance. Advancing such integrated solutions will require explainable models, robust data fusion, and validation across diverse building types and climatic conditions.

3.4. Explainable and Human-Aware AI Systems in Indoor Environments

Recent advances in indoor environmental quality (IEQ) research have increasingly embraced human-centric and adaptive modeling approaches prioritizing occupant health, behavioral diversity, and subjective comfort. These frameworks aim to bridge the gap between technical system optimization and user experience by incorporating individual preferences, perceptual feedback, and behavioral responses into AI-driven models for Indoor Air Quality (IAQ) and thermal comfort. Such integration is essential to support the development of inclusive, responsive, and health-oriented building systems.

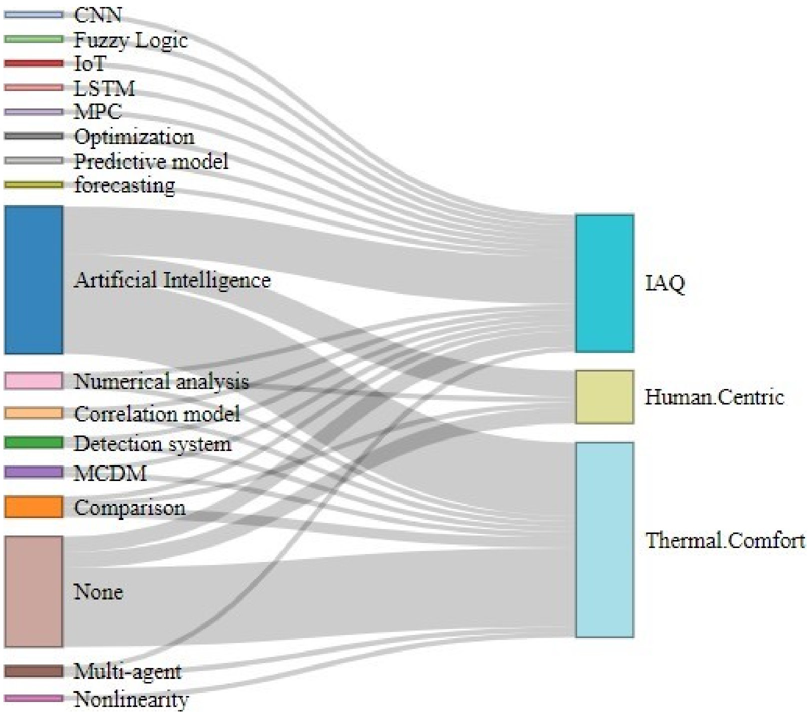

***Figure* 6.** Sankey diagram illustrating AI/ML method distribution across Indoor Air Quality (IAQ), Thermal Comfort, and Human-Centric studies.

Across the reviewed literature, multiple studies incorporated occupant-reported data to calibrate or personalize predictive models. These data sources include post-occupancy surveys, mobile apps, wearable sensors, and sensor-integrated feedback interfaces. Subjective responses—such as thermal sensation votes (TSVs) based on the ASHRAE 7-point scale—were linked with environmental parameters to enable real-time feedback loops and inform dynamic HVAC control that better aligns indoor conditions with user expectations.

As ASHRAE 55 and ISO 7730 define, adaptive thermal comfort models are particularly relevant in naturally ventilated or mixed-mode buildings. These models account for seasonal adaptation, clothing behavior, and external weather conditions to dynamically adjust comfort thresholds. Their integration into AI systems allows climate-sensitive control with minimal reliance on mechanical systems, making them especially suitable for resource-constrained environments.

On the modeling front, explainable AI (XAI) techniques—such as fuzzy logic systems, decision trees, and rule-based reasoning—demonstrated strong potential to embed qualitative perceptions into intelligent control. These models preserve interpretability by accepting linguistic inputs (e.g., "slightly warm," "too dry") and translating them into transparent control actions. A limited number of studies also leveraged deep learning, reinforcement learning, or biometric signals to support user profiling and personalized thermal trajectories.

As illustrated in Figure 7. Only 8 out of 72 studies simultaneously addressed IAQ, thermal comfort, and human-centric dimensions, revealing a significant gap in the current body of research. Most existing models treat occupant feedback as supplementary rather than a core design driver for AI-based control systems.

