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LESSONS FROM BIM AND AI FOR INDOOR ENVIRONMENTAL QUALITY MANAGEMENT: APPLICATIONS TO UNDERGROUND SPACE ENVIRONMENTAL QUALITY RESEARCH

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Abstract: Academic literature has well established the impact of indoor environmental quality on human wellbeing (health, comfort and productivity). In the case of underground spaces, increasing evidence suggests that the wellbeing of underground occupants may be compromised due to unique indoor environmental constraints. While Building Information Modelling (BIM) and artificial intelligence (AI) hold promise in addressing such risks, the potential these technologies to redefine the affordances of indoor environmental quality in underground spaces remains unknown. Through a bibliometric analysis of scholarly literature, a mapping of the evolution of BIM and AI technology usage in enhancing indoor environmental comfort is reported. The study identified seven thematic clusters of the use of BIM-AI in general IEQ research, with a surge in publications since 2019. However, a significant gap remains in applying BIM-AI technologies for underground space research. Among the technologies reviewed, supervised machine learning emerged as the predominant approach. Insight from the bibliographic themes suggests transformative opportunities to engineer underground spaces into adaptive environments that actively enhance human wellbeing. These include BIM-visualized early warning systems for occupant comfort management and AI-driven automated HVAC control. The results serve as a foundation for designers and policymakers to leverage BIM's data integration capabilities and AI's predictive insights to achieve both health-centric design and operation of underground spaces.

Keywords: Wellbeing, Indoor environmental quality, BIM, AI, Underground Space.

1. INTRODUCTION

Wellbeing is shaped by several factors, including external environmental stressors (e.g., climate), social determinants (e.g., lifestyle), and work-related factors (e.g., occupational stress) [1,2]. However, given the amount of time people stay indoors, significant attention has been directed toward the role of indoor parameters in shaping the psychophysiological wellbeing of building occupants [3,4,5]. A plethora of studies have demonstrated how indoor environmental variables (e.g., poor thermal conditions, inadequate lighting and noise) within suboptimal ranges act as stressors with cumulative effects on building occupants' psychophysiological wellbeing [4]. Hence there is the need to maintain optimal indoor environmental quality to safeguard building occupants' wellbeing. In addition, building use is dynamic, rarely remaining consistent over time. Shifts in occupancy patterns, functional changes and renovations can lead to deviations from initial design assumptions during the operational phase [6]. These changes necessitate proactive building management to address evolving occupant needs [6], while also considering locational constraints (e.g., aboveground vs. underground contexts) that may further complicate adaptations [7,8].

Emerging evidence suggests an increase in psychophysiological complaints of underground occupants [4]. Locating underground facilities within entrapped earth results in unconventional indoor environmental performance. This presents unique design challenges that differ significantly from those of aboveground considerations. Underground spaces are significantly impacted by site-specific geological conditions (e.g. soil composition, groundwater, thermal retention) [7,8]. In addition, the lack of comprehensive, context-sensitive

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design guidelines further complicates the design process, as the functional needs of each space (e.g., commercial malls versus subways) and geological variations give rise to unique demands for indoor environmental quality [4].

Adopting digital technologies in the AEC industry has unlocked opportunities to enhance IEQ. Among these, artificial intelligence (AI) and Building Information Modeling (BIM) stand out as transformative technologies (e.g. [9,10,11]). BIM has gained prominence as a core technology, enabling parametric design optimization during the design stage of a project. Supported by AI, it could facilitate active control and monitoring of IEQ during operations through early hazard prediction analysis [12]. However, despite the extensive application of these technologies in aboveground building projects, a preliminary literature search revealed a significant gap in their deployment for analyzing and managing IEQ in underground facilities. A possible reason could be the prioritization of construction productivity and safety-centric issues of underground facilities [13,4]. Thus, it remains unclear which technologies are most applicable and how they might address the unique complexities of underground spaces. Notably, this contrasts with aboveground IEQ research, where BIM-AI technologies have been successfully implemented in field studies to address IEQ issues. Therefore, analyzing the empirically validated aboveground applications provides transferable frameworks for adapting BIM-AI technologies to underground contexts. Hence, this study employed bibliographic coupling analysis to map knowledge networks in digital indoor environmental quality research. The goal was to visualize themes from implementing BIM-AI technologies in aboveground IEQ research, towards identifying transferable knowledge for underground space research. By doing so, the study reveals actionable insights for adapting Industry 4.0 solutions to solve underground space IEQ management challenges.

1.1. Overview of IEQ and health conditions in underground spaces

According to Chan et al. [4], post-occupancy IEQ evaluation studies show that actively controlled factors (e.g., lighting, air quality, thermal conditions, and noise) and design factors (e.g., building layout and ergonomics) significantly affect the health of underground occupants. The cumulative impact of these IEQ factors have also been confirmed in some studies. These studies span multiple scales, addressing not only the psychophysiological health effects, but also implications for comfort and work performance. In particular, indoor air quality is reported to have pronounced effects on health perceptions. Elevated pollutant levels have been found to increase stress, anxiety, and other negative psychological impacts. Likewise, sick building syndrome (SBS) is prevalent in various underground spaces, with affected individuals usually attributing it to perceived poor indoor air quality [4]. The evidence gathered to date spans various underground space types (e.g. shopping malls, subways, and offices) and suggests that the nature and intensity of indoor stressors may vary according to the functional use of the space [4]. Accordingly, there is a need for innovative approaches to address them.

1.2. The Concept of Healthy BIM

BIM describes the process of creating a digital representation of a building's physical and functional characteristics. The embedded information about the facility forms a reliable basis for decision-making throughout its lifecycle [14]. The end product is a digitized model comprising building components represented by digital objects that carry computable graphic and data attributes, identifying them to software applications, as well as parametric rules that enable them to be manipulated intelligently. Recognizing BIM's capacity to address IEQ hazards, Rice [15] introduced the 'Healthy BIM' framework. The framework describes BIM's capacity to incorporate key IEQ health indicators (e.g., illuminance, acoustics, thermal comfort) during the design phase. This allows simulations to optimize IEQ and reduce health risks. Through Delphi technique, 14 feasible health indicators were identified [15]. However, current implementations remain limited by their reliance on static IEQ assumptions. Hence, data-driven intelligence, real-time pattern-driven simulation, and analysis for the control and management of building systems, particularly those in underground spaces, could be beneficial.