This underrepresentation highlights a critical opportunity for innovation. The growing availability of biometric sensors, wearable health monitors, and interactive digital platforms presents new opportunities to integrate human agency and diversity into environmental control. Integrating real-time physiological and environmental data enables systems to respond more precisely to individual needs, thereby improving health, comfort, and energy efficiency.

From a public health and sustainability perspective, human-aware AI systems are particularly relevant in vulnerable, high-occupancy environments such as schools, healthcare facilities, and low-income housing. Occupants in these settings often face disproportionate exposure to environmental risks, with limited control over their environment. Embedding explainability and adaptability into predictive models can help bridge this equity gap and support the development of intelligent, just, and inclusive building environments.

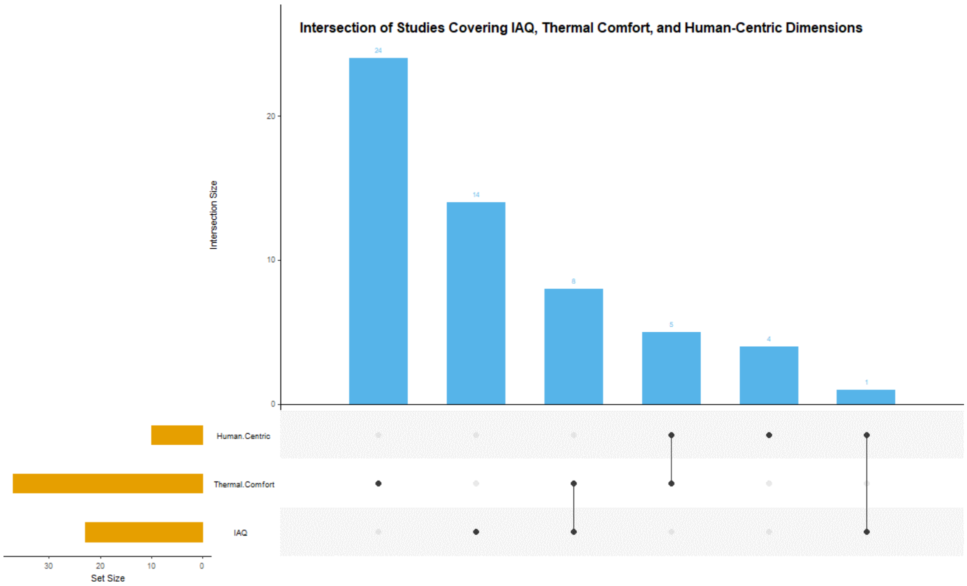

***Figure* 7.** UpSet plot illustrating the number of studies intersecting across Indoor Air Quality (IAQ), Thermal Comfort, and Human-Centric modeling domains. Only eight studies fully integrate all three dimensions, highlighting a substantial research gap.

In summary, explainable and human-aware AI represents a vital research direction for shaping inclusive, health-promoting, and resilient indoor spaces. Future studies should prioritize interpretable, behaviorally informed models that integrate real-world feedback and accommodate diverse needs, supporting data-driven yet empathetic environmental decision-making.

3.5. Research Gaps and Future Directions for Intelligent Indoor Environments

Despite significant progress in applying Artificial Intelligence (AI) for Indoor Air Quality (IAQ) and thermal comfort modeling, several persistent research gaps constrain scalability, deployment readiness, and human-centric alignment. Bridging these gaps is crucial for transitioning from experimental systems to deployable AI frameworks that enhance public health, energy efficiency, and climate resilience across diverse building contexts.

1. *Lack of Integrated, Multi-Objective Frameworks:* Many existing studies independently model IAQ and thermal comfort, failing to address their interdependencies or synergistic trade-offs. This siloed approach limits the development of intelligent systems capable of concurrently optimizing for air quality, thermal conditions, and energy consumption. Integrated multi-objective frameworks are crucial for advancing comprehensive environmental control, particularly in complex or resource-constrained environments.

2. *Limited Personalization and Occupant-Centric Design:* Although adaptive comfort is well-established, few models operationalize real-time personalization based on user preferences, vulnerability, or contextual diversity. Reliance on static standards (e.g., PMV, pollutant thresholds) constrains responsiveness—particularly in high-risk environments such as schools, hospitals, and social housing, where occupant needs may vary significantly. Occupant-centric intelligence remains an underexplored yet crucial area of focus.

3. *Underutilization of Interpretable and Adaptive AI Methods:* Current literature is dominated by black-box methods such as support vector machines and deep neural networks. These offer limited transparency, reducing trust and regulatory acceptance. Explainable and adaptive AI approaches—including fuzzy logic, decision rules, neuro-symbolic models, and reinforcement learning—remain underrepresented, despite their potential to balance performance, interpretability, and control logic alignment.

4. *Scarcity of Real-World Validation:* Most AI models in this domain are tested in simulation or controlled laboratory environments, with minimal field deployment in actual buildings. This limits generalizability across diverse climatic, cultural, and operational contexts. Real-world validation, particularly in naturally ventilated and mixed-mode buildings, is crucial for establishing the robustness and practical utility of these systems.

5. *Weak Integration of Subjective and Objective Data Streams:* While some models incorporate user feedback, they rarely integrate it continuously alongside environmental sensor data. Data fusion

challenges—including temporal alignment, noise handling, and semantic heterogeneity—impede real-time personalization and responsiveness. A lack of standardized protocols also hinders reproducibility and broader adoption.

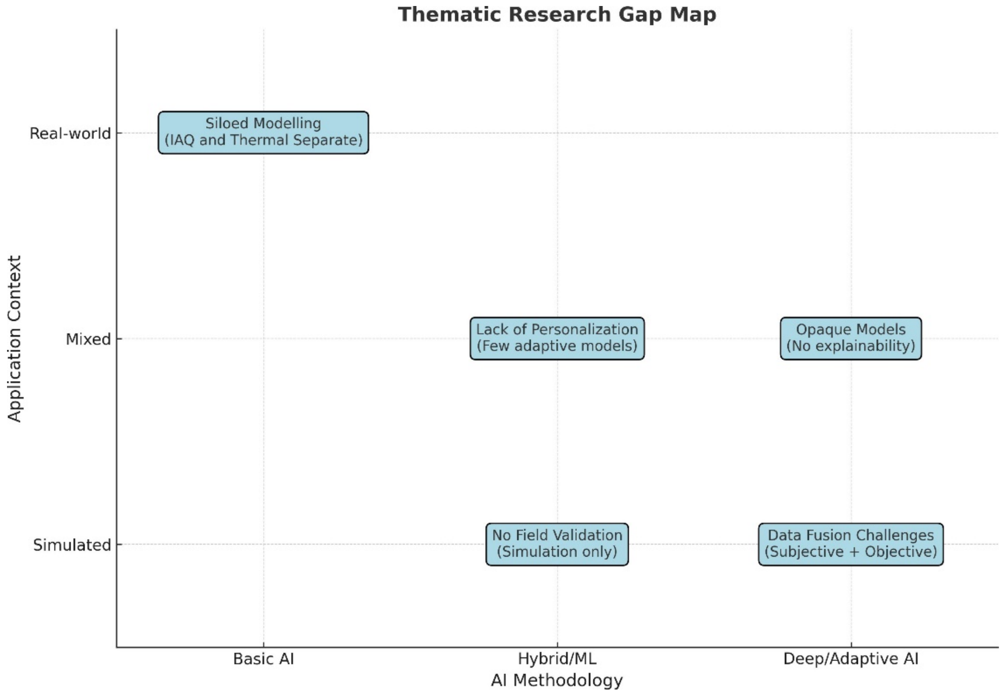

***Figure* 8.** Thematic Research Gap Map highlighting five major challenges across AI methodology (horizontal axis) and application context (vertical axis). Key gaps include siloed modeling, a lack of personalization, opaque models, inadequate field validation, and the fusion of subjective and objective data.

Figure 8 synthesizes these challenges, situating them across methodological sophistication (from basic to adaptive AI) and deployment maturity (from simulation to real-world contexts). Most existing work is clustered in simulation-based or opaque AI zones, with limited advancement into adaptive, interpretable, and field-validated territories.

Moving forward, future research should focus on four strategic directions:

- Developing interpretable, hybrid AI frameworks that combine data-driven accuracy with semantic transparency and regulatory compliance.
- Embedding occupant agency through real-time feedback, user profiling, and behavioral modeling to ensure inclusive, equitable comfort and health outcomes.
- Validating models in operational settings across diverse building typologies and climatic zones to establish transferability and robustness.
- Fusing subjective and objective indicators through multimodal data collection and standardized protocols to support user-informed control systems.