1.3. Overview of Artificial Intelligence

Artificial intelligence describes the concept of developing intelligent machines and computer systems that exhibit humanlike intelligence. These systems can reason, learn, and solve problems similarly to humans by processing and learning from data as input. Given these capabilities, researchers are exploring their usefulness in tackling AEC industry problems [16]. Abioye et al. [16] described several key technologies as summarized in table 1. Their framework served as the analytical basis for this review, guiding the identification and classification of AI applications in the IEQ research domain.

Table 1. *Types of AI technologies*

Field	Description
Machine learning	Concerned with the design and use of computer programs to learn from experience or past data for modelling, control or prediction
Computer Vision	Focuses on artificial simulation of the human visual system
Optimization	Concerned with making decisions and choices that provides the best outcomes given a set of constraints
Natural Language	Creating models that mimic linguistic capabilities of human beings
Robotics	Automated devices that carry out physical activities n real world
Knowledge-based systems	Concerned with machine decision making based on existing knowledge

2. RESEARCH METHODOLOGY

The authors adopted a two-step approach for this study. First, the state-of-the-art research on the applications of BIM-AI in the context of IEQ is presented. Subsequently, studies specific to underground spaces were identified. This approach enabled a direct comparison of the maturity of underground space research relative to the broader domain of BIM-AI and IEQ research.

2.1. PRISMA approach

A systematic literature review on BIM-AI applications for IEQ management was conducted, adhering to PRISMA guidelines [17]. PRISMA is widely accepted in AEC review studies [18,19], as it ensures reproducibility and transparency of review studies. Accordingly, only studies demonstrating practical applications of BIM-AI to IEQ challenges, with empirical validation or real-world implementation, were selected. Conceptual studies were excluded unless substantiated by data, ensuring the synthesis reflected evidence-based advancements. The steps followed by this study are outlined below and in Fig. 1.

2.2. Step 1: Collection of publications

In sourcing studies, Scopus database was selected due to its broader coverage of scientific publications, faster indexing [20], and usefulness for science mapping [21]. Given the varying terminologies used for available artificial intelligence variants, and to ensure comprehensive coverage, the authors leveraged the capability of ChatGPT to generate an initial list of 40 potential keywords. Subject-matter experts then refined this list by removing off-topic terms (e.g., “AI in Education,” “AI in Finance”), retaining only keywords relevant to IEQ outcomes (i.e. health, comfort, or productivity). The final search string (ref. Table 2) combined these terms with Boolean operators, targeting titles, abstracts, and keywords.

The authors limited the search to research articles and conference papers in the engineering field published in English-language journals from 1993 to 20th June 2025. The initial search yielded 726 records. After applying the specified limitation criteria, the Scopus database yielded 349records. Following the removal of 32 papers (comprising review articles and off-topic content identified through title, keyword, and abstract screening), 317 unique records remained for full-text evaluation. During the full-text assessment stage, each article was evaluated for eligibility to be included in the review. Out of this process, 21 other articles were omitted for several reasons (studies focusing on mathematical modelling rather than AI, outdoor transitional areas, etc.), leaving 296 studies deemed eligible for inclusion in the review.

Table 2. *Keywords employed*

Aim	Search strings
Environmental Quality	"Indoor environmental quality" OR “ieq” OR "thermal comfort" OR "air quality" OR "acoustic comfort" or “lighting comfort”
Digital technologies	"Building Information Modelling" OR "BIM" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "Supervised Learning" OR "Unsupervised Learning" OR "Reinforcement Learning" OR "Artificial Neural Networks" OR "Recurrent Neural Networks" OR "Pattern Recognition" OR "Predictive Analytics" OR "Fuzzy Logic" OR "Support Vector Machine" OR "Decision Trees" OR "Random Forest" OR "Clustering" OR "K-means"
Outcomes	"physiological" OR "psychological" OR "productivity" OR "well-being"

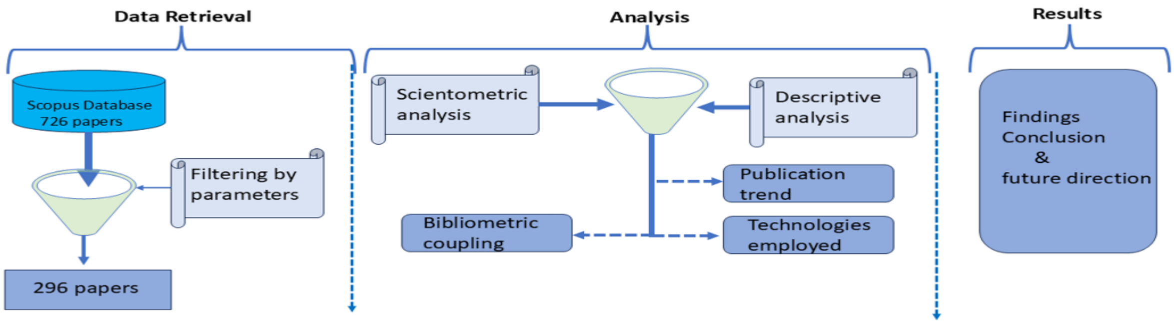


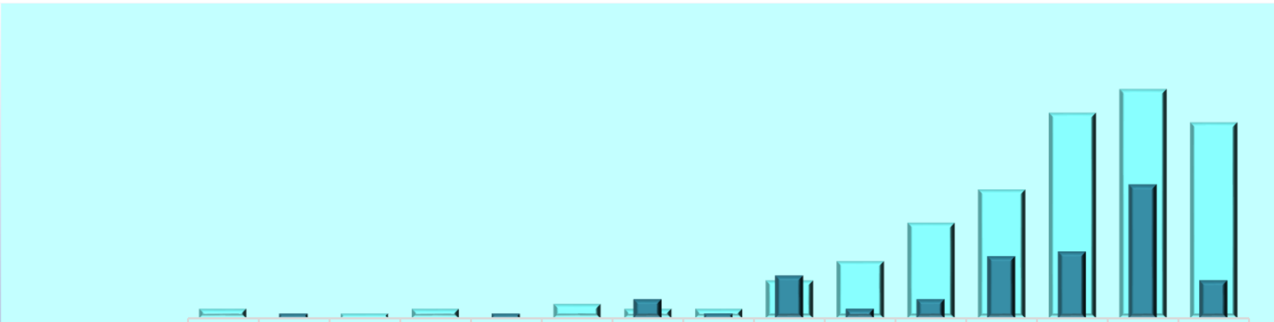
Figure 1. Overview of research methodology

2.3. Step 2: Quantitative analysis of studies

The selected papers were analyzed to map out publication trends, and BIM/AI employed for IEQ research. Following this, a Social Network Analysis was conducted using VOS viewer (v1.6.20) to examine intellectual structures and research networks [21]. Specifically, a bibliographic coupling network was generated. In this network, the size of the node reflects the influential nature of a study (i.e. Its citation frequency), line thickness indicates co-occurrence strength, and the proximity of nodes reveals thematic relationships.