In conclusion, achieving intelligent, human-aware, and sustainable indoor environments requires AI systems that are not only high-performing but also explainable, adaptive, inclusive, and field-proven. Addressing the identified gaps can accelerate the transition from theoretical potential to practical impact—advancing environmental health, energy justice, and occupant well-being at scale.

4. Discussion: Advancing AI-Based Indoor Environmental Modelling Toward Scalable, Health-Centric Building Systems

This review has systematically examined recent advancements in the use of Artificial Intelligence (AI) and soft computing techniques for modeling Indoor Air Quality (IAQ) and thermal comfort—two interdependent dimensions of Indoor Environmental Quality (IEQ) that significantly influence occupant health, building energy consumption, and adaptive system control. Drawing from 72 peer-reviewed studies published between 2020 and 2024, the review captures a critical period marked by the rise of sensor-integrated environments, post-pandemic attention to indoor health, and the growing role of intelligent systems in sustainable building management.

Our analysis highlights notable progress in algorithmic development, including the increasing adoption of deep learning, ensemble approaches, fuzzy logic systems, and hybrid AI models. However, several technical and practical limitations persist. These include fragmented IAQ and thermal comfort modeling, insufficient incorporation of behavioral diversity and contextual adaptation, underutilization of explainable AI (XAI) strategies, and a lack of real-world system validation. These limitations restrict the deployment of intelligent environmental models in dynamic and heterogeneous building contexts, especially those with energy constraints or vulnerable populations.

To support future advancements in soft computing-based indoor environmental systems, this discussion synthesizes key trends and challenges across five core domains: (i) the evolution of AI and soft computing methodologies; (ii) integration challenges across IAQ, thermal, and energy dimensions; (iii) adaptive and human-in-the-loop modeling strategies; (iv) deployment and field validation gaps; and (v) design considerations for inclusive, interpretable, and scalable AI frameworks. Collectively, these themes outline a pathway for developing intelligent, adaptive, and transparent decision-support systems that foster healthier and more resilient indoor environments.

4.1. Evolution of AI Techniques for Indoor Environmental Quality Modelling

The reviewed literature demonstrates a clear trajectory in the evolution of Artificial Intelligence (AI) and soft computing methods for Indoor Environmental Quality (IEQ) modelling, with a marked increase in research output between 2021 and 2024. A wide array of approaches has been employed across the 72 studies analyzed—including artificial neural networks (ANNs), support vector machines (SVMs), decision trees, ensemble methods such as Random Forest and XGBoost, fuzzy inference systems, and deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These techniques have been primarily applied for predictive modeling of Indoor Air Quality (IAQ), thermal comfort indices, and occupant-state recognition, as illustrated in Figures 4 and 5.

The proliferation of time-series models and sensor-driven architectures corresponds with the availability of Internet-of-Things (IoT) platforms and demand-responsive ventilation systems. In particular, hybrid architectures such as CNN-LSTM and optimization-based models have gained attention for their ability to handle nonlinearity, spatio-temporal dependencies, and heterogeneous input variables. Nevertheless, despite this algorithmic diversity, substantial gaps remain in transparency, reproducibility, and system integration.

A recurring issue is the limited disclosure of methodological details. Numerous studies reference "AI" or "machine learning" without specifying model configurations, hyperparameter settings, or evaluation protocols. This lack of standardization hinders comparative benchmarking and challenges the transferability of models across different building types, climates, or occupant profiles.

Moreover, the uptake of interpretable soft computing techniques—such as fuzzy logic systems, decision trees, and rule-based reasoning—remains relatively low. These methods offer inherent linguistic interpretability, making them suitable for environments where explainability, regulatory compliance, and user trust are paramount (e.g., schools, hospitals, and social housing). Their compatibility with subjective input (e.g., thermal sensation scales, IAQ perception) positions them as promising candidates for human-in-the-loop and context-aware systems. The growing relevance of Explainable AI (XAI) in this domain highlights the need to strike a balance between predictive performance and model transparency.

As shown in the Sankey diagram (Figure 6), AI/ML techniques are often unevenly distributed across IAQ, thermal comfort, and human-centric domains—highlighting a pattern of domain-specific silos rather than integrated modelling strategies.

Another emerging trend is the transition from passive prediction to active decision support. While early models focused predominantly on environmental forecasting, recent studies have begun to incorporate intelligent control mechanisms using reinforcement learning, neuro-fuzzy optimization, and Model Predictive Control (MPC). These strategies hold potential for real-time adjustment of HVAC settings, ventilation rates, or window actuation in response to sensor feedback and user preferences. However, implementation remains confined mainly to simulation environments, with limited evidence of deployment in operational buildings.

Collectively, these findings underscore the need for enhanced methodological rigor, clearer reporting of AI architectures, and wider adoption of interpretable soft computing techniques. Hybrid models that combine learning efficiency with explainability offer a promising direction for future research, particularly in applications requiring transparency, user trust, and regulatory accountability.

4.2. Overcoming Fragmentation: Toward Integrated, Multi-Objective Environmental Modelling

One of the most persistent limitations identified in this review is the siloed treatment of Indoor Air Quality (IAQ) and thermal comfort modelling. Among the 72 studies assessed, the vast majority addressed these dimensions independently, with only a small subset attempting to develop integrated frameworks that can simultaneously optimize air quality, thermal satisfaction, and energy consumption. This fragmented approach fails to capture the complex, interdependent nature of indoor environmental systems—where improvements in one domain can generate trade-offs in another.

For instance, increasing mechanical ventilation to dilute CO2 or PM2.5 concentrations may enhance IAQ but can simultaneously degrade thermal comfort or increase HVAC energy demand, particularly in hot-humid or cold climates. Conversely, reducing air exchange to maintain temperature stability or conserve energy can elevate pollutant levels,

leading to health risks or cognitive impairment. These interdependencies necessitate the development of AI-based systems that can reason across domains and provide context-aware control decisions.

As illustrated in Figure 6, most AI/ML techniques remain domain-specific, with limited cross-domain applications capable of addressing IAQ and thermal comfort. Hybrid methods—such as fuzzy logic, MPC architectures, or CNN-LSTM ensembles—are beginning to emerge in response to these challenges, but remain primarily confined to simulation environments with limited real-world evaluation.

Despite this clear need, integrated, multi-objective optimization frameworks remain relatively scarce. While a few studies explore hybrid or soft computing-based control architectures, few have been evaluated under operational conditions, and even fewer incorporate real-time feedback, uncertainty quantification, or adaptive reconfiguration capabilities.

A further challenge is the escalating complexity of integrated models, which often rely on deep learning or ensemble methods prioritizing predictive performance over interpretability. While such methods excel at learning complex data patterns, they often operate as opaque "black boxes," undermining stakeholder confidence and hindering deployment in settings that require transparency, auditability, or regulatory compliance (e.g., healthcare facilities, schools, and low-income housing). This raises the need for interpretable AI approaches—such as fuzzy rule-based systems, multi-criteria decision-making (MCDM), or symbolic reasoning—that can explain trade-offs and enable user-in-the-loop decision-making.

Another significant gap is the limited integration of energy performance metrics within environmental modelling. Despite the well-established links between IAQ, thermal regulation, and HVAC energy demand, few studies concurrently model all three. As a result, current systems are often ill-suited to support sustainable building operations or energy-resilient interventions in resource-constrained environments.

A shift toward holistic, modular, and human-aware frameworks is needed to address these challenges. Future work should develop AI systems that treat IAQ, thermal comfort, and energy use as co-evolving variables, leveraging hybrid soft computing techniques to strike a balance between accuracy, transparency, and adaptability. Developing open datasets, shared benchmarking protocols, and transferable models will be crucial to harmonizing research efforts and facilitating cross-domain innovation. Ultimately, overcoming this fragmentation is crucial to achieving AI systems that are intelligent, explainable, resilient, and aligned with global sustainability and health equity objectives.

4.3. Human-in-the-Loop Modelling: Toward Inclusive and Adaptive Environmental Systems

Despite growing interest in occupant-centric strategies, this review finds that operational implementation of human-in-the-loop modelling remains limited in current AI-based indoor environmental quality (IEQ) research. Fewer than 15% of the 72 reviewed studies integrated real-time occupant feedback, adaptive comfort thresholds, or personalized control strategies, revealing a significant disconnect between theoretical intent and practical execution.