3. RESULTS OF BIM-AI IN IEQ RESEARCH

3.1. Descriptive Analysis of Publications



	2009	2011	2012	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025*
Article	2	0	1	2	0	3	2	2	8	12	20	27	43	48	41
Conference	0	1	0	0	1	0	4	1	9	2	4	13	14	28	8

Article Conference

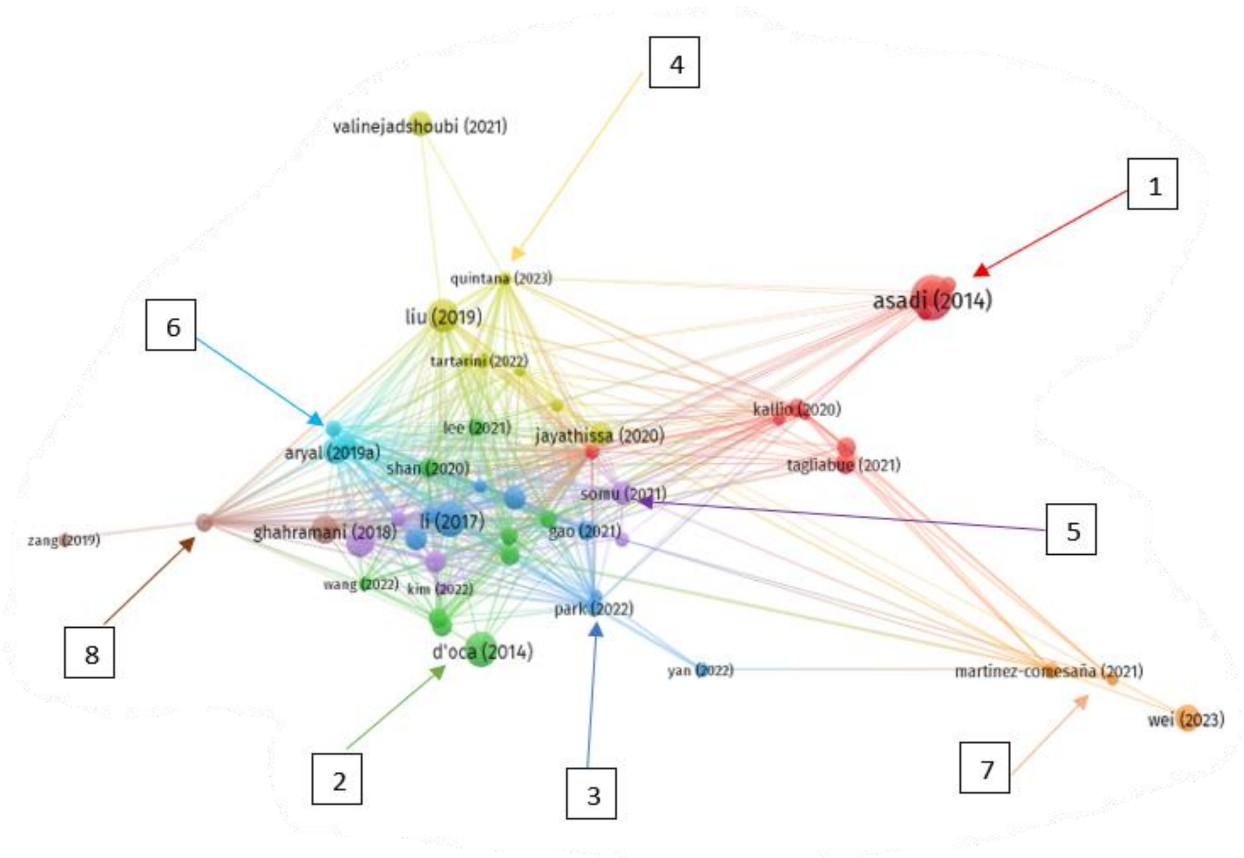
Figure 2. Trend of Publications

Figure 2 shows publication trends (from 1987 to 20th June 2025). Of the 296 studies reviewed, 211 (69%) were journal articles, while 85 others (31%) were conference papers. While the application of AI in AEC dates back to the 1980s [22], our dataset indicates AI as the first application for IEQ, and this emerged in 2009, demonstrating an adoption lag. Notably, 94% of publications (277 papers) appeared between 2019 and 2025, reflecting an accelerated research interest aligned with industry transformation trends [21]. This surge coincides with growing recognition of the value of data, from occupant behavior to indoor environmental metrics [23] for data-driven IEQ optimization.

3.2. Bibliographic coupling analysis

As a preliminary investigation, bibliographic coupling was employed to map the intellectual structure of the BIM-AI IEQ research domain. This method offers an advantage over keyword co-occurrence, by minimizing network noise from inconsistent terminology. Bibliographic coupling technique was particularly warranted given the wide and subtle application of BIM and AI technologies across the IEQ landscape, which often results in varied and fragmented keyword usage. Thus, instead of relying on frequently used terms, bibliographic coupling groups studies based on their shared citations [24, 25], allowing for a more stable and meaningful representation of thematic connections. A document is said to be bibliographically coupled when cited in two or more documents' references [25]. This technique helps discover clusters, similar to co-citation analysis, based on content similarity [24,25].