Most AI frameworks continue to model occupants as static or homogeneous variables, often relying on snapshot surveys or aggregated comfort metrics. While subjective responses such as thermal sensation votes and perceived air quality offer valuable insights, they are rarely captured dynamically or linked with real-time decision-making. The increasing availability of wearable sensors, mobile applications, and IoT-enabled devices presents untapped opportunities to continuously monitor physiological signals (e.g., skin temperature, heart rate), behavioral adaptations (e.g., window opening, clothing adjustment), and subjective comfort perceptions.

Interpretable AI methods—such as fuzzy logic systems, decision trees, and rule-based engines—offer a promising pathway for translating linguistic feedback (e.g., "slightly cool," "too stuffy") into actionable control logic. These approaches preserve semantic clarity and support transparency, making them wellsuited for deployment in sensitive environments such as schools, hospitals, or elderly care facilities. However, their application remains underrepresented in the reviewed literature.

In addition, modern explainability techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are rarely used to uncover how occupant-related features influence AI predictions in environmental control contexts. This limits model accountability, stakeholder engagement, and the interpretability necessary for regulatory compliance or public trust—particularly in environments where vulnerable populations are present.

A further gap is the limited attention to inter-individual variability and temporal dynamics in occupant preferences. Thermal comfort and IAQ perception are influenced by numerous factors, including circadian rhythms, metabolic state, age, gender, health status, clothing insulation, seasonal adaptation, and cultural context. The lack of adaptive systems capable of learning and evolving in response to user feedback restricts the personalization and inclusivity of AI-driven environmental control.

As illustrated in Figure 7, only a minority of studies intersect across IAQ, thermal comfort, and human-centric dimensions—highlighting a critical research gap in designing fully integrated and occupant-aware systems.

To advance human-in-the-loop modelling, future research should prioritize:

- Multimodal data fusion: Combining physiological, behavioral, environmental, and subjective inputs to develop context-aware, adaptive control frameworks;
- Personalized and interpretable AI: Leveraging fuzzy inference systems, user profiling, and explainable models to support transparent and individualized system behavior;
- Accessible feedback interfaces: Designing lightweight, user-friendly platforms—via wearables, mobile apps, or ambient sensors—for continuous and non-intrusive occupant interaction.

Embedding occupant agency into environmental modelling is essential for developing inclusive, responsive, and health-aligned indoor systems. By transitioning from passive, environment-centric designs to adaptive, user-informed frameworks, future AI applications can better support comfort, well-being, and energy efficiency while advancing broader environmental equity and public health goals.

4.4. Validation and Real-World Deployment: Bridging the Gap from Lab to Practice

This review highlights a critical bottleneck in the progression of AI-based indoor environmental modelling: the lack of systematic validation and deployment in real-world settings. While numerous studies demonstrate promising predictive accuracy in controlled experiments or simulation-based environments, only a small subset evaluate their models under operational conditions—such as in schools, hospitals, or naturally ventilated buildings. This gap significantly constrains the ecological validity, transferability, and impact potential of AI-driven approaches intended for health-centric and energy-aware building control.

The contextual sensitivity of indoor environments poses substantial challenges for generalization. Thermal loads, occupant behavior, HVAC interactions, and climatic influences vary dynamically and often nonlinearly—conditions rarely replicated in simulation setups. The robustness, adaptability, and real-time responsiveness of AI models remain largely untested without longitudinal, in-situ validation.

This issue is especially pressing in the post-pandemic era (2020–2024), during which public awareness of IAQ and occupant well-being has increased markedly. Despite a surge in research activity, most reviewed studies still operate within isolated lab settings, overlooking the operational complexities of real-world deployment. Moreover, very few models incorporate adaptive feedback mechanisms or test interoperability with existing building management systems (BMS), which limits their readiness for large-scale integration.

Another significant concern is the absence of standardized evaluation protocols. Across the 72 reviewed studies, there was notable inconsistency in reporting standard performance metrics such as RMSE, MAE, and $R2$. Additionally, considerable heterogeneity exists in data preprocessing, cross-validation strategies, feature selection, and hyperparameter tuning—factors hindering reproducibility and objective performance comparison.