Using VOS viewer, a network threshold of 27 citations per document was set. Of the 296 articles selected for this study, a network was established across 46 interconnected papers (Fig. 3a). In this network, the proximity of nodes reflects the similarity of the reference lists of the studies, suggesting a relatedness of their content [25]. Bigger nodes signify articles with more robust bibliometric connections [24]. Seven clustered were identified and were numerically labelled 1 to 7. In addition, the timeline visualization (Fig. 3b) was generated to complement the bibliographic network by showing how the field has developed. It uses a color gradient where older publications appear in purple and more recent studies are highlighted in yellow. Hence, a visual cue of the discipline's development is presented [24]. After carefully evaluating the studies in each cluster, descriptive names were manually assigned to highlight the primary research focus of each cluster.



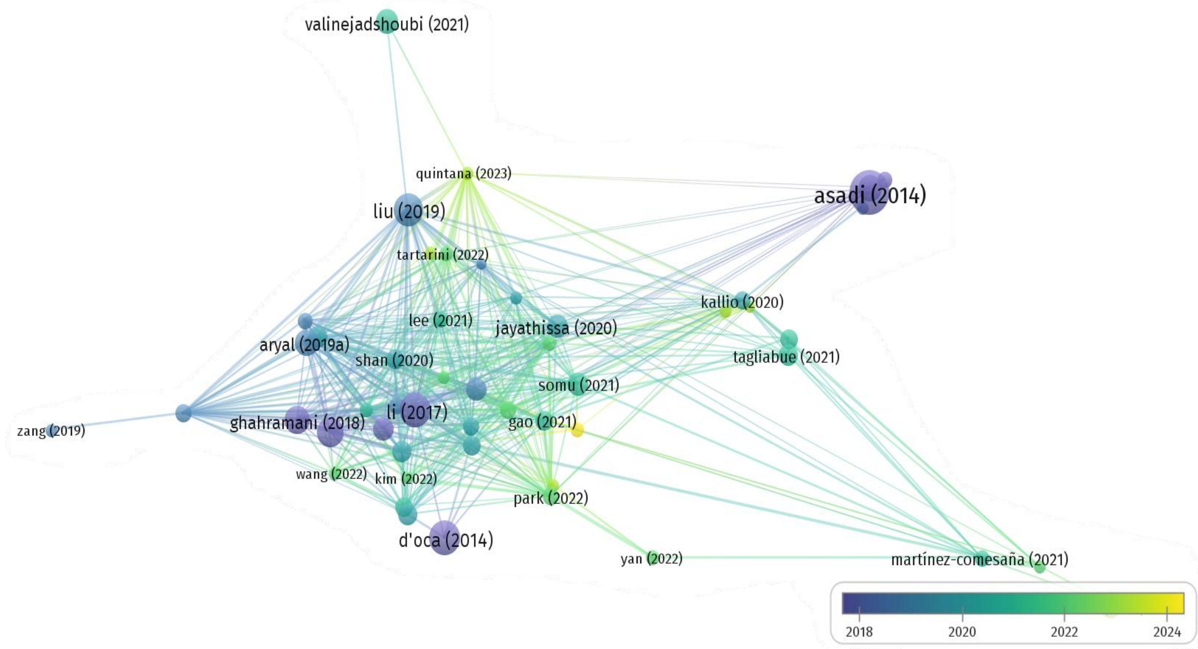


Figure 3. Bibliographic citation couplings and overlay timeline network clusters

3.2.1. Cluster 1: Towards non-intrusive personalized thermal comfort via physiological sensing

Cluster 1 encompasses a broad range of studies. The studies represent a shift from conventional thermal comfort modelling from traditional multi-input approaches (which combine environmental data, physiological signals, and subjective feedback) toward non-intrusive, physiology-driven personalized models.

Subjective perception of thermal conditions is a key input in comfort models, making user feedback essential [26]. Nevertheless, researchers have noted that obtaining longitudinal subjective input from building occupants can be disruptive and impractical, limiting its viability for continuous monitoring [26]. The studies in this cluster explore how accurate physiological sensing, such as bio signals from wearables, can autonomously infer thermal preferences, enabling real-time smart HVAC systems to operate dynamically without interrupting occupants. The studies also highlight the using machine learning to select between natural and mechanical ventilation based on current environmental conditions, balancing thermal comfort with energy efficiency. These approaches signal a shift toward adaptive, occupant-centered climate control that moves beyond traditional HVAC reliance [27].

3.2.2. Cluster 2: Occupant behavior and real-time automated HVAC control using physiological data from wearable devices

Buildings often use more energy than predicted, primarily due to unanticipated behaviors of building users at the design stage, particularly in HVAC (Heating, Ventilation, and Air Conditioning) systems [28]. This cluster explores how the actions and comfort perceptions of building occupants influence their control of building systems. Studies first collect data using sensors that track human actions and indoor conditions like temperature and humidity, subjective information on how warm or cold occupants feel, and physiological measurements like metabolic rate, heart rate or body temperature via wearing sensors to determine accurate thermal comfort models [28,29]. Such models lead to the development of real-time smart systems that adjust heating and cooling automatically, based on what indoor occupants actually need, using thermal sensor readings from smartwatch wearables. The goal is to make buildings more energy-efficient while keeping building occupants comfortable.

3.2.3. Cluster 3: Evaluating single sensor methods and scalable techniques for personalized thermal comfort modelling

Studies in this cluster evaluate the predictive accuracy of different sensing technologies, such as wearable devices, environmental sensors, and thermal imaging, for personalized thermal comfort assessment. Predicting human comfort in built environments is complex due to the input of several interacting variables (e.g. physiological, psychological, and environmental factors) [30]. Conventional data-driven personalized thermal comfort models rely on multi-sensor data, including environmental factors (e.g. humidity, temperature, air velocity), physiological inputs (e.g. skin temperature, variable heart rate, metabolic rate, blood pressure) and subjective feedback [e.g., 31]. However, these approaches can be impractical for real-world deployment since they are laborious and often require multiple sensors, which are expensive [31]. The studies in this cluster explore whether single-sensor models (using only environmental or physiological data) can achieve comparable accuracy at a lower cost, e.g. 31]. The goal of these studies is to reduce costs and complexity while maintaining the predictive power of the models developed. In parallel, some studies apply transfer learning to improve model adaptability across different spaces.

3.2.4. Cluster 4: Integrated multi-objective optimization approaches for high-performance indoor environments

Meeting the indoor environmental quality needs of building occupants is inextricably linked to a building's energy demands. Optimizing IEQ requires balancing multiple, often competing factors, including system types, their interaction with building materials, and the permeability of the building envelope [32]. Striking this balance is essential to ensuring a healthy and comfortable indoor environment while maintaining energy efficiency. By leveraging the capabilities of AI and BIM, complex trade-offs are optimized. For example, some studies focus on reducing energy consumption while maximizing comfort and health.

3.2.5. Cluster 5: Methodological advances in personalized thermal comfort modelling

This group explores efforts to advance personalized thermal comfort models. Researchers in this cluster test a range of input features and algorithms to determine the most effective parameters that significantly shape people's perception of indoor thermal conditions. [33]. In a similar manner, some studies explore strategies to overcome the challenges of data scarcity and imbalance, employing strategies such as transfer learning and synthetic data augmentation to address these limitations [34]. The overlay timeline indicates that this cluster is emerging as a shift to more recent core research work.

3.2.6. Cluster 6: Modeling and optimizing indoor environmental quality under data-constrained conditions

Machine learning techniques for modeling indoor environmental quality (IEQ) conditions and system diagnostics often depend heavily on the availability and quality of historical data. However, real-world datasets are frequently affected by gaps, noise, or imbalance, which can compromise model accuracy and reliability [35]. This research cluster focuses on developing optimized machine learning solutions that address data-related challenges [e.g. 36]. The studies leverage a range of strategies such as advanced optimization algorithms and cross-building knowledge transfer to enhance predictive accuracy in data-constrained settings.

3.2.7. Cluster 7: Real-time spatial monitoring and cohort-based onboarding approaches for personalized thermal comfort modeling

This cluster brings together two complementary research directions that aim to enhance personalized thermal comfort in buildings through practical, data-efficient, and scalable solutions. The first group of studies focuses on the development of real-time early warning systems for thermal discomfort. Leveraging BIM-IoT integration, these frameworks continuously monitor building conditions to detect thermal risks and deliver timely alerts via smartphones or smartwatches to responsible parties [37]. The systems support proactive interventions and facilitate dynamic environmental adjustments across various building zones.

The second set of studies focuses on developing personalized comfort models based on group dynamics. It involves cohort-based modeling, where individual comfort predictions are created by matching new occupants to similar profiles using new occupants' basic personal profile data [e.g. 38]. Together, the studies demonstrate a shared goal of supporting scalable thermal comfort adaptation, enabling multi-zone management across entire buildings for different group dynamics, and efficiently adapting thermal comfort for new building occupants.

Table 3. *List of BIM-AI in IEQ influential Studies*

S/N	Label	Description	Cluster	Citations
1	Li (2017)	Personalized human comfort in indoor building environments under diverse conditioning modes	1	247
2	Ghahramani (2018)	Towards unsupervised learning of thermal comfort using infrared thermography	1	148
3	Farhan (2015)	Predicting individual thermal comfort using machine learning algorithms	1	95
4	Wang (2019)	Predicting Older People's Thermal Sensation in Building Environment Through a Machine Learning Approach: Modelling, Interpretation, And Application	1	93
5	Shan (2020)	Towards Non-Intrusive and High Accuracy Prediction of Personal Thermal Comfort Using A Few Sensitive Physiological Parameters	1	71

6	Cheng (2019)	Nidl: a pilot study of contactless measurement of skin temperature for intelligent building	1	53
7	Na (2019)	Development Of a Human Metabolic Rate Prediction Model Based on the Use of Kinect-Camera Generated Visual Data-Driven Approaches	1	49
8	Yeom (2021)	Local Body Skin Temperature-Driven Thermal Sensation Predictive Model for The Occupant's Optimum Productivity	1	39
9	Song (2022)	Using machine learning algorithms to multidimensional analysis of subjective thermal comfort in a library	1	27
10	D'oca (2014)	A data-mining approach to discover patterns of window opening and closing behavior in offices	2	238
11	Pigliautile (2020)	Assessing occupants' personal attributes in relation to human perception of environmental comfort: measurement procedure and data analysis	2	81
12	Deng (2020)	Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband	2	70
13	Morresi (2021)	Sensing physiological and environmental quantities to measure human thermal comfort through machine learning techniques	2	64
14	Wu (2020)	Using electroencephalogram to continuously discriminate feelings of personal thermal comfort between uncomfortably hot and comfortable environments	2	59
15	Yang (2022)	Comparison of models for predicting winter individual thermal comfort based on machine learning algorithms	2	55
16	Lee (2021)	Physiological sensing-driven personal thermal comfort modelling in consideration of human activity variations	2	46
17	Wang (2022)	Towards wearable thermal comfort assessment framework by analysis of heart rate variability	2	31
18	Aryal (2019a)	A comparative study of predicting individual thermal sensation and satisfaction using wrist-worn temperature sensor, thermal camera and ambient temperature sensor	3	126
19	Jayathissa (2020)	Humans-as-a-sensor for buildings—intensive longitudinal indoor comfort models	3	92
20	Aryal (2020)	Thermal comfort modeling when personalized comfort systems are in use: comparison of sensing and learning methods	3	85
21	Gao (2021)	Transfer learning for thermal comfort prediction in multiple cities	3	74
22	Aryal (2019b)	Skin temperature extraction using facial landmark detection and thermal imaging for comfort assessment	3	45
23	Bueno (2023)	Hierarchical and k-means clustering to assess thermal dissatisfaction and productivity in university classrooms	3	31
24	Quintana (2020)	Balancing thermal comfort datasets: we gan, but should we?	3	31
25	Asadi (2014)	Multi-objective optimization for building retrofit: a model using genetic algorithm and artificial neural network and an application	4	427
26	Zhou (2009a)	Optimization of ventilation system design and operation in office environment, part i: methodology	4	134
27	Tagliabue (2021)	Data driven indoor air quality prediction in educational facilities based on iot network	4	87
28	Kallio (2021)	Forecasting office indoor co2 concentration using machine learning with a one-year dataset	4	73
29	Kallio (2020)	Assessment of perceived indoor environmental quality, stress and productivity based on environmental sensor data and personality categorization	4	54
30	Zhou (2009b)	Optimization of ventilation systems in office environment, part ii: results and discussions	4	46
31	Jalilzadehazhari (2019)	Achieving a trade-off construction solution using BIM, an optimization algorithm, and a multi-criteria decision-making method	4	31
32	Chaudhuri (2018)	Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology	5	165
33	Somu (2021)	A hybrid deep transfer learning strategy for thermal comfort prediction in buildings	5	91
34	Chaudhuri (2020)	Machine learning driven personal comfort prediction by wearable sensing of pulse rate and skin temperature	5	78
35	Nguyen (2024)	Modelling building HVAC control strategies using a deep reinforcement learning approach	5	36
36	Arakawa Martins (2022)	Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioral and environmental variables	5	34
37	Sulzer (2023)	Predicting indoor air temperature and thermal comfort in occupational settings using weather forecasts, indoor sensors, and artificial neural networks	5	29
39	Wei (2023)	Lstm-autoencoder-based anomaly detection for indoor air quality time-series data	6	132