Transparency in model development is also frequently lacking. Key methodological components such as overfitting prevention, uncertainty estimation, sensitivity analysis, and validation against external or unseen datasets are often omitted. Few studies assess the reliability of subjective data inputs (e.g., inter-rater agreement in comfort surveys), raising questions about data integrity and interpretability.

As visualized in Figure 8, current research efforts are concentrated in simulation-heavy, AI-centric quadrants with limited attention to real-world deployment and adaptive modelling. The lower-right quadrant—representing interpretable, validated, and context-aware systems—remains underexplored. Advancing this space is essential for translating AI innovations into practical, equitable, and sustainable indoor environmental solutions.

To bridge this validation gap and facilitate real-world impact, future research should focus on:

- Empirical validation: Deploying AI models in real-time, occupied buildings across diverse typologies and climate zones to test their resilience and contextual performance;
- Harmonized benchmarking: Establishing standardized performance metrics, reference datasets, and experimental protocols to support reproducibility and comparative evaluation;
- Transparent reporting: Providing detailed documentation of model architecture, training routines, feature selection, tuning procedures, and error analysis to ensure scientific rigor;
- Holistic evaluation frameworks: Integrating subjective occupant feedback, physiological signals, and environmental sensor data to assess the functional efficacy of predictive control systems.

Collaborative initiatives—such as open-access repositories, multi-institutional testbeds, and cross-disciplinary partnerships—will enable robust validation and accelerate the transition from proof-of-concept models to deployable intelligent environmental systems. Without such infrastructure, the transformative potential of AI for resilient, health-aligned, and adaptive indoor environments will remain unrealized.

4.5. Pathways Forward: Designing Inclusive and Deployable AI for Healthy, Resilient Buildings

Synthesizing insights from the thematic analysis, this review identifies four strategic directions to guide the next wave of innovation in AI-based modelling of Indoor Air Quality (IAQ) and thermal comfort. These directions offer a roadmap for transitioning from siloed, lab-scale prototypes to inclusive, scalable, and health-responsive systems capable of transforming indoor environmental quality in real-world buildings.

- Hybrid and Explainable AI Frameworks: Integrating interpretable AI techniques—such as fuzzy logic systems, decision trees, and model-agnostic explanation tools (e.g., SHAP, LIME)—with deep learning and reinforcement learning offers a powerful hybrid approach. These methods can model complex, nonlinear relationships while maintaining transparency, which is essential for stakeholder trust and deployment in sensitive environments, such as healthcare facilities and schools.
- Human-Centric Design and Adaptive Feedback: Future systems must embed human-in-the-loop paradigms that leverage real-time feedback from occupants. Incorporating subjective data—through mobile interfaces, wearable sensors, or thermal sensation surveys—enables personalization, supports user autonomy, and aligns building operation with actual comfort needs, especially for vulnerable or diverse user groups.
- Field-Tested and Generalizable Models: A critical priority is robust in-situ validation across different building types, climate zones, and user populations. Research should move beyond simulation and test AI systems in operational environments to evaluate their adaptability, effectiveness, and resilience. Creating open-access datasets, standardized protocols, and collaborative testbeds will accelerate reproducibility and real-world adoption.
- Fusion of Subjective and Objective Data Streams: Combining quantitative environmental measurements (e.g., CO2, temperature, humidity) with qualitative perceptions (e.g., comfort, freshness) in unified modelling frameworks can enhance prediction accuracy, contextual awareness, and user satisfaction. Multimodal data fusion—across physiological, behavioral, and environmental channels—will be pivotal in building intelligent systems that are both responsive and empathetic.

Collectively, these priorities represent a paradigm shift toward AI systems that are technically robust, inclusive, interpretable, and grounded in public health and environmental equity goals. The lower-right quadrant in Figure 8—representing validated, adaptive, and human-aware models—remains underexplored yet strategically vital for impact.

This review adhered to PRISMA guidelines and applied a rigorous screening methodology. However, some limitations warrant consideration. A few pre-protocol studies were included, and several reviewed articles lacked sufficient detail on AI architectures or training parameters, necessitating interpretive classification. A few full-text sources were excluded due to access constraints, and only English-language publications were considered.