40	Park (2022)	Prediction of individual thermal comfort based on ensemble transfer learning method using wearable and environmental sensors	6	53
42	Martínez-Comesaña (2021)	Use of optimized mlp neural networks for spatiotemporal estimation of indoor environmental conditions of existing buildings	6	47
38	Yan (2022)	Data-driven prediction and optimization of residential building performance in Singapore considering the impact of climate change	6	39
41	Martínez-Comesaña (2022)	Optimization of thermal comfort and indoor air quality estimations applied to in-use buildings combining nsga-iii and xgboost	6	30
44	Liu (2019)	Personal thermal comfort models with wearable sensors	7	231
45	Valinejadshoubi (2021)	Development of an IoT and BIM-based automated alert system for thermal comfort monitoring in buildings	7	108
46	Tartarini (2022)	Personal comfort models based on a 6-month experiment using environmental parameters and data from wearables	7	36
43	Quintana (2023)	Cohort comfort models using occupant's similarity to predict personal thermal preference with less data	7	27

4. REVIEW OF BIM-AI IN IEQ RESEARCH FOR UNDERGROUND SPACES

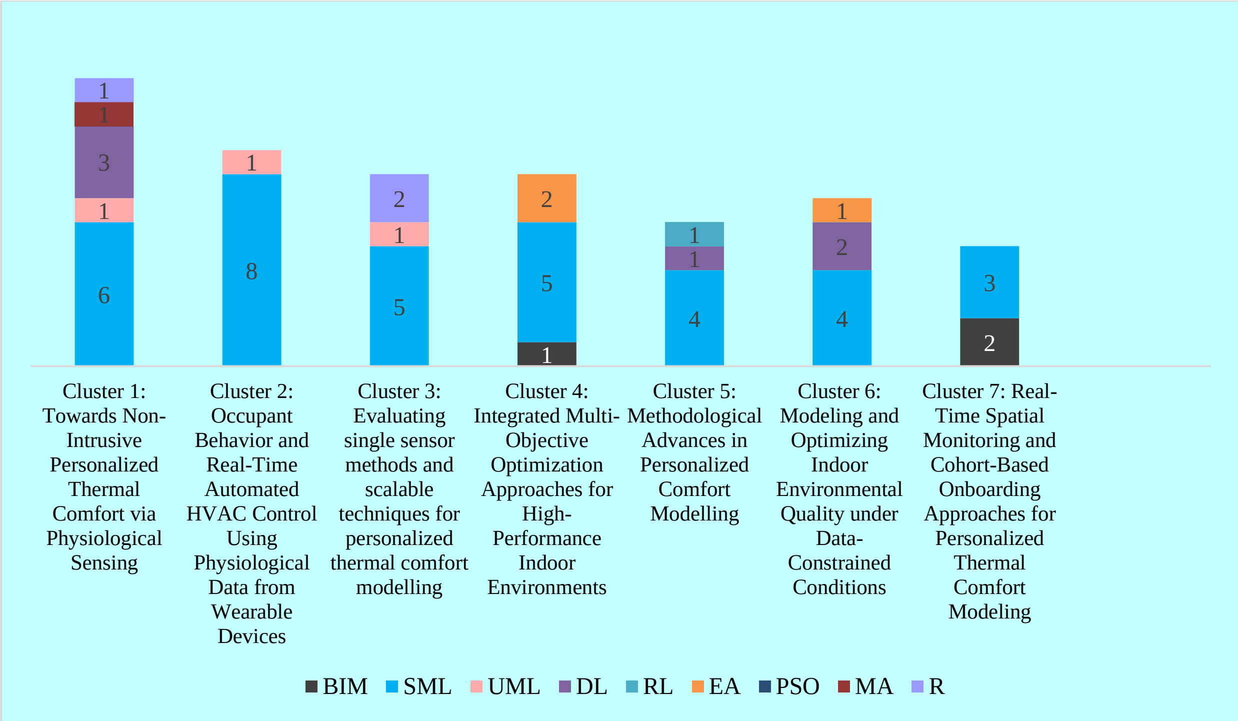
Following the same search protocol outlined in Sections 2.1 and 2.2, the authors extended the search to include underground space-related terms (“underground” or “tunnelling” or “subway”). The search yielded four initial results, of which only two met the inclusion criteria defined in Section 2.

Table 4. *Results from Underground Specific BIM-AI in IEQ Studies*

S/N	Authors	Title	Document Type	Relevance	Technologies used
1	Shi et al., 2024	A review of applications of electroencephalogram in thermal environment: Comfort, performance, and sleep quality	Article	✕	✕
2	Chen et al., 2025	Study of Factors Influencing Thermal Comfort at Tram Stations in Guangzhou Based on Machine Learning	Article	✕	✕
3	Wang et al., 2025	An efficient thermal comfort prediction method for indoor airflow environment using a CFD-based deep learning model	Article	☑	Deep Learning (CNN, LSTM)
4	Marzouk et al.,2013	Evaluation of indoor environmental quality for subways in Egypt using BIM	Conference	☑	BIM

5. BIM-AI TECHNOLOGIES IN IEQ RESEARCH

Fig.4 visually maps the spread of BIM-AI technologies across seven thematic clusters, indicating the methodological concentration within each. Analysis of the 46 bibliographic coupling studies reveals that supervised machine learning (SML) algorithms dominate the field, accounting for 64% of implementations (35 studies). The skew towards SML likely stems from the predominance of studies focusing on thermal comfort prediction, where labeled data (e.g., occupant feedback, sensor-derived variables) have conventionally served as inputs for regression models, which align conceptually with SML. All technologies were systematically classified using Abioye et al.’s [12] framework, which provides a comprehensive taxonomy of AI subtypes deployed in AEC research.



Key= BIM =Building information modelling, SML=Supervised machine learning, UML= Unsupervised machine learning, DL= Deep Learning, RL=Reinforcement Learning, Evolutionary algorithms, PSO= Particle Swarm Optimization, MA= Motion Analysis, R= Recognition

Figure 4. Distribution of BIM-AI Technologies employed across bibliographic clusters

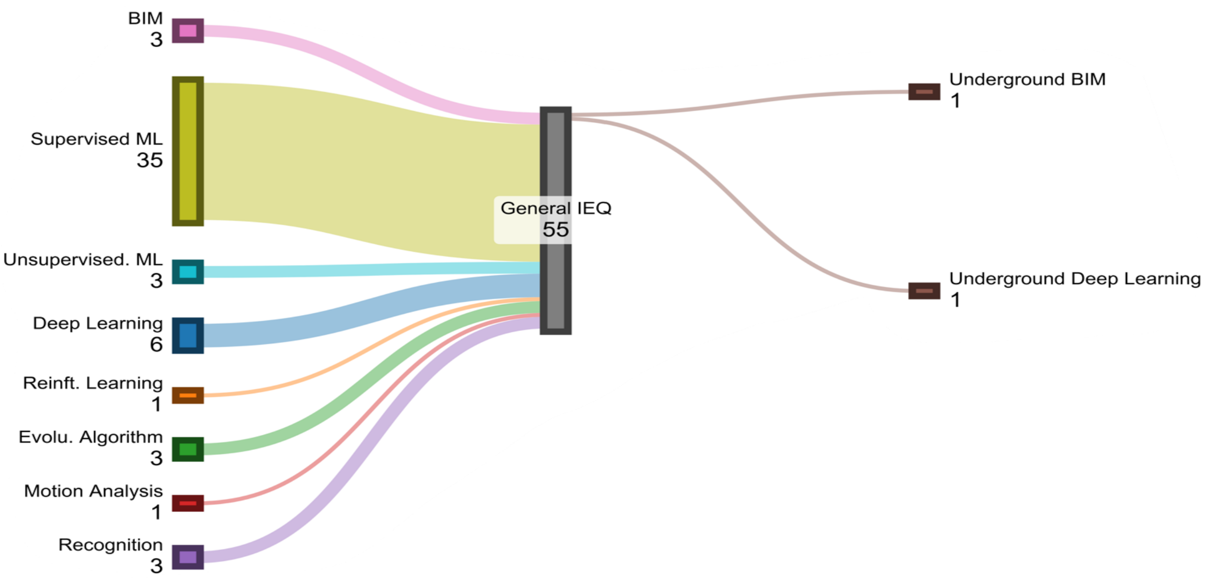


Figure 5. A Comparative Analysis of BIM-AI Technologies in General IEQ Research versus Underground Space Studies

6. CONCLUSION

This study presents a scientometric analysis of the evolution of BIM and AI applications in IEQ research. Bibliographic coupling analysis revealed 46 core influential studies, grouped under 7 themes. Whereas the analyzed themes revealed significant advancements in using BIM-AI technologies for above-ground IEQ management, a gap in applying such technologies in underground space IEQ optimization was noted. This is particularly concerning, given the heightened psychophysiological health risks associated with underground environments, where factors such as perceived confinement and limited natural stimuli may amplify occupants' responses to IEQ conditions. The integration of AI technologies, leveraging multivariate data (e.g., environmental sensors, human physiological responses, and energy metrics), could bridge this gap by enabling real-time IEQ optimization and improving social acceptance of underground spaces. Current literature predominantly focuses on thermal comfort, yet opportunities exist to explore underrepresented variables such as acoustic quality (critical in subway stations) and lighting dynamics (vital in windowless environments). Furthermore, while supervised learning dominates existing research, future studies should expand into unsupervised learning (for pattern discovery in unlabeled data) and computer vision (to analyze human behavior interactions in underground spaces). Such advancements could reveal more profound insights into occupant adaptation mechanisms and context-specific IEQ thresholds, ultimately leading to healthier and more productive underground environments. In particular, given that humans are multimodal and experience IEQ holistically, AI techniques like unsupervised machine learning can help identify hidden patterns through multivariate analysis (e.g. interactions between lighting and thermal comfort or lighting and acoustics) [20], revealing new affordances for enhancing IEQ in underground spaces.

7. ACKNOWLEDGEMENT

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8. BIBLIOGRAPHY

[1] Intergovernmental Panel on Climate Change (IPCC). (2022). Climate change 2022: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama, Eds.). Cambridge University Press.
[2] Burgard, S. A., & Lin, K. Y. (2013). Bad jobs, bad health? How work and working conditions contribute to health disparities. American Behavioral Scientist, 57(8), 1105-1127.
[3] Mujan, I., Anđelković, A. S., Munćan, V., Kljajić, M., & Ružić, D. (2019). Influence of indoor environmental quality on human health and productivity - A review. Building and Environment, 144, 208-220.
[4] Chan, I. Y., Twum-Ampofo, S., Ababio, B. K., Ghansah, F. A., & Li, S. (2025). Towards a whole process engineering approach for enhancing physical and psychological health in underground environments: A systematic review. Tunnelling and Underground Space Technology, 161, 106530.
[5] Sadick, A. M., & Issa, M. H. (2018). Assessing physical conditions of indoor space enclosing elements in schools in relation to their indoor environmental quality. Journal of Building Engineering, 20, 520-530.
[6] Langston, C., Wong, F. K., Hui, E. C., & Shen, L. Y. (2008). Strategic assessment of building adaptive reuse opportunities in Hong Kong. Building and environment, 43(10), 1709-1718.
[7] Tan, Z., Roberts, A. C., Christopoulos, G. I., Kwok, K. W., Car, J., Li, X., & Soh, C. K. (2018). Working in underground spaces: Architectural parameters, perceptions and thermal comfort measurements. Tunnelling and Underground Space Technology, 71, 428-439.
[8] Zhou, Y., & Zhao, J. (2016). Assessment and planning of underground space use in Singapore. Tunnelling and Underground Space Technology, 55, 249-256.
[9] D'Amico, A., Bergonzoni, G., Pini, A., & Currà, E. (2020). BIM for healthy buildings: An integrated approach of architectural design based on IAQ prediction. Sustainability, 12(24), 10417.
[10] Opoku, D. G. J., Perera, S., Osei-Kyei, R., Rashidi, M., Bamdad, K., & Famakinwa, T. (2024). Digital twin for indoor condition monitoring in living labs: University library case study. Automation in Construction, 157, 105188.
[11] Aguilar, A. J., de la Hoz-Torres, M. L., Ruiz, D. P., & Martínez-Aires, M. D. (2022). Monitoring and assessment of indoor environmental conditions in educational building using building information modelling methodology. International Journal of Environmental Research and Public Health, 19(21), 13756.
[12] Tang, S., Shelden, D. R., Eastman, C. M., Pishdad-Bozorgi, P., & Gao, X. (2019). A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. Automation in Construction, 101, 127-139.
[13] Tender, M. L., & Couto, J. P. (2016). "Safety and health" as a criterion in the choice of tunnelling method.
[14] Chen, K., Lu, W., Peng, Y., Rowlinson, S., & Huang, G. Q. (2015). Bridging BIM and building: From a literature review to an integrated conceptual framework. International Journal of Project Management, 33(6), 1405-1416.
[15] Rice, L. (2021). Healthy BIM: the feasibility of integrating architecture health indicators using a building information model (BIM) computer system. Archnet-IJAR: International Journal of Architectural Research, 15(1), 252-265.
[16] Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., ... & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. Journal of Building Engineering, 44, 103299.