The 2020–2024 scope was intentionally selected to capture shifts in research behavior following the COVID-19 pandemic—particularly increased awareness of indoor health, the uptake of low-cost sensing technologies, and the rise of AI integration in building systems. Despite the temporal restriction, the review provides a focused yet comprehensive synthesis of a rapidly evolving field.

In conclusion, converging hybrid-XAI frameworks, occupant-centered design, validated real-world deployment, and multimodal data fusion offer a transformative pathway for AI-enabled indoor environments. Future systems should be adaptive, equitable, and responsive—supporting energy and operational efficiency, human well-being, comfort, and environmental resilience in an increasingly uncertain world.

4.6. Limitations and Future Directions

This review is subject to several limitations that should be acknowledged. First, the analysis focuses on studies published between 2020 and 2024 to capture post-pandemic research behavior; however, this may exclude earlier foundational work relevant to AI-based IAQ and thermal comfort modeling. Second, only English-language publications were considered, which may introduce language bias. Third, some studies lacked sufficient methodological detail—particularly regarding AI architectures, hyperparameters, and validation procedures—requiring interpretive classification. Future reviews should expand the temporal scope, include additional language sources, and incorporate meta-analysis techniques where datasets are comparable. Future research in this domain should prioritize interpretable hybrid AI frameworks, standardized evaluation protocols, real-world deployment and validation, and the fusion of subjective and objective data streams to support more adaptive, inclusive, health-oriented building environments.

5. Conclusion

This review comprehensively analyzes 72 peer-reviewed studies published between 2020 and 2024, focusing on the application of Artificial Intelligence (AI) and soft computing techniques for modeling Indoor Air Quality (IAQ) and thermal comfort. The review bridges engineering, environmental health, and human-centric design domains by adopting a holistic perspective to evaluate how AI-driven approaches reshape predictive modelling and control in built environments.

A key contribution of this work lies in its synthesis of AI methods across both IAQ and thermal comfort—two traditionally siloed domains—through an integrated, multi-objective lens. The review highlights the growing methodological sophistication in the field, including the emergence of deep learning, hybrid CNN–LSTM models, and soft computing methods such as fuzzy inference systems and rule-based reasoning. It also highlights how these approaches are applied for environmental prediction, personalized comfort estimation, and intelligent control.

Through thematic synthesis and visual analytics—including streamgraphs, bubble charts, Sankey diagrams, UpSet plots, and thematic research gap maps—this review identifies four critical challenges that constrain the scalability and real-world utility of current AI-based systems for indoor environmental quality modeling. First, there is limited adoption of unified, multi-objective frameworks that jointly optimize Indoor Air Quality (IAQ), thermal comfort, and energy performance, despite their inherent interdependencies. Second, interpretable AI approaches—such as fuzzy logic systems, decision trees, SHAP, and LIME—remain underrepresented, limiting transparency and stakeholder accountability. Third, few studies incorporate dynamic human feedback or account for behavioral diversity, highlighting a lack of occupant-aware modeling and personalization. Finally, the scarcity of real-world validation and in-situ deployment raises concerns about the generalizability, adaptability, and operational robustness of current models across diverse building contexts and climates.

To address these limitations, the review advocates for a new generation of AI-enabled indoor environmental systems that are predictive, adaptive, explainable, human-centric, and context-aware. Future research should prioritize hybrid AI–XAI frameworks that combine learning efficiency with transparency; integrate multimodal data sources, including real-time subjective and physiological feedback; and validate models through field trials in diverse building types and climate zones.

These directions are particularly relevant for advancing intelligent building systems in sensitive or resource-constrained environments, such as schools, healthcare facilities, and affordable housing, where the stakes for health, comfort, and equity are high. By aligning AI development with principles of explainability, personalization, and environmental justice, future systems can support sustainable indoor management that responds to both technical and human needs.

While this review was limited to studies published in English and focused on the 2020–2024 period, its findings provide a robust foundation for guiding interdisciplinary research at the intersection of AI, environmental quality, and soft computing. Ultimately, this review outlines a strategic roadmap for transforming indoor environments into adaptive, inclusive, and intelligent spaces, thereby contributing to the broader goals of sustainable development, public health, and the deployment of trustworthy AI.

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