[17] Petticrew, M., & Roberts, H. (2008). Systematic reviews in the social sciences: A practical guide. John Wiley & Sons.

[18] Chen, H., Dong, Z., & Chan, I. Y. (2025). Biometric Evaluation and Immersive Construction Environments: A Research Overview of the Current Landscape, Challenges, and Future Prospects. Journal of Construction Engineering and Management, 151(7), 03125005.

[19] Martin, M.L., Prince, A.A., Frimpong, S. and Thomas, N.S., 2025. Material Passports in Construction Waste Management: A Systematic Review of Contexts, Stakeholders, Requirements, and Challenges. Buildings, 15(11), p.1825.

[20] Čulić, A., Nižetić, S., Gambiroža, J. Č., & Šolić, P. (2025). Progress in data-driven thermal comfort analysis and modeling. Energy and Buildings, 327, 115599.

[21] Darko, A., Chan, A. P., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. Automation in Construction, 112, 103081.

[22] Gero, J. (Ed.). (2012). Design optimization. Elsevier.

[23] Minassian, R., Mihăiță, A. S., & Shirazi, A. (2025). Optimizing indoor environmental prediction in smart buildings: A comparative analysis of deep learning models. Energy and Buildings, 327, 115086.

[24] Zhang, Y., Chen, J., Liu, H., Chen, Y., Xiao, B., & Li, H. (2024). Recent advancements of human-centered design in building engineering: A comprehensive review. Journal of Building Engineering, 84, 108529.

[25] Pandey, D. K., Hassan, M. K., Kumari, V., Zaied, Y. B., & Rai, V. K. (2024). Mapping the landscape of FinTech in banking and finance: A bibliometric review. *Research in International Business and Finance*, *67*, 102116.

[26] Ghahramani, A., Castro, G., Karvigh, S. A., & Becerik-Gerber, B. (2018). Towards unsupervised learning of thermal comfort using infrared thermography. Applied Energy, 211, 41-49.

[27] Li, D., Menassa, C. C., & Kamat, V. R. (2017). Personalized human comfort in indoor building environments under diverse conditioning modes. Building and Environment, 126, 304-317.

[28] D'Oca, S., & Hong, T. (2014). A data-mining approach to discover patterns of window opening and closing behavior in offices. Building and Environment, 82, 726-739.

[29] Pigliautile, I., Casaccia, S., Morresi, N., Arnesano, M., Pisello, A. L., & Revel, G. M. (2020). Assessing occupants' personal attributes in relation to human perception of environmental comfort: Measurement procedure and data analysis. Building and Environment, 177, 106901.

[30] Jayathissa, P., Quintana, M., Abdelrahman, M., & Miller, C. (2020). Humans-as-a-sensor for buildings—intensive longitudinal indoor comfort models. Buildings, 10(10), 174.

[31] Aryal, A., & Becerik-Gerber, B. (2019). A comparative study of predicting individual thermal sensation and satisfaction using wrist-worn temperature sensor, thermal camera and ambient temperature sensor. Building and Environment, 160, 106223.

[32] Asadi, E., Da Silva, M. G., Antunes, C. H., Dias, L., & Glicksman, L. (2014). Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. Energy and buildings, 81, 444-456.

[33] Chaudhuri, T., Soh, Y. C., Li, H., & Xie, L. (2020). Machine learning driven personal comfort prediction by wearable sensing of pulse rate and skin temperature. Building and Environment, 170, 106615.

[34] Somu, N., Sriram, A., Kowli, A., & Ramamritham, K. (2021). A hybrid deep transfer learning strategy for thermal comfort prediction in buildings. Building and Environment, 204, 108133.

[35] Wei, Y., Jang-Jaccard, J., Xu, W., Sabrina, F., Camtepe, S., & Boulic, M. (2023). LSTM-autoencoder-based anomaly detection for indoor air quality time-series data. IEEE Sensors Journal, 23(4), 3787-3800.

[36] Park, H., & Park, D. Y. (2022). Prediction of individual thermal comfort based on ensemble transfer learning method using wearable and environmental sensors. Building and Environment, 207, 108492.

[37] Valinejadshoubi, M., Moselhi, O., Bagchi, A., & Salem, A. (2021). Development of an IoT and BIM-based automated alert system for thermal comfort monitoring in buildings. Sustainable Cities and Society, 66, 102602.

[38] Quintana, M., Schiavon, S., Tartarini, F., Kim, J., & Miller, C. (2023). Cohort comfort models—Using occupant's similarity to predict personal thermal preference with less data. Building and Environment, 227, 109685.

[39] Chinazzo, G., Andersen, R. K., Azar, E., Barthelmes, V. M., Becchio, C., Belussi, L., ... & Wei, S. (2022). Quality criteria for multi-domain studies in the indoor environment: Critical review towards research guidelines and recommendations. Building and Environment, 226, 109719.